ONLINE APPENDIX

“The Perpetuity of the Past: Transmission of Political Inequality across Multiple Generations”

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A.1 Details on Data and Measures

This section provides a description of the data availability, data sources and the main variables used in this study.

A.1.1 Data Availability and Replication

We use individual level data from Swedish registers. The data material is located on an encrypted server to which we have to log in through a remote desktop application in order to perform all of our data analyses. Due to the sensitivity of the data, we are under contractual and ethical obligation not to distribute these data to others.

For those researchers who want to replicate our results there are two ways to get access to the administrative data. The first way is to order the data directly from Statistics Sweden (SCB). Statistics Sweden presently requires that researchers obtain a permission from a Swedish Ethical Review Board before data can be ordered (a description of how to order data from Statistics Sweden is available at: `https://www.scb.se/en/services/guidance-for-researchers-and-universities/`). We will also make available a complete list all of the variables that we ordered from Statistics Sweden for this project, together with our computer scripts.

The second way to replicate our analyses is to come to Sweden and reanalyze the data through the same remote server system that we used. Researchers interested in using this option should reach out to us prior to coming to Sweden so that we can apply for approval from the Ethical Review Board for the researcher to temporarily be added to our research team, which is mandatory in order to get access to the remote server system.

A.1.2 Variables and Data Sources

A.1.2.1 Voter Turnout

The Swedish registers do not contain population-wide turnout information. Although Statistics Sweden (SCB) has collected information on individual turnout for each election since 1991, their samples only cover about 1 percent of the electorate. However, the electoral rolls are still maintained in paper form, and each roll lists all eligible voters living in a particular voting district. The electoral rolls contain preprinted information on the full name and a unique personal identification number (*personnummer*) for all eligible voters, and handwritten information, filled in by the election officials, on whether particular individuals chose to vote in each of the three different elections at the municipal, county and national levels. To date, the election rolls of five general elections have been scanned and digitized: 1970, 1982, 1994, 2010, and 2018.

The reliability of the digitized data is very high. Analyses of the data for 2010 show that the digitized data conform with the data collected by Statistics Sweden in 99.7 percent of the cases. See Lindgren, Oskarsson, and Persson (2019) for a more complete description of the procedures with regards to scanning and digitizing these election rolls.

A.1.2.2 Data from Administrative Registers

In the main analysis we make use of data from various administrative registers. In this subsection we describe the main variables in somewhat more detail.

`Voting, children` – The average turnout in the 1994, 2010, and 2018 national elections among individuals in the child generation. Only non-missing values are used when calculating average turnout.

`Municipality turnout, children` – Turnout in an individual's municipality of residence, calculated as the average across the elections in 1994, 2010, and 2018.

`Sex, children` – Equal to 1 if female and 0 for male. The information originates from the Swedish Population Register.

`Immigrant background, children` – Equal to 1 if the individual or at least one of the parents are foreign-born. The information comes from the Swedish Population Register.

`Voting, parents` – The average turnout of fathers and mothers in the 1970, 1982, 1994, 2010, and 2018 national elections. Only non-missing values are used when calculating average turnout.

`Voting, grandparents` – The average turnout of all paternal and maternal grandparents in the 1970, 1982, 1994, 2010, and 2018 national elections. Only non-missing values are used when calculating average turnout.

`Voting, great-grandparents` – The average turnout of all paternal and maternal great-grandparents in the 1970, 1982, 1994, 2010, and 2018 national elections. Only non-missing values are used when calculating average turnout.

`Municipality turnout, parents` – Turnout in an individual's municipality of residence, calculated as the average across both parents and elections in 1970, 1982, 1994, 2010, and 2018.

`Municipality turnout, grandparents` – Turnout in an individual's municipality of residence, calculated as the average across all grandparents and elections in 1970, 1982, 1994, 2010, and 2018.

`Municipality turnout, great-grandparents` – Turnout in an individual's municipality of residence, calculated as the average across all great-grandparents and elections in 1970, 1982, 1994, 2010, and 2018.

`Education, children` – Years of completed education. Following the manual for classifying educational programmes in OECD countries (ISCED-97), we assigned the following years of schooling to each category: (old) primary school (7); (new) compulsory school (9); (old) junior secondary education (9.5); high school (10-12 depending on the program); short university (13); longer university (14-16 depending on the program); short postgraduate (17); long post-graduate (19) The original data were obtained from the LISA database and the Census of 1970.

`Education, parents` – Average years of completed education for the mother and father. The original data were obtained from the LISA database and the Census in 1970.

`Education, grandparents` – Average years of completed education for the grandparents. The original data were obtained from the LISA database and the Census in 1970.

`Education, great-grandparents` – Average years of completed education for the great-grandparents. The original data were obtained from the LISA database and the Census in 1970.

`Income, parents` – The average of the percentile ranked total income of the mother and the father. The original data were obtained from the censuses in 1970, 1975, 1985, and 1990, and from the LISA database for the years 1995, 2000, 2005, 2010 and 2015. In a first step we percentile ranked income by census year, birth year, and sex. In the next step we calculated the average income of the mother and the father across the two census years, including only non-missing observations.

`Income, grandparents` – The average of the percentile ranked total income of all paternal and maternal grandparents. The original data were obtained from the censuses in 1970, 1975, 1985, and 1990, and from the LISA database for the years 1995, 2000, 2005, 2010 and 2015.

`Income, great-grandparents` – The average of the percentile ranked total income of all paternal and maternal great-grandparents. The original data were obtained from the censuses in 1970, 1975, 1985, and 1990, and from the LISA database for the years 1995, 2000, 2005, 2010 and 2015.

`Occupational status, parents` – The average occupational status of the mother and the father as measured by the International Cambridge Scale (ICAMS). The ICAMS score uses detailed information on inter-occupational marriage patterns to statistically estimate the "social distance" between different types of occupations (Prandy and Jones 2001). The indicator thus measures occupational stratification. For reasons of international comparison, we here use the international CAMSIS scale developed by Meraviglia, Ganzeboom, and Luca (2016) based on information available in surveys of the International Social Survey Programme (ISSP) for the years 2001 to 2007. The measure was constructed in three steps. First, we converted the occupational codes available in the censuses in 1960, 1975, 1985, 1990 and the LISA database for the years 2005, 2010, and 2013 into ISCO-88 format by using conversion keys developed by Statistics Sweden and Erik Bihagen (2007). In the next step, we mapped the ISCO codes to ICAMS scores using a key provided by Harry Ganzeboom `http://www.harryganzeboom.nl/isco88/index.htm`. In the final step, we calculated the average ICAMS score for the mother and the father across all census years, using only non-missing observations.

`Occupational status, grandparents` – The average occupational status of all maternal and paternal grandparents as measured by the International Cambridge Scale (ICAMS). The original data were obtained from the censuses in 1960, 1975, 1985 and 1990 and the LISA database for the years 2005, 2010 and 2013.

`Occupational status, great-grandparents` – The average occupational status of all maternal and paternal great-grandparents as measured by the International Cambridge Scale (ICAMS). The original data were obtained from the censuses in 1960, 1975, 1985, and 1990 and the LISA database for the years 2005, 2010 and 2013.

A.2 Supplementary Analyses

A.2.1 Distinguishing between the Socialization and Genetic Pathways

In order to show the difficulty in distinguishing between the socialization and genetic pathways we can consider a simplified version of the model presented in equation (4) of the main text, in which we abstract from all control variables:

$$y_{i,t} = \alpha + \gamma_1 y_{i,t-1} + \gamma_2 y_{i,t-2} + \rho e_t + \epsilon_{i,t} \tag{1}$$

$$e_t = \lambda e_{t-1} + \nu_t \tag{2}$$

where $y_{i,t-1}$, $y_{i,t-2}$ are the voting behavior of parents and grandparents, e denotes the latent factor inherited from parents to their children, and ϵ and ν are two random components.

The model described in equation 1 then give rise to the following intergenerational correlation coefficients (assuming stationarity):

$$r_1^* = \frac{\gamma_1}{(1-\gamma_2)} + \frac{\lambda\theta}{(1-\gamma_2)} \tag{3}$$

$$r_2^* = \gamma_1 r_1^* + \gamma_2 + \lambda^2\theta \tag{4}$$

$$r_3^* = \gamma_1 r_2^* + \gamma_2 r_1^* + \lambda^3\theta \tag{5}$$

$$\theta = \rho r_{ye} = \frac{\rho^2}{(1-\gamma_1\lambda-\gamma_2\lambda^2)}, \tag{6}$$

where r_{ye} captures the correlation between the unobserved latent trait and voting, and r_1^* is the correlation in voting between children and parents, r_2^* between children and grandparents, and r_3^* between children and great-grandparents. Two things are worth noting. First, there will be excess persistence in voting, i.e., $r_m^* > (\gamma_1)^m$, if $\gamma_2 > 0$ or $\lambda\theta > 0$, i.e., if the behavior of grandparents directly influences that of their grandchildren or if voting is affected by a latent trait inherited from parents to child. Second, even if we have access to data on four consecutive generations, this system of equations is under-identified as it contains more unknowns than equations.

An important implication of this is that a positive, and statistically significant, coefficient for grandparental voting is not sufficient to show that grandparents directly influence their grandchildren (cf., Braun and Stuhler 2018). To see this, note that if we estimate equation (1) by means of linear regression, without observing e, the slope coefficient of grandparent voting is given by:

$$\hat{\gamma_2} = \frac{r_2^* - r_1^{*2}}{1 - r_1^{*2}}. \tag{7}$$

By combining equation (1) and equations (3) and (4), it becomes apparent that $\hat{\gamma_2}$ will pick up both the direct influence of grandparents on their grandchildren and the impact of the imperfectly measured latent trait. Consequently, even if we have data on voter turnout for four different generations, there is not enough information to empirically distinguish between the socialization and genetic mechanisms.

A.2.2 Results from the Youth Parent Socialization Panel Study

In the main text we briefly discuss the external validity of our results and refer to estimates based on the *Youth Parent Socialization Panel Study* (YPSPS) (Elliot 2007; Jennings et al. 2005). YPSPS is a four-wave panel study covering three biologically related generations of Americans. The original study was based on a national probability sample of 1,669 individuals who were high school seniors in 1965. The grandparental generation was surveyed once in 1965. The members of the parental generation have been surveyed four times: in

1965, 1973, 1982, and 1997. The 1997 survey also attempted to include all third-generation cohort members who had reached an age of 15 or greater.

In Table A.1, we present transmission results based on the YPSPS sample. In the first three columns, we focus on voter turnout[1] whereas columns 4 through 6 display transmission results for a political activity index[2]. We use the same model specification as employed in columns 1 through 3 in Table 2 in the main text.

Given that the sample size is several orders of magnitude smaller compared to the Swedish data we use for the main analyses, the lack of precision in some of the estimates should come as no surprise. Still, it is comforting to note that the magnitude of the estimates displayed in columns 1–3 are very similar to the corresponding estimates based on the Swedish data in columns 1–3 in Table 2. Above all, there is a positive association between the turnout behavior of grandparents and their grandchildren even when controlling for parental voting. Moreover, the pattern of results when using the political activity index as outcome in columns 4–6 closely resembles the turnout results in columns 1–3.

[1] We measure voter turnout by averaging turnout in all presidential elections for which we have data for each generation: 1964, 1972, and 1980 for the grandparents; all presidential elections between 1968 and 1996 for the parental generation; 1988, 1992, and 1996 for the child generation. The turnout information is averaged within each individual and, in case we have information from both grandparents, across the two grandparents.

[2] The political activity index is based on the following five survey items asked to individuals in all three generations in different survey waves: "Since [yyyy] have you talked to any people and tried to show them why they should vote one way or the other?"; "Since [yyyy], have you gone to any political meetings, rallies, dinners, or other things like that?"; "Since [yyyy], have you done any other work for a party, candidate or issue?"; "Since [yyyy], have you worn a campaign button or put a campaign sticker on your car?"; and "Since [yyyy], have you given money or bought any tickets to help a particular party, candidate, or group pay campaign expenses?". In case we have information from both grandparents, we have averaged the political activity scores across the two grandparents.

Table A.1: Political Transmission in YPSPS

	Voter turnout	Voter turnout	Voter turnout	Political activity	Political activity	Political activity
Turnout P/ Activity P	0.227*** (0.043)		0.223*** (0.046)	0.216*** (0.054)		0.205*** (0.057)
Turnout GP/ Activity GP		0.080 (0.054)	0.029 (0.051)		0.061 (0.047)	0.037 (0.047)
Num.Obs.	558	558	558	687	687	687
Mean	0.63	0.63	0.63	0.24	0.24	0.24

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.
All models include controls for sex and fixed effects for birth year of the child and (rounded) average birth year of the parents. Models 2, 3, 5 and 6 also include fixed effects for (rounded) average birth year of grandparents. Standard errors are clustered on mother-father pairs and shown in parentheses. Complete model results are included in the files uploaded to the APSR Dataverse.

A.2.3 Results by Grandparental Time of Death

In Table 5 in the main text we present standardized transmission coefficients depending on whether all (great) grandparents were dead or alive at the time their (great) grandchild was born. These coefficients were calculated on the basis of a simple linear interaction model where (great) grandparental turnout is interacted with a dummy indicating whether a particular (great) grandparent was dead or alive at the time the (great) grandchild was born. In order to understand the specification of this model, it is useful to begin by considering the following extension of our main model:

$$\begin{aligned}
Y_c =& \delta_m Y_m + \delta_f Y_f + \delta_{mm} Y_{mm} + \delta_{mf} Y_{mf} + \delta_{fm} Y_{fm} + \delta_{ff} Y_{ff} + \\
& \alpha_{mm} A_{mm} + \alpha_{mf} A_{mf} + \alpha_{fm} A_{fm} + \alpha_{ff} A_{ff} + \\
& \psi_{mm}(A_{mm} \times Y_{mm}) + \psi_{mf}(A_{mf} \times Y_{mf}) + \psi_{fm}(A_{fm} \times Y_{fm}) + \psi_{ff}(A_{ff} \times Y_{ff}),
\end{aligned} \tag{8}$$

where Y is turnout, A a binary variable that takes on the value of 1 if the grandparent is alive when the child is born, and the subscripts c indicate the grandchild, m the mother, f the father, mm the mother's mother, mf the mother's father, fm the father's mother, and ff the father's father.

When estimating the models presented in the main text we have averaged turnout across all individuals within a particular generation. In terms of equation (8) this is equivalent to constraining the transmission coefficients to be the same for all individuals in a particular generation. If we apply this constraint to equation (8) we obtain:

$$
\begin{aligned}
Y_c &= \delta_p Y_p + \delta_{gp} Y_{gp} + \alpha A_{gp} + \psi A Y_{gp}, \text{where} \\
Y_p &= (Y_m + Y_f) \\
Y_{gp} &= (Y_{mm} + Y_{mf} + Y_{fm} + Y_{ff}) \\
A_{gp} &= (A_{mm} + A_{mf} + A_{fm} + A_{ff}) \\
AY_{gp} &= (A_{mm} \times Y_{mm} + A_{mf} \times Y_{mf} + A_{fm} \times Y_{fm} + A_{ff} \times Y_{ff})
\end{aligned} \tag{9}
$$

The results presented in models 1 and 2 in Table 5 are based on this model, whereas the results of models 3 and 4 are obtained by extending the same reasoning to great-grandparents. The non-standardized regression coefficients from these interaction models are presented in Table A.2. To keep the metric the same as that used for our main results, all the sums in equation 9 (i.e., Y_p. Y_{gp} etc.) have been divided by the number of individuals used to calculate these variables. That is, if we have data on all four grandparents Y_{gp} is divided by 4, and so on.

Table A.2: Transmission by Grandparental Time of Death

	Outcome: Turnout, Children					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Turnout P (Y_p)	0.384***	0.326***	0.384***	0.323***	0.271***	0.229***
	(0.002)	(0.002)	(0.002)	(0.002	(0.018)	(0.018)
Turnout GP (Y_{gp})	0.053***	0.042***	0.117***	0.083***	−0.005	−0.011
	(0.003)	(0.003)	(0.003)	(0.003)	(0.023)	(0.023)
Alive ($A_{(g)gp}$)	0.009***	−0.003*	0.006**	−0.001	−0.022*	−0.021*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.013)	(0.013)
Turnout GP x Alive (AY_{gp})	0.029***	0.017***			0.044**	0.036*
	(0.003)	(0.003)			(0.022)	(0.021)
Turnout GGP (AY_{ggp})			0.014***	0.007***		
			(0.002)	(0.002)		
Turnout GGP x Alive (AY_{ggp})			0.003	0.003		
			(0.002)	(0.002)		
SES Controls	No	Yes	No	Yes	No	Yes
Context Controls	No	Yes	No	Yes	No	Yes
Num.Obs.	2,733,689	2,733,689	1,092,423	1,092,423	35,866	35,866

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.
All models include controls for sex, immigrant background and fixed effects for birth year of the child, (rounded) average birth year of the parents and grandparents, and fixed effects for number of parents observed in the data. Standard errors are clustered on mother-father pairs and shown in parentheses. Complete model results are included in the files uploaded to the APSR Dataverse.

The coefficient of Y_{gp} in model 2 indicates that turnout can be expected to be about 4 percentage points higher for an individual whose grandparents always voted but who all died before their grandchild was born, compared to an otherwise similar individual whose grandparents never voted. However, if all grandparents were alive when the grandchild was born the corresponding difference between these two cases is instead about 6 percentage points (0.042 + 0.017). Moreover, this difference is also statistically significant at conventional significance levels. However, the extra boost from having great-grandparents who were all alive at the time of their great grandchild's birth is only 0.003 percentage points, and this difference is not statistically significant (model 4).

A.2.4 Results by Grandparental Type

Researchers in neighboring disciplines have examined how much time different types of grandparents spend with their grandchildren. A common finding in these studies is that maternal grandmothers have the most contact with their grandchildren, whereas paternal grandfathers have the least contact. Maternal grandfathers and paternal grandmothers tend to place themselves in between these two extremes (Uhlenberg and Hammill 1998; Pollet, Nettle, and Nelissen 2006; Coall and Hertwig 2010).

To the extent that grandparental influence is due to a direct transfer of values or socioeconomic status, such differences in contact frequencies can be important since the opportunities for these transfers depend on the frequency of interactions between grandparents and grandchildren. One means to examine whether grandparents actually influence their grandchildren could therefore be to analyze how the strength of the transmission varies by grandparental type. Toward this end, Figure A.1 displays the results from an analysis in which we have estimated separate transmission coefficients for each grandparent.

To understand how we do this, we can exemplify with the case of maternal grandmothers. To obtain the transmission coefficient of maternal grandmothers we estimate a model of the following type:

$$Y_c = \delta_p Y_p + \delta_{mm} Y_{mm} + \delta_o (Y_{mf} + Y_{fm} + Y_{ff}). \tag{10}$$

That is, when estimating the individual grandparental transmission coefficients, we control for the average turnout among the remaining grandparents. This procedure is then repeated for each type of grandparent. The (partial) standardized regression coefficients for each grandparent are shown in Figure A.1, which is based on a regression model including the full set of controls used in the main analyses.

As can be seen from the figure, we find the largest transmission coefficient for maternal grandmothers and the smallest for paternal grandfathers, whereas the coefficients for maternal grandfathers and paternal grandmothers fall in between (the error bars indicate 95%

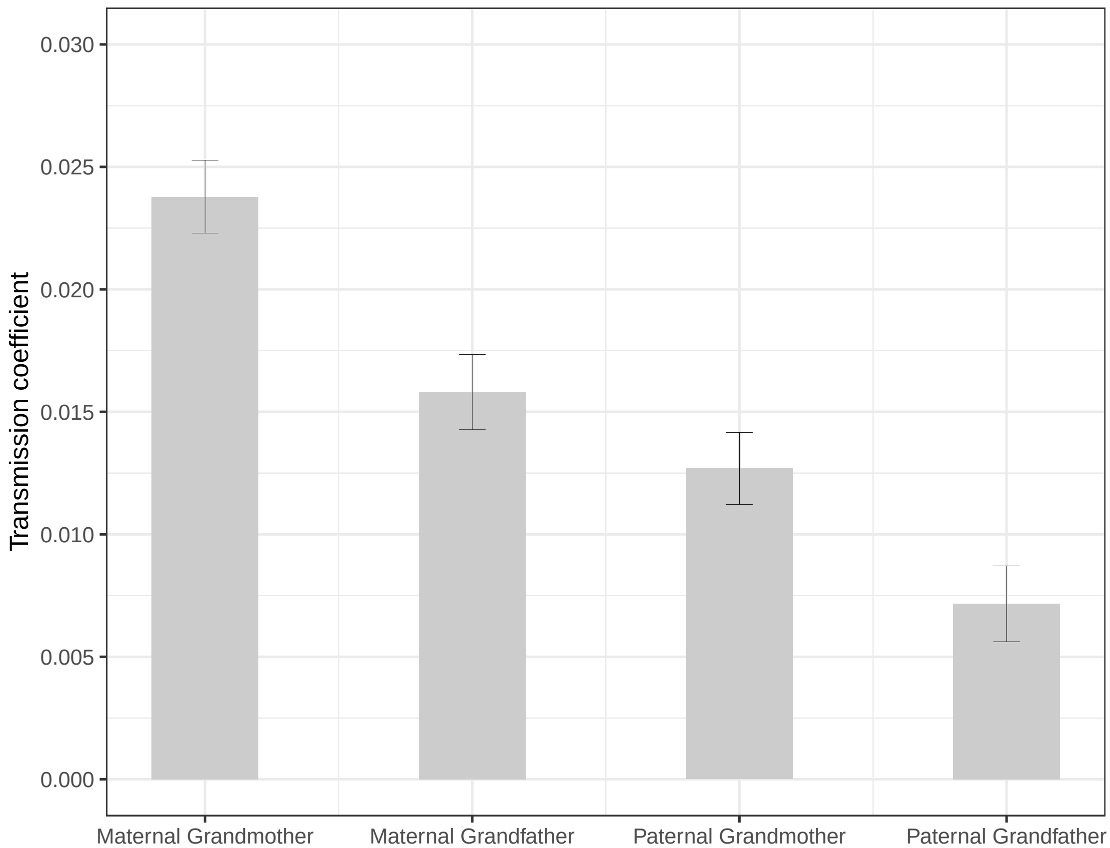

Figure A.1: Transmission Coefficient across Different Grandparents

confidence intervals).

A key thing to note is that the overall pattern of coefficients in Figure A.1 mimics the pattern of interaction frequencies found in previous research on grandparent-grandchildren relationships. That is, we find the strongest transmission for the maternal grandmothers who tend to spend most time with their grandchildren, and the weakest for paternal grandfathers who are known to interact the least with their grand-offspring.

A.2.5 Results by Number of Grandparents in the Data

As mentioned in the main text we are not able to observe the full set of grandparents for all individuals in our data, either because we lack data on voter turnout for these individuals or because the grandchild-grandparent link is missing in the multigeneration register. This is the reason why we control for the number of grandparents in all of the analyses reported in the main text. As an alternative means to deal with this problem Table A.3 reports results obtained when estimating separate models depending on the number of grandparents observed in the data.

Table A.3: Transmission by Number of Grandparents in the Data

	Outcome: Turnout, Children			
	Model 1	Model 2	Model 3	Model 4
Turnout P	0.232***	0.216***	0.211***	0.196***
	(0.005)	(0.003)	(0.002)	(0.001)
Turnout GP	0.029***	0.035***	0.033***	0.038***
	(0.004)	(0.002)	(0.002)	(0.001)
SES Controls	Yes	Yes	Yes	Yes
Context Controls	Yes	Yes	Yes	Yes
Nr GP	1	2	3	4
Mean Turnout	0.85	0.86	0.88	0.89
Num.Obs.	76,655	348,308	508,124	1,800,602

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.
All models include controls for sex, immigrant background and fixed effects for birth year of the child, (rounded) average birth year of the parents and grandparents, and fixed effects for number of parents observed in the data. Standard errors are clustered on mother-father pairs and shown in parentheses. Complete model results are included in the files uploaded to the APSR Dataverse.

As can be seen from the results, the main findings remain intact regardless of the number of grandparents observed in the data. With that said, we obtain the largest grandparental transmission coefficient when all four grandparents are included in the turnout measure (which applies to about 65 percent of the cases). One likely reason for this is that the amount of measurement error in grandparental turnout increases as the number of grandparents observed in the data decreases, which is likely to attenuate the transmission coefficient.

A.2.6 Results by Number of Elections in the Data

As mentioned in the main text, the number of elections in which we observe turnout for the child generation varies between 1–3. To check whether this matters for the results, Table A.4 reports separate estimates depending on the number of elections in which an individual is observed. For reasons of comparison, the first column reports the results from the main analysis whereas the latter three columns show the results for individuals observed in 1, 2, and 3 elections, respectively. As can be seen from the results, the grandparental transmission coefficient remains very similar regardless of the number of elections in which an individual is observed.

Table A.4: Results by Number of Elections

	Outcome: Turnout, Children			
	Model 1	Model 2	Model 3	Model 4
Turnout P	0.205***	0.180***	0.210***	0.238***
	(0.001)	(0.002)	(0.001)	(0.002)
Turnout GP	0.035***	0.036***	0.034***	0.037***
	(0.001)	(0.001)	(0.001)	(0.002)
Num.Obs.	2,733,689	784,712	1,433,344	515,633
SES Controls	Yes	Yes	Yes	Yes
Context Control	Yes	Yes	Yes	Yes
Nr. Elections	All	1	2	3

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.
All models include controls for sex, immigrant background and fixed effects for birth year of the child, (rounded) average birth year of the parents and grandparents, and fixed effects for number of parents observed in the data. Standard errors are clustered on mother-father pairs and shown in parentheses. Complete model results are included in the files uploaded to the APSR Dataverse.

A.2.7 Alternative Controls for SES and Local Context

In the main analyses we used average income, education, and occupational status within each generation to measure SES. However, an alternative is to calculate the SES of a generation by taking the maximum, rather than the average, value of income, education, and occupational status. For instance, to calculate the educational attainment of the grandparental generation we then simply take the maximum years of education among all maternal and paternal grandparents. In Table A.5 we present results obtained when using this alternative way of controlling for SES. By comparing these results to the corrpesponding ones in Table 2 in the main text it is evident that we obtain virtually identical results irrespective of how we measure SES.

Directly related to this it could also be argued that economic wealth is a potentially important variable that is missing from our set of SES controls. The reason for this is simply that we lack population data on economic wealth in the data that we currently have access to. With that said, in a related project we have access to wealth data for a sample of Swedish twins. By connecting these twins to their parents and children we have been able to construct a smaller intergenerational sample with three generations. Because we do not have access to information about the spouses of the twins, the parental generation includes only one parent (the twin, which is either a father or a mother to the individuals in the children generation). Moreover, for reasons unrelated to the current study the sex composition of

Table A.5: Political Transmission with Alternative SES Controls

	Outcome: Turnout, Children			
	Model 1	Model 2	Model 3	Model 4
Turnout P	0.206***	0.205***	0.197***	0.196***
	(0.001)	(0.001)	(0.001)	(0.001)
Turnout GP	0.036***	0.035***	0.039***	0.039***
	(0.001)	(0.001)	(0.001)	(0.001)
Turnout GGP			0.006***	0.006***
			(0.001)	(0.001)
SES Controls	Yes	Yes	Yes	Yes
Context Controls	No	Yes	No	Yes
Sample	3-gen	3-gen	4-gen	4-gen
Num.Obs.	2,733,689	2,733,689	1,092,423	1,092,423

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.
All models include controls for child immigrant background and fixed effects for birth year of the child, (rounded) average birth year of the parents and grandparents, and fixed effects for number of parents and grandparents observed in the data. Standard errors are clustered on mother-father pairs and shown in parentheses. Complete model results are included in the files uploaded to the APSR Dataverse.

the twins making up the parental generation is fairly skewed in that about two-thirds of the individuals are men.

The twin data contains information on economic wealth from the tax registers for all individuals included in the sample for the period from 1999 to 2007. To measure economic wealth within each generation we follow our standard procedure and calculate the average gross wealth among all individuals belonging to the same family and generation (missing values are disregarded). In Table A.6 we examine to what extent adding wealth to the set of SES controls affects the results. The first and second columns in the table corresponds to columns 3 and 4 of Table 2 in the main text. As can be seen we obtain fairly similar transmission results in the twin sample as we do in our main sample. The fact that the parental transmission coefficient is slightly smaller in the twin sample could possibly be attributed to the fact that we only observe one of the parents, and that this parent is more likely to be the father than the mother. Most importantly, however, the transmission coefficients decrease only marginally when we add the wealth controls to the model (see Model 3). This indicates, that the fact that we are unable to control for economic wealth in our main analyses only marginally influences the results we obtain.

Another control that we include in the main text is the (average) municipality turnout in an individual's municipality of residence. An alternative means to account for the impact

Table A.6: Results when Controlling for Economic Wealth

	Outcome: Turnout, Children		
	Model 1	Model 2	Model 3
Turnout P	0.178***	0.146***	0.142***
	(0.010)	(0.011)	(0.010)
Turnout GP	0.052***	0.037***	0.033***
	(0.008)	(0.008)	(0.008)
Num.Obs.	30,686	30,686	30,686
SES Controls	No	Yes	Yes
Wealth Controls	No	No	Yes
Context Control	No	No	No

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.
All models include controls for sex, immigrant background and fixed effects for birth year of the child, (rounded) average birth year of the parents and grandparents, and fixed effects for number of parents observed in the data. Standard errors are clustered on mother-father pairs and shown in parentheses. Complete model results are included in the files uploaded to the APSR Dataverse.

of shared local political context is instead to create an indicator for whether an individual in the child generation and his or her older relatives live in the same municipality at the time of voting. A problem with this procedure, is that both the children and their relatives may have lived in different municipalities during different elections. To overcome this problem, we first identify the modal municipality of residence for each individual, i.e., the municipality in which an individual lived for most of the elections included in the data (in case of ties we use the most recent observation as the modal municipality). In the next step we calculate the number of individuals in each generation who have the same modal municipality as the individual in the child generation. For parents this measure can vary between 0 (if neither the mother nor the father have the same modal municipality as the child) and 2 (if both the mother and the father have the same modal municipality as the child), whereas it can vary between 0 and 4 for the grandparental generation, and between 0 and 8 for the great grandparental generation. We then use these indicators to capture the impact of shared local political context across generations.

In Table A.7 we show that our main findings remain very similar also when using this alternative measure of shared local context. In columns 1 and 3 of the table we report the results for the model used in the main text where we control for average municipality turnout. In columns 2 and 4 we instead include a full set of dummy variables for the number of parents, grandparents, and great-grandparents (in column 4) who have the same modal

Table A.7: Alternative Control for Local Context

	Outcome: Turnout, Children			
	Model 1	Model 2	Model 3	Model 4
Turnout P	0.205***	0.204***	0.195***	0.194***
	(0.001)	(0.001)	(0.001)	(0.001)
Turnout GP	0.035***	0.035***	0.039***	0.039***
	(0.001)	(0.001)	(0.001)	(0.001)
Turnout GGP			0.006***	0.006***
			(0.001)	(0.001)
SES Controls	Yes	Yes	Yes	Yes
Context Controls	Turnout	Modal Mun.	Turnout	Modal Mun.
Sample	3-gen	3-gen	4-gen	4-gen
Num.Obs.	2,733,689	2,733,689	1,092,423	1,092,423

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.
All models include controls for child immigrant background and fixed effects for birth year of the child, (rounded) average birth year of the parents and grandparents, and fixed effects for number of parents and grandparents observed in the data. Standard errors are clustered on mother-father pairs and shown in parentheses. Complete model results are included in the files uploaded to the APSR Dataverse.

municipality as the individual in the child generation. As can be seen, both the transmission coefficients associated with grandparents and great-grandparents remain virtually identical when using this alternative approach to account for shared political context.

A.2.8 The Impact of Aunts and Uncles

In the main text we attempt to obtain an estimate of the genetic pathway linking the voting behavior of grandchildren and their grandparents by studying grandparents who died before their grandchildren were born. As discussed in the main text this estimate is likely to provide an upper bound of the genetic component since part of this relationship could be due to unmeasured non-genetic factors.

One such factor is political socialization due to other close relatives such as aunts and uncles. If the political behavior of children are affected by that of their aunts and uncles part of the correlation that we find between children and the grandparents who died before their grandchildren were born may be due to indirect socialization through aunts and uncles, rather than due to genetic inheritance.

A straightforward way to check whether the strength of grandparental transmission changes when we take the political behavior of aunts and uncles into account is to create an indicator that measures the average turnout of the parents as well as all the aunts and uncles of an individual in the child generation. In the first two columns of Table A.8 we have therefore replaced the variable measuring parental turnout with an indicator of the average turnout of the parents and all the parents' siblings. In the third and fourth columns then we extend this approach to the four generation model. That is, the variable measuring average turnout among the grandparents has now been replaced by an indicator measuring the average turnout of the grandparents and all grandparent's siblings. That is, when studying the transmission of great-grandparents we now effectively control for the turnout of parents and grandparents as well as all their siblings (for which we have data).

Table A.8: Controlling for Turnout of Other Close Relatives

	Outcome: Turnout, Children			
	Model 1	Model 2	Model 3	Model 4
Transmission GP - All dead	0.022***	0.019***		
	(0.003)	(0.002)		
Transmission GP - All alive	0.041***	0.031***		
	(0.002)	(0.001)		
Δ GP	0.019***	0.012***		
Transmission GGP - All dead			0.010***	0.005***
			(0.001)	(0.001)
Transmission GGP - All alive			0.013**	0.008***
			(0.001)	(0.001)
Δ GGP			0.003*	0.003*
SES Controls	No	Yes	No	Yes
Context Controls	No	Yes	No	Yes
Sample	3-gen	3-gen	4-gen	4-gen
Num.Obs.	2,733,689	2,733,689	1,092,423	1,092,423

${}^{*}p < 0.10$, ${}^{**}p < 0.05$, ${}^{***}p < 0.01$.
All models include a control for average turnout of parents and all their siblings, and models 3 and 4 also include a control for average turnout among grandparents and all their siblings. In addition to this, all models include controls for sex, immigrant background and fixed effects for birth year of the child, (rounded) average birth year of the parents and grandparents, as well as fixed effects for number of parents and grandparents observed in the data. Standard errors are clustered on mother-father pairs and shown in parentheses. Complete model results are included in the files uploaded to the APSR Dataverse.

If we compare the first two columns of Table A.8 to those of Table 5 in the main text we can see that the transmission coefficients of grandparents who died before their grandchildren were born have decreased by about 25 percent. This could be taken to indicate that part of the effect that we previously labelled as a genetic pathway may instead be due to indirect socialization through other close relatives, such as aunts and uncles. However, from the perspective of the Clark model it could be argued that the reason for the drop in the coefficient is that adding the turnout of aunts and uncles to the model reduces the measurement error in the unobserved latent trait. Therefore, if we consider the estimate presented in Table 5 in the main text as an upper bound of the genetic component, we could consider the estimates presented here as a lower bound of that component.

Equally important, however, we can see that we obtain very similar estimates for the socialization effect when controlling for the turnout of aunts and uncles. In the main text we found the difference in transmission between dead and living grandparents (Δ GP) to be 0.017 and 0.010, whereas the corresponding differences in Table A.8 are 0.019 and 0.012.

Turning to the results from the four generation sample in columns 3 and 4, these results are very similar to those presented in the main text.

A.2.9 Alternative Cut-Offs for Grandparental Death

In the main text we attempt to block the socialization pathway by studying the intergenerational correlation among individuals whose grandparents died before they were born. It may, however, be argued that this limit may be overly conservative since political socialization is mainly believed to take place during adolescence.

We have therefore examined the robustness of the results presented in Table 5 in the main text, by estimating a more flexible interaction model in which we replace the binary dead-alive indicator with a categorical variable that takes on four different values. The first category identifies all (great) grandparents who died before the grandchild was born, the second category identifies those who died when their grandchild was between 0–8 years old, the third category identifies those who died when their grandchild was between 9–17, and the fourth category, finally, identifies the (great) grandparents who were still alive when their grandchild turned 18. We then interact this categorical indicator with the turnout variables in the same way as we did with the binary indicator used for the main analysis (see the description above).

The results from this exercise are displayed in Table A.9. To ease interpretation, we present the transmission coefficients implied by our model when all the (great) grandparents of an individual fall within either of these four categories.

First, we can note that the difference in transmission between the two end categories remain very similar when estimating this more flexible model. The difference in the standardized coefficients of grandparental turnout when they all died before the grandchild was born, and when they all survived their granchild's 18th birthday is 0.018 without controls (model 1) and 0.012 with controls (model 2), whereas the corresponding differences in the

Table A.9: Political Transmission by Grandparents' Time of Death

	Outcome: Turnout, Children			
	Model 1	Model 2	Model 3	Model 4
Transmission GP - All dead before birth	0.032***	0.025***		
	(0.002)	(0.002)		
Transmission GP - All dead bw 0–8	0.041***	0.029***		
	(0.001)	(0.002)		
Transmission GP - All dead bw 9–17	0.042***	0.030***		
	(0.001)	(0.001)		
Transmission GP - All alive at 18	0.050***	0.037***		
	(0.001)	(0.001)		
Transmission GGP - All dead before birth			0.009***	0.005***
			(0.001)	(0.001)
Transmission GGP - All dead bw 0–8			0.011***	0.006***
			(0.001)	(0.001)
Transmission GGP - All dead bw 9–17			0.013***	0.008***
			(0.002)	(0.002)
Transmission GGP - All alive at 18			0.011***	0.006***
			(0.002)	(0.002)
SES Controls	No	Yes	No	Yes
Context Controls	No	Yes	No	Yes
Sample	3-gen	3-gen	4-gen	4-gen
Num.Obs.	2,733,689	2,733,689	1,092,423	1,092,423

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.
Apart from parental turnout, all models include controls for sex and immigrant background, fixed effects for birth year of the child, (rounded) average birth year of the parents and grandparents, as well as fixed effects for number of parents and grandparents observed in the data. Standard errors are clustered on mother-father pairs and shown in parentheses. Complete model results are included in the files uploaded to the APSR Dataverse.

main text are 0.017 and 0.010, respectively. Moreover, the estimated transmission coefficients in the two middle groups fall in between those of the two end categories. This could be taken to indicate that the socialization process is gradual rather than discrete, i.e., the more years the children get to spend with their grandparents the more similar is their voting behavior.

The transmission coefficients of great-grandparents vary less across the different categories. Although we should take care not to overinterpret these findings, since statistical precision may be an issue here, these results indicate that the timing of death among great-grandparents is fairly inconsequential for the overall strength of intergenerational transmission from great-grandparents to their great grandchildren. This could be taken as evidence that the great grandparental transmission coefficient is not due to socialization.

A.2.10 Does Geographical Proximity Matter?

As discussed in the main text, it seems reasonable to assume that the opportunities for political socialization depend on the frequency of interactions between a child and their relatives. One implication of this is that grandparents who live close to their grandchildren should be more likely to assert influence over their political behavior.

To check whether this is the case we have examined whether the strength of the intergenerational correlations in our data depends on the geographical proximity between the children and their (great) grandparents. More precisely we calculate the (as the crow fly) distance between an individual's municipality of birth and the municipalities where their grandparents lived the year the grandchild in question was born. In the next step we extend the approach described by equation 9 and interact this distance measure with (great) grandparental turnout. A problem then becomes how to handle those (great) grandparents who were not alive when their grandchild was born. We use two different approaches. In the first, we set the distance to diseased (great) grandparents to the maximum distance found in the data, which is 1438 kilometers. Second, we restrict the analysis to the subset of (great) grandchildren for which we have access to turnout and distance data for the same number of (great) grandparents. In Table A.10 we refer to this subset as the *restricted* sample.

The upper part of Table A.10 presents the unstandardized regression coefficients from this interaction model. The lower part of the table shows the estimated standardized regression coefficients implied by this model for two particular cases. The first case is when all (great) grandparents, for which we can observe turnout, live in the municipality in which the grandchild was born (Distance – 0 km), whereas the second case represent a situation in which all (great) grandparents live in a municipality situated 1000 km from the municipality in which their grandchild was born (Distance – 1000 km).

Starting with model 1 we can see that the standardized transmission coefficient for grandparents is 0.037 when the distance is 0 km and 0.024 when the distance is 1000 km. This difference thus come fairly close to the difference observed between living and "dead" grandparents, which was 0.010. It is also comforting to note that the difference remain similar when focusing on the more restricted subset of grandparents for which we can observe both turnout and geographical distance (model 2).

Turning instead to great-grandparents in models 3 and 4, we find similar transmission coefficients regardless of the geographical distance. This is yet another indication that great-grandparents are less important as socialization agents.

Table A.10: Transmission by Geographical Distance

	Outcome: Turnout, Children			
	Model 1	Model 2	Model 3	Model 4
Turnout P (Y_p)	0.325***	0.325***	0.326***	0.310***
	(0.002)	(0.002)	(0.002)	(0.005)
Turnout GP (Y_{gp})	0.062***	0.069***	0.083***	0.075***
	(0.001)	(0.002)	(0.003)	(0.005)
Distance ($D_{(g)gp}$)	0.000	−0.000	−0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Turnout GP x Distance (DY_{gp})	−0.002***	−0.003***		
	(0.000)	(0.000)		
Turnout GGP (Y_{ggp})			0.010***	0.010***
			(0.002)	(0.003)
Turnout GGP x Distance (DY_{ggp})			−0.000	−0.000
			(0.000)	(0.000)
Transmission GP — Distance = 0 km	0.037***	0.039***		
	(0.001)	(0.001)		
Transmission GP — Distance = 1000 km	0.024***	0.025***		
	(0.001)	(0.002)		
Transmission GGP — Distance = 0 km			0.007***	0.008***
			(0.001)	(0.002)
Transmission GGP — Distance = 1000 km			0.005***	0.006***
			(0.001)	(0.003)
Generations	3-gen	3-gen	4-gen	4-gen
Sample	Full	Restricted	Full	Restricted
Num.Obs.	2,733,689	1,922,826	1,092,423	211,384

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.
All models include controls for the sex, immigrant background and fixed effects for birth year of the child, (rounded) average birth year of the parents and grandparents, and fixed effects for number of parents observed in the data. Standard errors are clustered on mother-father pairs and shown in parentheses. Complete model results are included in the files uploaded to the APSR Dataverse.

A.2.11 The Impact of Grandparental Age

In the main text we discuss the possibility that the reason why great-grandparents do not appear to be a very important socialization agent could be that they are usually fairly old when their great grandchildren are born (if they are alive). This line of reasoning could also be applied to older grandparents. To examine the validity of this possible objection we have estimated an interaction model in which we allow the transmission coefficients to differ between (great) grandparents who were 70 or younger when their (great) grandchildren were born. The results are presented in Table A.11.

Table A.11: Political Transmission by Grandparents' Age

	Outcome: Turnout, Children			
	Model 1	Model 2	Model 3	Model 4
Transmission GP - All ≤ 70	0.048***	0.035***		
	(0.001)	(0.001)		
Transmission GP - All > 70	0.041***	0.030***		
	(0.001)	(0.001)		
Δ GP	−0.007***	−0.005***		
Transmission GGP - All ≤ 70			0.007***	0.008***
			(0.002)	(0.002)
Transmission GGP - All > 70			0.011***	0.006***
			(0.001)	(0.001)
Δ GGP			0.004***	−0.002
SES Controls	No	Yes	No	Yes
Context Controls	No	Yes	No	Yes
Sample	3-gen	3-gen	4-gen	4-gen
Num.Obs.	2,733,689	2,733,689	1,092,423	1,092,423

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.
Apart from parental turnout, all models include controls for sex, immigrant background and fixed effects for birth year of the child, (rounded) average birth year of the parents and grandparents, as well as fixed effects for number of parents and grandparents observed in the data. Standard errors are clustered on mother-father pairs and shown in parentheses. Complete model results are included in the files uploaded to the APSR Dataverse.

Similar to before, we focus on two extreme cases. In the first case all (great) grandparents were 70 or younger when the (great) grandchild in question was born, and in the second all (great) grandparents were above 70 (or diseased) when the grandchild was born. For grandparents we find some support for the hypothesis that transmission declines with grandparental age, but we find no evidence for this among great-grandparents. To judge from these results, their old age is thus not the only reason why great-grandparents are not able to influence the voting behavior of their great grandchildren.

A.2.12 Logit Results

In the main text we use standard OLS to calculate the intergenerational transmission coefficients between adjacent generations. However, given that voter turnout is very high in Sweden the amount of variation in the turnout measures is indeed somewhat limited. In most cases all individuals in a specific generation are always voters. To check whether this coarseness of the turnout measures affects the results, tables A.12 and A.13 present the results from logit models where all turnout measures have been dichotomized to take on the value 1 if average turnout in a generation is 1, and 0 if average turnout is below 1. The coefficients in the tables are raw logit coefficients, whereas the numbers in square brackets display fully standardized logit coefficients, which is the closest analogue to the standardized regression coefficients presented in the main text.

Table A.12: Political Transmission across Three Generations, Logit Results

	Outcome: Binary Turnout, Children				
	Model 1	Model 2	Model 3	Model 4	Model 5
Turnout P	0.976^{***}		0.926^{***}	0.711^{***}	0.707^{***}
	(0.004)		(0.004)	(0.004)	(0.004)
	[0.233]		[0.220]	[0.161]	[0.160]
Turnout GP		0.384^{***}	0.256^{***}	0.174^{***}	0.170^{***}
		(0.004)	(0.004)	(0.004)	(0.004)
		[0.101]	[0.066]	[0.043]	[0.042]
SES Controls	No	No	No	Yes	Yes
Context Controls	No	No	No	No	Yes
Mean Turnout	0.88	0.88	0.88	0.88	0.88
Num.Obs.	2,733,683	2,733,682	2,733,676	2,733,676	2,733,676

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.
All models include controls for sex, immigrant background and fixed effects for birth year of the child, (rounded) average birth year of the parents, and fixed effects for number of parents observed in the data. Models 2 to 5 also include fixed effects for (rounded) average birth year of grandparents and fixed effects for number of grandparents observed in the data. Standard errors are clustered on mother-father pairs and shown in parentheses, and fully standardized logit coefficents are shown in square brackets. Complete model results are included in the files uploaded to the APSR Dataverse.

As can be seen, the logit results presented in tables A.12 and A.13 closely resemble the OLS results presented in the main text. Thus, we do not find any evidence that the coarseness of the turnout measures unduly drives the results.

Table A.13: Political Transmission across Four Generations, Logit Results

	Outcome: Binary Turnout, Children				
	Model 1	Model 2	Model 3	Model 4	Model 5
Turnout P	0.713^{***}		0.937^{***}	0.708^{***}	0.704^{***}
	(0.006)		(0.006)	(0.006)	(0.006)
	[0.163]		[0.222]	[0.162]	[0.161]
Turnout GP	0.184^{***}		0.275^{***}	0.175^{***}	0.171^{***}
	(0.006)		(0.006)	(0.006)	(0.006)
	[0.045]		[0.069]	[0.042]	[0.041]
Turnout GGP		0.164^{***}	0.083^{***}	0.051^{***}	0.049^{***}
		(0.006)	(0.006)	(0.006)	(0.006)
		[0.043]	[0.021]	[0.012]	[0.012]
SES Controls	No	No	No	Yes	Yes
Context Controls	No	No	No	No	Yes
Mean Turnout	0.88	0.88	0.88	0.88	0.88
Num.Obs.	1,092,410	1,092,419	1,092,404	1,092,404	1,092,404

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.
All models include controls for sex, immigrant background and fixed effects for birth year of the child, (rounded) average birth year of the parents, and fixed effects for number of parents observed in the data. Models 2 to 5 also include fixed effects for (rounded) average birth year of grandparents, and fixed effects for number of grandparents observed in the data. Standard errors are clustered on mother-father pairs and shown in parentheses, and fully standardized logit coefficents are shown in square brackets. Complete model results are included in the files uploaded to the APSR Dataverse.

A.2.13 Results from a Marginal Structure Model

The transmission models analyzed in the main text are examples of traditional mediation analysis in which the effects of causally prior variables, such as grandparental turnout, are divided into direct and indirect effects by including controls for subsequent mediators, such as parental voting (Baron and Kenny 1986). As is well-known, this type of model rests on rather strong assumptions (e.g., Imai et al. 2011; Elwert and Winship 2014).

The problem is the following: To examine the existence and sources of excess persistence in voting it is necessary that we condition on variables that are on the causal path between grandparents' and grandchildren's voting, e.g., the voting behavior of parents. However, controlling for variables on the causal path risks inducing over-control and collider bias (Elwert and Winship 2014). That is, by controlling for parental characteristics, we may incorrectly ascribe some of the grandparental effects to the parents.

In their study of intergenerational associations in wealth and education Hällsten and

Pfeffer (2017) adopt an approach first developed by Sharkey and Elwert (2011) in an attempt to handle these types of problems. More precisely, they estimate a marginal structure model with inverse probability-of-treatment weights (IPTW) to relax some of the assumptions of traditional mediation analysis.

The marginal structure model involves two steps (Sharkey and Elwert 2011). First, we estimate the probability of voting separately for the parental and grandparental generations controlling for potential confounders influencing each generation's turnout. Second, we use the predicted probabilities to calculate the probability that parents and grandparents voted to the extent they did (actual treatment status). Finally, we take the product of the parents' and the grandparents' treatment probabilities to obtain the probability of the multigenerational voting history for each family:

$$W = P(Voting_{gp}|\mathbf{X}_{gp}) \times P(Voting_p|\mathbf{X}_p, Voting_{gp}, \mathbf{X}_{gp}), \tag{11}$$

where $\mathbf{X}$ denotes the set of controls included in our main analyses, such as the SES indicators, municipality turnout, and year of birth.

Next, we weight the individual cases by the inverse of each family's voting history (W^{-1}). By doing so, we create a pseudo-population in which the values of all the variables used to calculate the weights are balanced in expectations. As a result of this, the treatment status (turnout) in each generation is no longer confounded by the observables (Sharkey and Elwert 2011). Therefore, we can now identify the parameters of interest by applying a standard regression model to the weighted data.

$$E_w[Voting_c|Voting_p, Voting_{gp}] = a + b_1 Voting_p + b_2 Voting_{gp}, \tag{12}$$

where E_w denotes the expectation in the weighted pseudo-population, and $Voting$ refers to the discrete turnout indicator described above. The total multigenerational effect is then given by $b_1 + b_2$ whereas the individual contribution of each generation is given by b_1 and b_2, respectively. To improve the efficiency of the marginal structure model many authors recommend that the standard weights in equation (11) should be stabilized by multiplying the weights by the marginal probability of the observed treatment history. That is, in our case we get: $W_s = P(Voting_{gp}|\mathbf{X}_{gp}) \times P(Voting_p|\mathbf{X}_p, \mathbf{X}_{gp}) \times W$.

Because the marginal structure model requires the treatment indicator to be discrete, we begin by splitting all our turnout measures into four ordered categories, using the following ranges: 0-0.25, 0.25-0.50, 0.50-0.75, and 0.75-1.00. Following a similar approach as taken by Hällsten and Pfeffer (2017), we derive the individual weights for the grandparents from an ordinal logistic regression of the grandparents' (discrete) turnout on the full set of controls in the grandparental generation. We obtain the parental weights from an ordinal logit regression of the (discrete) parental turnout on grandparental turnout and grandparental and parental controls. Subsequently, we use a similar procedure to obtain the marginal probabilities used in the nominator when calculating the stabilized weights.

The results from the marginal structure model with stabilized weights are reported in Table A.14. The main coefficients in the table are unstandardized regression coefficients, whereas the standardized coefficients are shown in square brackets.

Table A.14: Marginal Structure Model

	Outcome: Turnout, Children		
	Model 1	Model 2	Model 3
Turnout P	0.328***		0.299***
	(0.008)		(0.007)
	[0.212]		[0.194]
Turnout GP		0.194***	0.103***
		(0.006)	(0.003)
		[0.120]	[0.064]
Num.Obs.	2,733,689	2,733,689	2,733,689

${}^{*}p < 0.10$, ${}^{**}p < 0.05$, ${}^{***}p < 0.01$.

The models in columns 1 and 2 are reported to enable a comparison with the results in the main text, but our main interest here lies in the estimates from model 3. As can be seen from the table, the standardized coefficient associated with grandparental turnout is 0.064, which is somewhat larger than the corresponding estimate reported in the main text (0.035). Although we should be somewhat careful when comparing the magnitude of the coefficients from the marginal structure model to those reported in the main text, because all turnout measures have now been discretized, these results corroborate the finding that the standard two-generation model of intergenerational transmission is likely to underestimate the true intergenerational persistence in voting. If anything, the MSM results indicate that the models presented in the main text underestimate the influence that grandparents assert over the voting habits of their grandchildren.

A.2.14 Disentangle Voting and Non-Voting Signals

In the related study of Gidengil et al. (2021) the authors suggest that it can be important to distinguish between the signals conveyed by voting and non-voting, respectively. In particular, they hypothesize that "having grandparents who do not vote may convey a particularly strong negative message about the value of voting" (2021, 1139). This is a very interesting hypothesis, but it is not obvious to us how it can be assessed empirically with the type of data used here. Unlike Gidengil et al. (2021) we have therefore made no attempts to distinguish between voting and non-voting signals in our analyses. In this section we briefly elaborate on our reasons for this decision.[3]

The root of the problem is that voting and non-voting, at least in the type of data studied here, are two sides of the same coin. If someone *votes* this necessarily implies that he or she does not *not vote*. For an individual with a given number of grandparents the number of voting grandparents will thus be perfectly collinear with the number of non-voting grandparents.

To examine their theoretical hypothesis, Gidengil et al. (2021) therefore compare the predicted probabilities of voting between individuals who have a different number of grandparents who are alive at the time of the election. The following quote illustrates the logic of their approach:

> The predicted probability of voting is only 38.3 percent when all four living grandparents were non-voters in 1999, compared with 53.6 percent when the only living grandparent stayed home on Election Day. By contrast, the predicted probabilities only range from 58.7 percent when the sole living grandparent voted to 66.0 percent when all four living grandparents voted. (Gidengil et al. 2021, 1142)

Because the difference in predicted turnout, between families with one and four observed grandparents, is considerably larger when all living grandparents are non-voters than it is when they are all voters, Gidengil et al. draw the conclusion "that having grandparents who were non-voters in 1999 has much more of an effect on the grandchildren's probability of voting than having grandparents who voted" (2021, 1142).

Although inventive, we see two drawbacks with the empirical approach adopted by Gidengil et al. (2021). First, there may be systematic differences between individuals with a different number of living grandparents that can affect the comparison. Second, and perhaps more importantly, observing zero voting grandparents may mean something rather different when we only observe the turnout of a single grandparent compared to the case when we observe turnout of all four grandparents. In the latter case we know for sure that all four grandparents were non-voters, whereas in the former case it is likely that some of the non-observed grandparents would have voted had they been observed. For instance, if average turnout among grandparents is about 70 percent (which it was in the Finnish case) we would expect slightly more than two of the (three) non-observed grandparents to be voters (0.7×3). An individual who has one observed grandparent that does not vote may therefore in reality be more comparable to an individual with four observed and two voting grandparents than

[3] We were encouraged by a couple of our reviewers to discuss this issue in more detail. However, to avoid overburdening the main text with this fairly long and somewhat technical discussion we decided to place it in this appendix

to an individual with four observed and zero voting grandparents. Likewise, on average we should expect the political activity of the grandparents in a family with one observed grandparent who votes to be on par with that of a family in which we observe four grandparents and three of them are voters.

The reason why it may be important to consider how likely it is that deceased, and thereby non-observed, grandparents would have voted had they been alive at the time of the election is that grandchildren could have been influenced by their grandparents while they were still alive. The children in the Finnish sample are aged between 2 and 29 when the turnout of their grandparents is measured, which means that many grandchildren could have spent most of their childhood and adolescence together with their grandparents even if the grandparents were not alive in 1999 when their turnout is measured. In addition, and as our results show, the voting activity of grandparents can predict the voting behavior of their grandchildren even if the grandparents die before the grandchildren are born, due to unmeasured genetic inheritance. Consequently, we have reasons to assume that grandchildren whose grandparents are politically active are more likely to vote even if these grandparents happen to die before Gidengil et al. (2021) measure their turnout. That is, differences in voting behavior between grandchildren in families with a different number of observed grandparents can be driven by both living and deceased grandparents.

The above reasoning thus suggests that there may be an alternative explanation for the pattern reported by Gidengil et al. (2021) in the quote above. The difference in turnout between an individual with four living grandparents who are all non-voters and that of an individual with a sole living and non-voting grandparent could, in fact, be akin to the difference between having zero or two voting grandparents when the turnout of all four grandparents is observed. Likewise, the difference in turnout of an individual with a sole living grandparent who votes and that of an individual with four voting grandparents could resemble the difference between having three or four voting grandparents when they are all observed. An alternative reason why Gidengil et al. (2021) observe the turnout difference to be twice as large in the first case could therefore be that the difference in the “expected” number of voting grandparents is twice as large (2 vs. 1) in this case.

To be clear, we do not mean to say that Gidengil et al. (2021) are necessarily wrong when suggesting that non-voting among grandparents may convey a stronger signal to their grandchildren than voting does. Our point is merely that there are multiple, and in our view equally credible, potential explanations for the patterns found in the Finnish data. Consequently, whereas the study of Gidengil et al. (2021) contains plenty of interesting and valuable results we do not think that a comparison across individuals with a different number of living grandparents is sufficient to disentangle the relative strength of voting and non-voting signals. Unfortunately, we have not been able to come up with any better idea of how to empirically assess the intriguing hypothesis of Gidengil et al. (2021) with the type of data at our disposal. In the main text we therefore encourage future research to examine whether other data and methods can be used to shed light on this issue.

References

Baron, Reuben M. and David A. Kenny. 1986. "The Moderator–Mediator Variable Distinction in Social Psychological Research: Conceptual, Strategic, and Statistical Considerations." *Journal of Personality and Social Psychology* 51 (6): 1173.

Bihagen, Erik. 2007. "Nya Möjligheter För Stratifieringsforskning i Sverige." *Sociologisk Forskning* 44 (1).

Braun, Sebastian Till and Jan Stuhler. 2018. "The Transmission of Inequality across Multiple Generations: Testing Recent Theories with Evidence from Germany." *The Economic Journal* 128 (609): 576–611.

Coall, David A. and Ralph Hertwig. 2010. "Grandparental Investment: Past, Present, and Future." *Behavioral and Brain Sciences* 33 (1): 1–19.

Elliot, Patrick. 2007. *Three Generations Combined, 1965-1997: Version 1.*

Elwert, Felix and Christopher Winship. 2014. "Endogenous Selection Bias: The Problem of Conditioning on a Collider Variable." *Annual Review of Sociology* 40 (1): 31–53.

Gidengil, Elisabeth, Hannu Lahtinen, Hanna Wass, and Jani Erola. 2021. "From Generation to Generation: The Role of Grandparents in the Intergenerational Transmission of (Non-)Voting." *Political Research Quarterly* 74 (4): 1137–1151.

Hällsten, Martin and Fabian T. Pfeffer. 2017. "Grand Advantage: Family Wealth and Grandchildren's Educational Achievement in Sweden." *American Sociological Review* 82 (2): 328–360.

Imai, Kosuke, Luke Keele, Dustin Tingley, and Teppei Yamamoto. 2011. "Unpacking the Black Box of Causality: Learning about Causal Mechanisms from Experimental and Observational Studies." *American Political Science Review* 105 (4): 765–789.

Jennings, M. Kent, Gregory B. Markus, Richard G. Niemi, and Laura Stoker. 2005. *Youth-Parent Socialization Panel Study, 1965-1997: Four Waves Combined: Version 1.*

Lindgren, Karl-Oskar, Sven Oskarsson, and Mikael Persson. 2019. "Enhancing Electoral Equality: Can Education Compensate for Family Background Differences in Voting Participation?" *American Political Science Review* 113 (1): 108–122.

Meraviglia, Cinzia, Harry B. G. Ganzeboom, and Deborah De Luca. 2016. "A New International Measure of Social Stratification." *Contemporary Social Science* 11 (2): 125–153.

Pollet, Thomas, Daniel Nettle, and Mark Nelissen. 2006. "Contact Frequencies between Grandparents and Grandchildren in a Modern Society: Estimates of the Impact of Paternity Uncertainty." *Journal of Cultural and Evolutionary Psychology* 4 (3): 203–213.

Prandy, Ken and Frank L. Jones. 2001. "An International Comparative Analysis of Marriage Patterns and Social Stratification." *International Journal of Sociology and Social Policy* 21 (4/5/6). 165–183.

Sharkey, Patrick and Felix Elwert. 2011. "The Legacy of Disadvantage: Multigenerational Neighborhood Effects on Cognitive Ability." *American Journal of Sociology* 116 (6): 1934–81.

Uhlenberg, Peter and Bradley Hammill. 1998. "Frequency of Grandparent Contact with Grandchild Sets: Six Factors That Make a Difference." *The Gerontologist* 38 (3): 276–285.