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Why do wealthy parents have wealthy children?*

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Abstract: We show that family background matters significantly for children's accumulation of wealth and investor behavior as adults, even when removing the genetic connection between children and the parents raising them. The analysis is made possible by linking Korean-born children who were adopted at infancy by Norwegian parents to a population panel data set with detailed information on wealth and socio-economic characteristics. The mechanism by which these Korean-Norwegian adoptees were assigned to adoptive families is known and effectively random. This mechanism allows us to estimate the causal effects from an adoptee being raised in one type of family versus another.

Keywords: Intergenerational transmission; wealth; financial risk taking; family background

JEL codes: D31; J62

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1 Introduction

Why do children of wealthy parents tend to be well off themselves? The evidence of an acceleration of wealth inequality over the past few decades has fueled a growing interest in this question among policymakers and researchers alike.[1] Several explanations have been proposed. One is a pure selection story; parents may genetically pass on abilities and preferences, creating intergenerational associations in income, savings behavior or financial risk taking. This can generate a strong correlation in wealth across generations even if there is no actual effect of parents' wealth or behavior on the child. Another story is one of causation, where children's accumulation of wealth depends on the actions of their parents. An intergenerational causal link can operate through a number of channels, including direct transfers of wealth (inter vivos or through inheritance), parental investment that promotes children's human capital and earnings capacity, or learning of attitudes and traits that influence children's savings propensity or financial risk taking.

The research to date has been limited in its ability to distinguish between selection and causation in the intergenerational correlation of wealth (for a review, see Black and Devereux, 2011). However, sorting out these scenarios is central to understand how economic conditions or government policies may shape the persistence of wealth inequality across generations. In this paper, we investigate the role of family background in determining children's accumulation of wealth and investor behavior as adults. The research design we use allows us to credibly control for genetic differences in abilities and preferences and to identify the effects on children's outcomes of being raised in one type of family versus another.

The analysis is made possible by using the identification strategy of Sacerdote (2007). His study takes advantage of information on Korean-born children who were quasi-randomly assigned to American families. He finds large effects on adoptees' risky behavior and smaller but significant impacts on their education and income from assignment to adoptive parents with more education or fewer biological children. Our analysis uses the same identification strategy though applied to different data and a distinct set of questions and outcomes. In particular, we link Korean-born children who were adopted at infancy by Norwegian parents to a population panel data set with detailed information on disaggregated wealth portfolios and socio-economic characteristics. We provide empirical evidence and institutional details showing that

[1] For evidence on the evolution of wealth inequality over time, see e.g. Piketty and Zucman (2014), Roine and Waldenstrom (2015), and Saez and Zucman (2016).

the mechanism by which these Korean-Norwegian adoptees were assigned to pre-approved adoptive families is known and effectively random. Any relation between the outcomes of the adoptees and their adoptive parents is therefore driven by the influence parents have on their children's environment and not by parents passing on their genes.

We use the quasi-random assignment of the Korean-Norwegian adoptees to estimate the causal effects from a child being raised in one type of family versus another. Our findings show that family background matters significantly, even after removing the genetic connection between children and the parents raising them. In particular, adoptees raised by wealthy parents are more likely to be well off themselves, and adoptees' stock market participation and portfolio risk are increasing in the financial risk taking of their adoptive parents.

To help interpret the economic significance of these results, we compare the intergenerational associations in wealth for adoptees to those for non-adopted children. This enables us to compare the predictive influence of parental wealth when there is and is not a genetic link between children and the parents raising them. We find that the intergenerational association in wealth is about twice as large for parents and own birth children as compared to parents and adoptees.

To assess the sensitivity of our results, we perform a number of robustness checks. We show that the causal effects from a child being raised by wealthier parents do not change appreciably if we use high quality measures of financial wealth or imperfect measures of net worth; if we estimate the impacts on the mean wealth or the median wealth; if we measure wealth at the household or the individual level; if we vary the age at which wealth is measured; and if we use level-level, rank-rank or log-log specifications to characterize the intergenerational associations in wealth.

Our study of Korean-born children who were adopted at infancy by Norwegian parents provide new insights into the causal effects of family background on children's wealth accumulation and investor behavior as adults. At the same time, the results raise a number of questions such as: What are the mechanisms through which parents influence children? What can we learn from adoptees about the population of children at large? We take several steps to shed light on these important but difficult questions.

To learn about mechanisms, we first investigate whether the impacts from assignment to wealthier parents operate through other observable characteristics of childhood rearing environment that are correlated with parental wealth. Our estimates suggest the effects are not operating through parents' education and household income or children's sibship size and place of residence in childhood. Next, we follow

Heckman et al. (2013) in applying mediation analysis to quantify the empirical importance of alternative channels. Mediation analyses can be used to understand how a treatment may influence an outcome variable through intermediate variables, called mediators. Our mediation analysis considers four observable mediators: children's education, income and financial literacy as well as direct transfer of wealth from parents. We find that changes in these mediator variables explain nearly 40 percent of the average causal effect on children's accumulation of wealth of being assigned to wealthier families. Parental transfers of wealth is the most important mediator.

To assess the question of generalizability, we examine three possible reasons why the external validity of adoption results might be limited: Adoptive parents may be different from other parents; adoptees may be different from other children; and parents may invest differently in adoptees as compared to own-birth children. Using the rich Norwegian data, we try to infer whether any of these differences are empirically important in our setting with Korean-born children who were adopted at infancy. We find suggestive evidence that adoptive parents do not differ significantly from other parents when it comes to intergenerational wealth transmission. Furthermore, the socio-economic characteristics of the Korean-Norwegian adoptees and their adoptive parents are broadly similar to that of other parents and children (who are born in the same period as the adoptees). Additionally, controlling for or matching on child and parental characteristics do not materially affect the size of intergenerational wealth transmission for the non-adoptees as compared to the adoptees. This is also true if we restrict the sample to a set of families with both a Korean-Norwegian adopted child and a non-adopted child. Within these families, we still find that wealth shows much less transmission from parents to adoptees as compared to non-adoptees.

Our study complements a small but growing literature that documents the intergenerational correlations in wealth across countries (see e.g. Charles and Hurst 2003; Boserup, Kopczuk, and Kreiner, 2014; Adermon, Lindahl, and Waldenstrom, 2018). What makes our study unique is the ability to credibly control for genetic differences in abilities and preferences and, thereby, to understand why children of wealthy parents tend to be well off themselves. Our paper is the first to utilize quasi-random assignment of adoptees to estimate the impact of family background on wealth accumulation and investor behavior.

As discussed above, the closest study to ours both in methodology and target population is Sacerdote (2007). We use the same identification strategy, but in terms of substantive empirical results, there is little if any link between the papers. We use different data, consider different treatments, and look at different outcomes. Unlike Sacerdote (2007), we also explore mechanisms, consider the generalizability of the lessons from adoptees, and extend the genetic decomposition analysis to incorporate correlations between the nature and the nurture components.

Our paper also relates to a larger body of work that uses adoption data to study intergenerational transmission in a wide range of socio-economic variables.[2] These studies have been important in documenting various dimensions of intergenerational persistence and social mobility. One concern, however, is that it can be difficult to establish a causal relationship between family background and children's outcomes because of selective placements of the adoptees. Selection effects can occur because parents request children with certain characteristics (such as gender and age) or because the adoption agencies may use information about the adoptees (or their biological parents) to assign children to adoptive families. We document that such selection effects do indeed occur for domestic adoption in Norway, in contrast to the quasi-random assignment of the Korean-born adoptees. To address concerns about selection bias, Björklund, Jäntti, and Solon (2007) and Black et al. (2020) use information on the adoptees' biological parents to control for their observable characteristics, hoping that any remaining bias is small.

Our paper is also related to a literature in household finance on why observationally equivalent individuals make widely different financial decisions, such as whether to invest in the stock market and the choice of portfolio risk (Campbell, 2006; Guiso and Sodini, 2013). Important evidence comes from Cesarini, Johannesson, Lichtenstein, Sandewall, and Wallace (2010), who employ a behavioral genetics decomposition to study financial risk-taking of identical and fraternal twins.[3] They find that an individual's financial decisions have a significant genetic component, while family environment plays a modest role. However, these results need to be interpreted with caution as the behavioral genetics model relies on a number of

[2]See, for example, Dearden, Machin, and Reed (1997); Plug and Vijverberg (2003); Plug (2004); Björklund, Lindahl, and Plug (2006); Björklund, Jäntti, and Solon (2007); and Holmlund, Lindahl, and Plug (2011). These papers differ from our study in several important ways. First, they do not know the mechanisms by which the adoptees are assigned to families, making it difficult to draw causal inferences about the role of family background. Second, they do not perform a mediation analysis to understand the mechanisms behind the intergenerational transmission. Third, they consider intergenerational links in outcomes other than wealth and financial risk taking. An exception is Black et al. (2017; 2020), who use data from domestic adoption in Sweden to study intergenerational transmission in financial risk taking and wealth. Consistent with our results, they find evidence that family background is important. An important advantage of our data is that the assignment of children to families is arguably random, allowing us to address concerns about selection on unobservables.

[3] See also Barnea, Cronqvist, and Siegel (2010) and Cronqvist and Siegel (2015).

strong assumptions (see e.g. Goldberger, 1978). For example, recent work opens the possibility that twin studies overestimate the genetic pre-determination of individual behavior at the expense of family environment (see e.g. Björklund et al., 2006; Sacerdote, 2010; Calvet and Sodini, 2014). Instead of relying on the restrictive behavioral genetics model, our main analysis takes advantage of the quasi-random assignment of adoptees to show significant causal links between family background and individuals' stock market participation and portfolio risk. Yet to directly compare what we find to the household finance literature, we also provide an interpretation of our data through the lens of a behavioral genetics model. In contrast to the standard model, our analysis incorporates correlations between genetics and family environment. Our findings indicate that both family environment and genetics are important in explaining the variation in children's wealth accumulation. In contrast to existing studies using data on twins, we find no evidence of a significant genetic component in financial risk taking.

The remainder of this paper proceeds as follows. Section 2 presents our data and Section 3 describes how the adoptees were assigned to families. Section 4 presents our research design, describes the estimates of intergenerational wealth transmission, and discusses their economic significance and robustness. Section 5 explores mechanisms and assesses the generalizability of the lessons from adoptees. Section 6 presents estimates of intergenerational links in financial wealth and investor behavior. Section 7 compares our findings to results from behavioral genetics decompositions. The final section summarizes and concludes.

2 Data and descriptive statistics

Below we describe our data and sample selection, while details about the data sources and each of the variables are given in Appendix Table B.1.

2.1 Main data sources

Our analysis employs several data sources from Norway that we can link through unique identifiers for each individual and family. Information on adoptees comes from the national adoption registry, which contains records on all native-born and foreign-born adoptees since 1965. The data set includes information about the adoptees (such as date of birth, gender, country of origin, date of adoption) and identifiers of the adoptive parents. We merge this information with administrative registers provided by Statistics Norway, using a rich longitudinal database that covers every resident from 1967 to 2014. For each year, it contains individual socio-economic information (including sex, age, marital status, educational attainment) and geographical identifiers. Over the period 1994-2014, we can link these data sets with tax records for every Norwegian. The tax records contain information about nearly all sources of annual income (including earnings, self-employment income, capital income, and cash transfers) as well as most types of assets holdings and liabilities. Income data are reported in annual amounts, while the values of assets holdings and liabilities are measured as of the last day of each year.

The Norwegian data have several advantages over those available in most other countries. First, there is no attrition from the original sample due to refusal by participants to consent to data sharing. In Norway, these records are in the public domain. Second, our income and wealth data pertain to all individuals, and not only to workers, individuals who respond to wealth surveys, or households that file estate tax returns. Third, most components of income and wealth are third-party reported (e.g. by employers, banks and financial intermediaries) and recorded without without any top or bottom coding. And fourth, unique identifiers allow us to match spouses to one another and parents to (biological or adoptive) children.

2.2 Definition and measurement of key variables

Our main analysis uses data on parental wealth in 1994-1996 and children's wealth in 2012-2014. We take three year averages of wealth to reduce the influence of transitory changes, as often done in the literature (see e.g. Charles and Hurst, 2003; Boserup et al., 2014). The estimates do not change appreciably if we instead use yearly data on wealth (see Section 4.3). Our main analysis is based on household level measures of wealth, in part to incorporate any effect of family background that operates through assortative mating but also to avoid making arbitrary splits across spouses of jointly owned assets.[4] In Section 4.3, however, we investigate the sensitivity of the results to whether children's wealth and their portfolio risk are measured at the household or the individual level; the estimates do not differ appreciably.

In most of our study, we focus on *net wealth*, defined as the value of non-financial and financial assets minus the value of outstanding liabilities. Measuring net wealth is challenging, and reliable measures requires accessing and linking data other than the tax records. The key challenge is that the tax data record the full mortgage amount but not necessarily the actual market value of the property. To address this challenge, we have obtained data from the Norwegian Land Register, which offers

[4]In Norway, spouses are generally taxed separately for income and jointly for wealth.

comprehensive information on real estate transactions. For nearly all properties in Norway, this data set contains information on the last transaction prior to 1994. In addition, it records nearly all real estate transactions during the period 1994-2014. The data set provides detailed information about the transactions, including unique identifiers for both the seller, the buyer and the property, the selling price, and characteristics of the property. Using the transaction data, we first find the market value for a given property at one or several points in time between 1986 and 2015. To estimate market values in other years, we combine our data on the characteristics of the properties with house price indices for specific regions and types of homes. We refer to Appendix A for a detailed description of how we measure net wealth and for an empirical validation of our measures.

While our main analysis focuses on net wealth, we also present results for *financial wealth* which is measured with little error. Financial wealth includes bank deposits, bonds, stocks, mutual funds and money market funds. To analyze how people compose their investment portfolio, we follow the literature in considering a two asset-portfolio: Risky assets are defined as the sum of mutual funds with a stock component and directly held stocks; the other components of financial wealth are classified as non-risky assets. Our primary measure of portfolio risk, which we denote the *risky share*, is the proportion of the financial wealth invested in risky assets over the three year period. We complement this measure of portfolio risk with a *stock market participation* indicator, taking the value one if at least some fraction of financial wealth is invested in risky assets over the three year period. Similar measures of financial risk taking have been used by recent studies of financial risk-taking, such as Cesarini et al. (2010), Barnea et al. (2010), and Calvet and Sodini (2014).

2.3 Sample selection and summary statistics

In most of our analysis, we study Korean-born children who were adopted by Norwegian parents. We refine the sample of these Korean-Norwegian adoptees to be appropriate for studying the role of family background in determining children's wealth accumulation and investor behavior as adults. We begin by restricting the sample to children who were adopted at infancy (eighteen months or less). This sample restriction allows us to capture most of the differences in early child environment across adoptive families. We further restrict the sample to adoptees who were born between 1965 and 1986. This sample restriction allows us to observe the variables of interest for a sizable sample of adoptees as adults (in 2012-2014) and their parents (in 1994-1996).

Taken together, these restrictions give us a baseline sample of 2,254 Korean-Norwegian adoptees. The solid line in Figure 1 shows the distribution of net wealth of adoptees, while the upper left panel of Table 1 displays summary statistics of variables other than net wealth for the same sample.[5] The adoptees are between the ages of 28 and 49 in 2014; the average age is nearly 36.[6] The adoptees are more likely to be female, and they have on average 15 years of schooling and about USD 70,000 in household income. Over the period 2012-2014, the average net wealth is about USD 105,000, of which USD 38,000 is financial wealth. About 13 percent of the financial wealth is invested in risky assets, and around two out of five adoptees participate in the stock market at least once over the period 2012-2014.

In Table 1 and Figure 1, we also provide a comparison of the Korean-Norwegian adoptees and the population of non-adoptees (children raised by their biological parents), both groups of children are born between 1965 and 1986. The distribution of net-wealth of the non-adoptees is given by the dashed line in Figure 1 and shows that the Korean-Norwegian adoptees are comparable to the Norwegian non-adoptees in their distribution of net wealth. The amount of financial wealth and investor behavior are also similar across the two samples (upper panel of Table 1). The adoptees tend to be a few years younger than Norwegian non-adoptees,[7] they are more likely to be female, and they are on average slightly higher educated. In the lower panel of Table 1 we present summary statistics for the parents of the adoptees and non-adoptees. Adoptive parents have, on average, higher income and wealth than parents who do not adopt. These differences are largely because the adoptive parents in our sample tend to be a bit older. As shown in Figure 2, the distributions of net wealth are quite similar for the two groups of parents once we condition on their birth years. Conditioning on age also help eliminate most the differences in income and education between adoptive and non-adoptive parents, as evident from Appendix Table B.7,

While Figures 1 and 2 display the marginal distribution of net wealth of parents and children, Figure 3 summarizes the dependence in net wealth across generations by displaying the relationship between parent and child ranks in the net wealth

[5]Throughout this paper, all monetary values are measured in USD, 2014 prices, using the average exchange rate in 2014, NOK/USD = 6.3019.

[6]The minimum age is similar to what is used in the analysis of intergenerational wealth correlations in Charles and Hurst (2003). By comparison, Boserup et al. (2014) include children who are as young as 21 years of age, whereas Adermon et al. (2018) takes advantage of survey data from a Swedish data to study intergenerational correlations with measures of wealth that are recorded at older ages.

[7]The reason is that adoption from Korea increases over time in the period we consider.

Table 1. Descriptive statistics of key outcomes and characteristics for Korean-Norwegian adoptees and Norwegian non-adoptees

	Korean-Norwegian adoptees		**Norwegian non-adoptees**	
Variable	Mean	Std. Dev	Mean	Std. Dev
A. Children, 2014				
Age	35.81	5.10	39.04	6.36
Female	0.75		0.49	
Years of schooling	14.96	2.89	14.12	3.02
Income	72,574	37,754	72,843	36,985
Financial wealth	38,235	65,555	40,791	75,048
Risky assets:				
Participation	0.38		0.41	
Share	0.13	0.22	0.15	0.25
B. Parents, 1994				
Mother's:				
Age	46.94	6.05	45.66	8.13
Years of schooling	12.69	2.54	12.06	2.46
Father's:				
Age	49.14	6.59	48.64	8.81
Years of schooling	13.37	2.89	12.60	2.73
Number of children	1.89	0.75	2.26	1.00
Income	46,539	19,423	39,490	20,363
Financial wealth	26,636	42,145	22,007	38,067
Risky assets:				
Participation	0.42		0.33	
Share	0.13	0.22	0.11	0.21
Number of children	2,254		1,206,650	

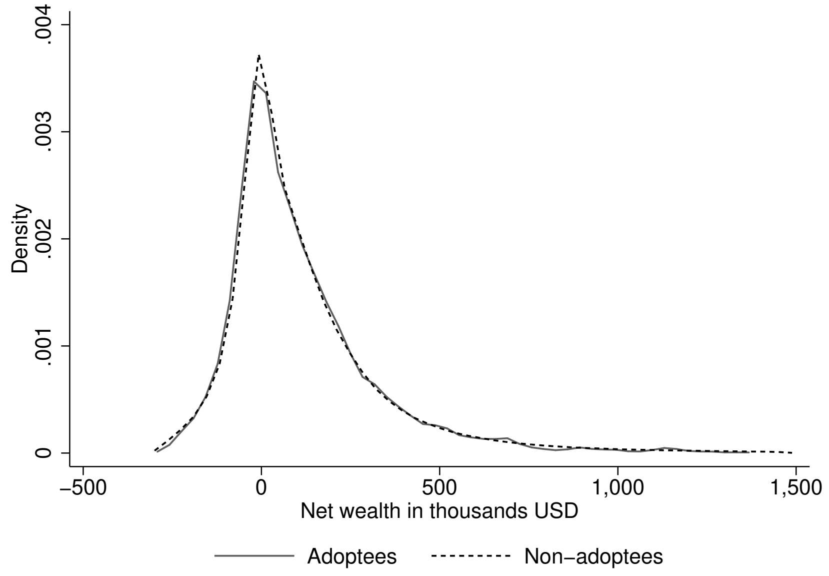
Notes: The Korean-Norwegian adoptees are born in South Korea between 1965 and 1986, and adopted at infancy (not older than 18 months) by Norwegian parents. The non-adoptees are born in Norway between 1965 and 1986, and raised by their biological parents. All monetary values are measured in USD, 2014 prices, using the average exchange rate in 2014, NOK/USD=6.3019. Income, wealth and assets are measured at the household (per capita) level. For these variables, we take three year averages of the years 1994-1996 for parents and of the years 2012-2014 for children. Risky assets are defined as the sum of mutual funds with a stock component and directly held stocks. Risky share is measured as the proportion of the financial wealth invested in risky assets over the three year period. Stock market participation is an indicator variable taking the value one if at least some fraction of financial wealth is invested in risky assets over the three year period. Number of children of the parents includes own-birth and adopted children.

distributions.[8] Panel A focuses on the Korean-Norwegian adoptees, whereas panel B compares the best linear prediction of the child's wealth rank for the adoptees and the non-adoptees. In both panels, we measure the percentile rank of parents based on their positions in the entire distribution of parental wealth, pooling parents of the non-adoptees and the Korean-Norwegian adoptees. Similarly, we define children's percentile ranks based on their positions in the entire distribution of child wealth, including both the non-adoptees and adoptees. To adjust for differences in age across children and parents, we condition on a full set of indicator variables for child and parent birth years.

Panel A presents a binned scatter plot of the relationship for the sample of Korean-Norwegian adoptees. Each dot represents the mean child rank (measured on the y-axis) for a given parental rank (binned over 5 percentiles due to small sample sizes). The solid thick line shows a local linear regression of the child's wealth rank on her parent's wealth rank. The solid thin line represents the best linear prediction of the child's net wealth rank. Panel B compares the prediction of child net wealth for the sample of adoptees (solid line) to the best linear prediction for the sample of non-adoptees (stippled line). For comparison, we also graph the 45-degree line (dotted line). The linear rank correlations are 0.24 and 0.16 for the samples of non-adoptees and adoptees, respectively. This means that, on average, a 10 percentile increase in parent net wealth is associated with a 2.4 percentile increase in a biological child's net wealth and a 1.6 percentile increase in an adoptees' net wealth. The conditional expectation of child net wealth given parent net wealth is relatively linear in percentile ranks across most of the net wealth distribution. At the top of the net wealth distribution, however, the dependence is stronger than what is predicted from a linear regression of child rank on parent rank.

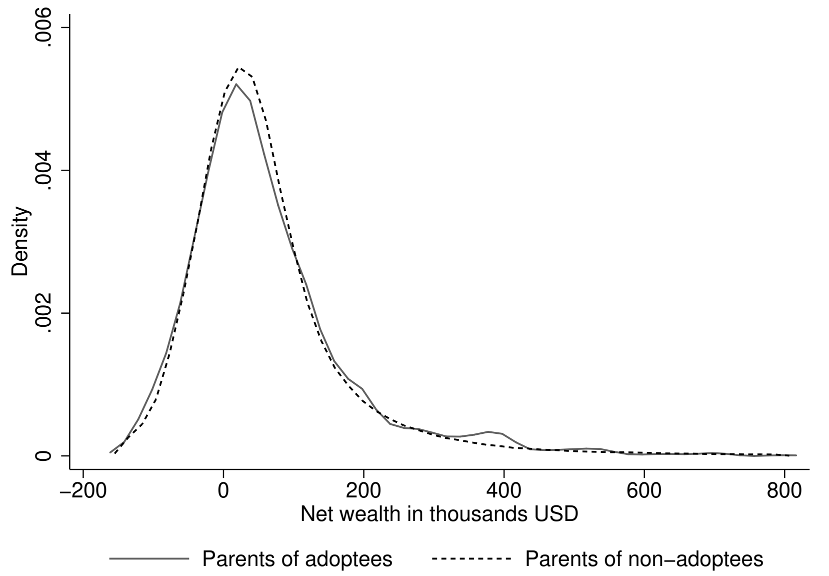
[8] The joint distribution of parent and child wealth can be decomposed into two components: the joint distribution of parent and child percentile ranks (the copula) and the marginal distributions of parent and child wealth. The rank-rank slope depends purely on the copula.

Figure 1. Distribution of net wealth for Korean-Norwegian adoptees and Norwegian non-adoptees



Notes: The figure plots kernel density estimates of the distribution of net wealth for Norwegian non-adoptees and Korean-Norwegian adoptees. Net wealth is measured as an average over three years, 2012-2014.

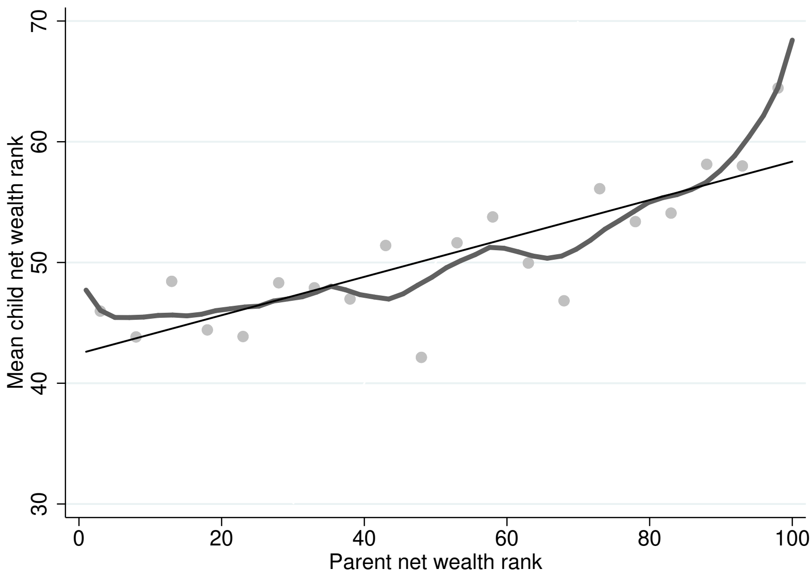
Figure 2. Distribution of net wealth for the parents of Korean-Norwegian adoptees and Norwegian non-adoptees



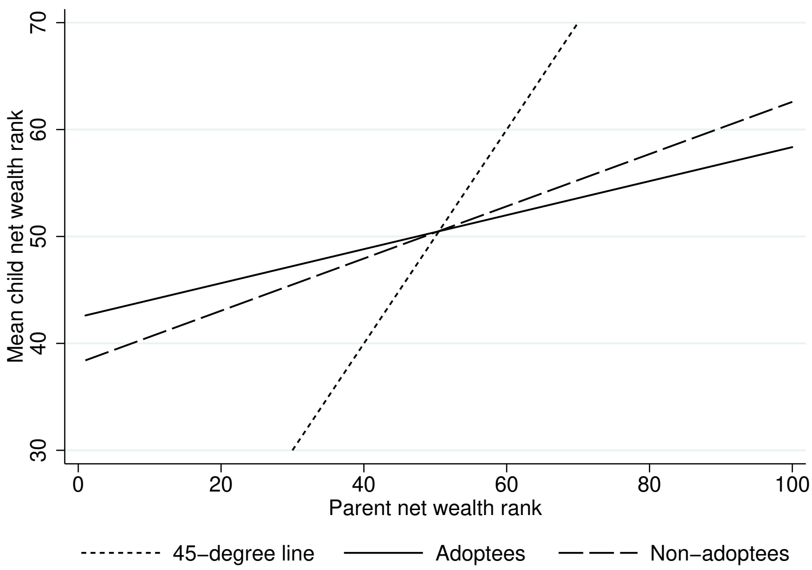
Notes: The figure plots kernel density estimates of the distribution of net wealth for the parents of the Norwegian non-adoptees and Korean-Norwegian adoptees. Net wealth is measured as the average net wealth over three years, 1994-1996. We adjust for differences in age by regressing net wealth on a set of indicator variables for child and parent birth years.

Figure 3. Dependence in net wealth across generations

(a) Mean child net wealth rank vs. parent net wealth rank, Korean-Norwegian adoptees



(b) Comparison of best linear prediction of child net wealth for adoptees and non-adoptees



Notes: The figure displays the relationship between children's and parent's percentile net wealth ranks for the samples of non-adoptees and adoptees. The ranks (1-100) are calculated in the joint distribution of adoptees and non-adoptees. We adjust for differences in age by conditioning on a set of indicator variables for child and parent birth years.

Panel A presents a binned scatter plots of the relationship for the sample of Korean-Norwegian adoptees. Each dot represents the mean child rank (measured on the y-axis) for a given parental rank (binned over 5 percentiles due to small sample sizes). The solid thick line shows a local linear regression of the child's wealth rank on her parent's wealth rank. The solid thin line represents the best linear prediction.

Panel B presents the best linear prediction of child net wealth for the sample of non-adoptees (stippled line), with a slope of 0.244, and the best linear prediction for the sample of adoptees (solid line), with a slope of 0.159. The dotted line is the the 45-degree line.

3 Assignment of adoptees to families

This section documents how the Korean born adoptees were assigned to Norwegian families.[9]

3.1 Assignment process

Between 1965 and 1986, a large number of South Korean children were adopted by Norwegian families, making Korean-born children the largest group of foreign adoptees in Norway. The majority of these Korean-Norwegian adoptees were born to working- or middle-class unwed mothers.

During the period we consider, virtually all the Korean-Norwegian adoptees were handled through the organization called Children of the World, Norway (CNW). This organization has its origin in the Norwegian Korean Association, which was founded in 1953 by personnel at the Norwegian field hospital stationed in South Korea during the Korean War. In the 50s and early 60s, CNW conveyed contact between Norwegians who wanted to adopt children and Korean institutions that arranged adoption to foreign countries. In the 1960s, the organization was granted a unique license for adoption arrangement from South Korea to Norway and started its cooperation with Holt International Children's Services in Korea.

The process of adoption from South Korea to Norway consisted of several steps. The first step was the submission of an application to CNW for review by case examiners. Adoptive parents had to meet several pre-specified criteria, including being married for three years or longer, an age difference between the spouses of less than ten years, and a minimum family income. At the time of application, the adoptive parents also had to be between the ages of 25 and 40, and have no more than 4 children. If the applicant satisfied these formal criteria, a case examiner met the adoptive parents to discuss their personal history and family relationships. This home study had to be approved before a family was qualified to adopt. The entire review process usually took about one year.

In the adoption application, parents were not given the opportunity to specify gender, family background or anything else about their future adoptee. One exception to this rule is that parents could indicate if they would be open to adopting an older child. This does not present a problem for our study since we restrict the sample to children adopted during infancy or very early childhood (eighteen months or less).

[9] Our description of the process is based on written documentation from CNW and interviews with its employees. See Sacerdote (2007) for a discussion of a similar assignment process of Korean-born children to American families.

A majority of Korean-Norwegian children were 18 months or younger at time of adoption.

The next step in the adoption process was that CNW sent the approved files to Holt Korea. Young children in the Holt system were assigned to the Norwegian adoptive families in the order the applications arrived. This first come, first served policy meant that precisely which adoptee that was assigned to which family depended on the order the application arrived rather than the characteristics of the child or the adoptive parents. As a result, assignment of young children to pre-approved adoptive families should be as good as random conditional on time of application.

3.2 Verifying quasi-random assignment

Table 2 verifies that the first come, first served policy created a setting where assignment to adoptive families is as good as random conditional on time of adoption. This table conducts the same type of statistical tests that would be done for a randomized controlled trial to verify compliance with randomization. We regress pre-assignment (i.e. measured at the time of birth of the child) characteristics of the adoptee on pre-assignment characteristics of the adoptive family. The dependent variables are the adoptee's age at adoption and gender.[10] These are important characteristics to test for selective placements, as many countries other than South Korea allowed adopting parents to choose or request the age or gender of their child. The explanatory variables are the same (pre-determined) family background characteristics as Sacerdote (2007) used in his randomization test: the log of family income, father's years of schooling, mother's years of schooling, and median log income in the municipality of residence in childhood.[11]

In the first and third column of Table 2, we run separate regressions for each characteristic of the adoptive family. In columns 2 and 4, we present estimates from multivariate regressions including all the characteristics of the adoptive family. All regressions include dummies for calendar year of adoption. Conditional on time of adoption, we expect to find no significant relationship between the pre-assignment characteristics of the adoptees and the pre-assignment characteristics of the adoptive families. It is therefore reassuring to find that none of the family background

[10] Sacerdote (2007) also has information about the Korean adoptees' weight and height upon entering the Holt system. His results show that the queuing policy of the Holt system generates no correlation between these variables and the pre-assignment characteristics of the adoptive family.

[11] These balancing checks are robust to including additional covariates (e.g. political affiliation in the municipality of residence in childhood), to excluding families who already had children (less than 200 families), and to adding controls for calendar quarter of adoption (i.e. four indicator variables per year). Furthermore, we have used disability benefit receipt as a proxy for child health (which we do not observe). When regressing it on the set of pre-determined family characteristics, there is no indication that these variables are correlated with the proxy for child health.

Table 2. Testing for quasi-random assignment of Korean-Norwegian adoptees

	Dependent variable:			
	Age at adoption		Gender	
	Specification:			
Regressors	Bivar. reg.	Multivar. reg.	Bivar. reg.	Multivar. reg.
Parent net wealth	-0.002	-0.002	0.005	0.004
	(0.003)	(0.0037)	(0.004)	(0.004)
Mother's years	0.002	0.003	0.002	0.001
of schooling	(0.002)	(0.003)	(0.003)	(0.004)
Father's years	0.001	-0.000	0.002	-0.000
of schooling	(0.002)	(0.002)	(0.003)	(0.004)
(Log) parent income	0.001	0.007	0.059	0.037
at birth	(0.035)	(0.038)	(0.0488)	(0.054)
Median (log) income	-0.046	-0.047	0.051	0.036
in childhood municipality	(0.034)	(0.035)	(0.0459)	(0.047)
Dependent mean	0.78	0.78	0.75	0.75
F-stat, joint significance of regressors		0.882		0.356
[p-value]		[0.540]		[0.956]

Notes: The table contains estimates from regressions of a pre-determined characteristic of the adoptee (age at adoption or indicator for female) on family background variables such as parental net wealth, education (in years) of the mother and father, the log of parents income and the log the median income in parents' municipality of residence, all measured at the time of birth of the child. In columns 1 and 3, we run separate regressions for each of the family background variables (conditional on a full set of indicators for adoption years of the children). In columns 2 and 4, we run multivariate regressions with all the family characteristics (conditional on a full set of indicators for adoption years of the children). The estimation sample consists of 2,254 Korean-Norwegian adoptees adopted at infancy by Norwegian parents. Standard errors (in parentheses) are clustered at the mother. ***p<.01, **p<.05, *p<.10.

characteristics are statistically significant predictors (at the 10 % significance level) of child age at adoption or gender. In fact, the point estimates are small, and taken together, the family characteristics explain very little of the variation in the adoptee characteristics.

To assess the power of the randomization test, we run the same regressions for native-born children who were adopted by Norwegian families as well as for Korean-Norwegian adoptees who were older than 18 months at the time of adoption (see Appendix Tables B.2 and B.3). The domestic adoptions were not assigned through a queuing policy, and some of them may occur between related family members. Selective placement can also occur between unrelated individuals because adoptive parents could request children with certain characteristics or because the adoption agencies used information about the adoptees (or their biological parents) to assign children to adoptive families. Indeed, the regression results show strongly significant correlations between adoptive parents' education and family income and the adoptee characteristics. When we look at Korean-Norwegian adoptees who were older than 18 months at the time of adoption, we also find some evidence of non-random assignment (as expected since parents could indicate if they would be open to adopting an older child). The evidence of significant non-random assignment of domestic adoptees and older Korean-Norwegian adoptees is not driven by larger sample sizes. A majority of the Korean-Norwegian adoptees were younger than 18 months at time of adoption, and there are a similar number of native-born adoptees and young Korean born adoptees. Our findings of significant non-random assignment of domestic adoptees raise concerns about the credibility of findings in previous studies based on data of domestic adoptions.

4 Empirical analysis

This section presents our research design, describes the main findings, and discusses the robustness of the results.

4.1 Research design and parameters of interest

Our interest is centered on estimating an average causal effect of being raised in one type of family versus another. While most of our empirical analyses focus on the impact of being raised by parents with high versus low wealth, we consider, in Section 6, dimensions of family background other than parental wealth. To be concrete, however, we fix the discussion of the research design to the intergenerational transmission of wealth.

To make precise what we can (and cannot) identify under the assumption of random assignment of adoptees conditional on year of adoption, consider the following regression model linking the adult outcome Y (e.g. net wealth) of child i to her own characteristics and the characteristics of the family j in which she was raised:

$$Y_i = \sum_k \alpha_k Z_{k,i} + \beta W_{j(i)} + \boldsymbol{X'_{j(i)}}\boldsymbol{\eta} + \gamma\kappa_{j(i)} + \boldsymbol{X'_i}\boldsymbol{\lambda} + \delta\chi_i + u_i \quad (1)$$

The characteristics of the family consist of parental net wealth $W_{j(i)}$, a vector of observable family characteristics other than wealth $\boldsymbol{X_{j(i)}}$ (parental education, income and birth year, family size, neighborhood) and an unobservable component $\kappa_{j(i)}$. Similarly, the characteristics of the adoptee are given by a vector of observables $\boldsymbol{X_i}$ (birth year, gender), an unobservable component χ_i, and, if the child is an adoptee, an indicator variable variable $Z_{k,i}$ that equals one if she was adopted in year k (and 0 otherwise). The idiosyncratic error term u_i is a scalar unobservable that is – by definition – orthogonal to $W_{j(i)}$, $\boldsymbol{X_{j(i)}}$, $\kappa_{j(i)}$, $\boldsymbol{X_i}$, χ_i, and $Z_{k,i}$. In other words, unobservable variables that may correlate with the variable of interest $W_{j(i)}$ are captured by χ_i and $\kappa_{j(i)}$, not u_i.

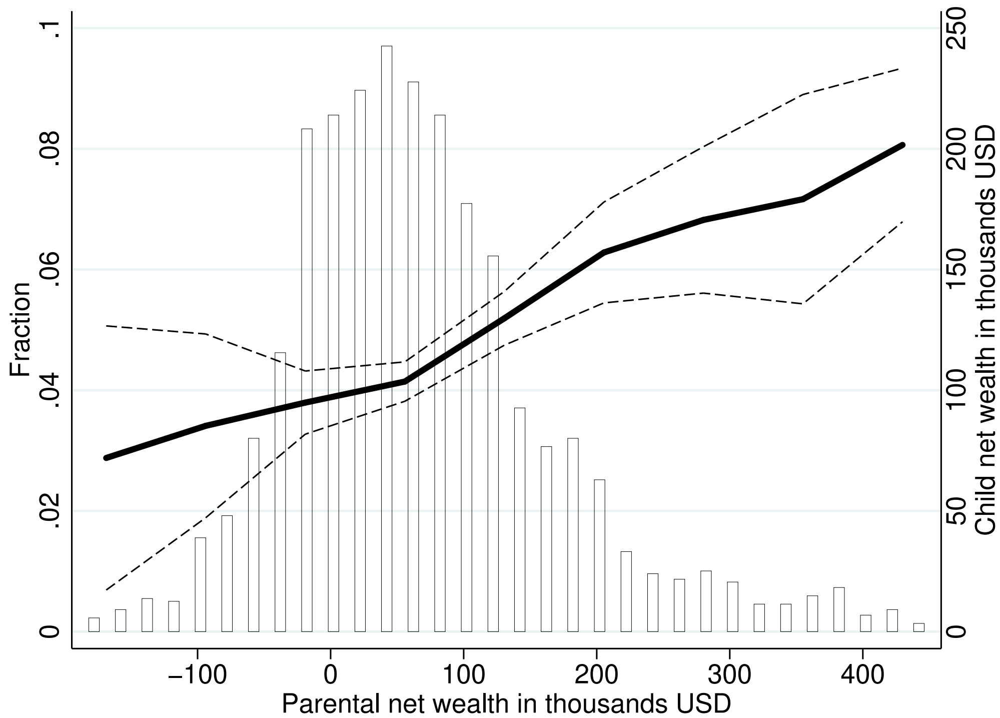
If we consider a sample of non-adoptees, then the variable of interest $W_{j(i)}$ may be correlated with the unobservable individual characteristics χ_i and the unobservable family characteristics $\kappa_{j(i)}$, even conditional on observables. Thus, for non-adoptees, the estimated β does *not* capture the causal effect of being raised by richer parents. To avoid this selection bias, we will instead use the sample of randomly assignment adoptees (conditional on year of adoption $Z_{k,i}$). Then, the family components $(W_{j(i)}, \boldsymbol{X_{j(i)}}, \kappa_{j(i)})$ are conditionally independent of the characteristics of the adoptees $(\boldsymbol{X_i},\ \chi_i)$. However, $W_{j(i)}$ may still be correlated with $\kappa_{j(i)}$, even conditional on $(Z_{k,i}, \boldsymbol{X_{j(i)}}, \boldsymbol{X_i})$. Thus, we cannot, without further assumptions, identify the effect of an exogenous increase in parental wealth. Instead, what we aim to draw causal inference about is the *total effect* of being assigned to an adoptive family with high versus low wealth, and the *partial effect* of assignment to wealthier parents holding other observable family characteristics fixed.

To do so, we estimate equation (1) for the adoptees without (total effect) and with (partial effect) controls for pre-determined observable family characteristics $\boldsymbol{X_{j(i)}}$. Under the assumption of conditional random assignment of adoptees, OLS produces consistent estimates of the total and partial effect of being assigned to wealthier parents. Next, we compare these estimates to those we obtain when estimating equation (1) for the sample of non-adoptees. This comparison allows us to learn about how the estimates of β differ across children for which there is and is not a correlation between $W_{j(i)}$ and χ_i (e.g. a correlation could reflect to a genetic link between non-adoptees and the parents raising them). Of course, the estimates of β might also differ for other reasons, such as non-comparability of adoptees and non-adoptees. After presenting the main results, we investigate, in Section 5, the comparability of the adoptees and the non-adoptees, which is informative about the external validity and generalizability of the findings based on the sample of adoptees.

4.2 Main results

Before we present the regression results, we show, in Figure 4, the variation in our data that we use to estimate the total effect of being assigned to an adoptive family with high versus low wealth. In the background of the graph is a histogram for the density of families by their net wealth. This figure also plots the net wealth of the adoptee as an adult (in 2012-2014) as a function of the net wealth of her

Figure 4. Association between adoptee's net wealth and adoptive parents' net wealth



Notes: This figure is based on the baseline sample consisting of 2,254 Korean adoptees adopted at infancy and their adoptive parents. The histogram shows the density of parental wealth (the left y-axis). The solid line shows estimates from a local linear regression of net wealth of the adoptee as an adult (measured as an average of 2012-2014) on the net wealth of her adoptive parents (measured as an average of 1994-1996), conditional on full set of indicators for year of adoption and birth years of child and parents. Dashed lines show 90% confidence intervals.

adoptive parents (in 1994-1996). The graph is a flexible analog to equation (1), plotting estimates from a local linear regression (with a full set of indicators for year of adoption and birth years of child and parents). Child wealth is monotonically increasing in parental wealth. This graphical evidence indicate that being raised by wealthy parents tend to make the child wealthier as an adult.

In Table 3, we turn attention to the regression results for the intergenerational associations in net wealth. Each column reports OLS estimates from equation (1), including a full set of indicators for year of adoption and birth years of the adoptees and their adoptive parents. The first three columns present the associations between the adoptive parents and their Korean-Norwegian adoptive children, removing the genetic connection between children and the parents raising them. The next three columns present the associations between parents and their own-birth children (born in the same years as the adoptees), maintaining the genetic link between children and the parents raising them. The last two columns restrict the sample to families with both a Norwegian-Korean adopted child and a non-adopted child. The sample restriction ensures that we are comparing adoptees and non-adoptees with exactly the same set of parents.

In the first column, we find a point estimate of 0.225 with a standard error of 0.041. This estimate reveals that the adoptees who were assigned to wealthier parents tend to become significantly richer themselves. On average, the adoptees accrue an extra USD 2,250 of wealth if she is assigned to an adoptive family with USD 10,000 of additional wealth. The magnitude of this estimate suggest that adoptees raised by parents with a wealth level that is 10 percent above the mean of the parent generation can expect to obtain a wealth level that is almost 3.7 percent above the mean of the child generation. The second column controls for the adoptee's age at adoption and gender. The intergenerational associations in net wealth do not change if we add these controls, which is consistent with the evidence of random assignment of adoptees to adoptive families.

Moving from the second to the third column, we shift attention to the partial effect of assignment to wealthier parents holding other observable family characteristics fixed. Column 3 adds controls for a range of observable characteristics of the childhood rearing environment other than parental wealth. We include controls for parental income and education at the time of adoption, as a large literature documents that these variables are correlated between parents and their children; we control for number of siblings, so that we only exploit the variation within families of a given size; and we condition on the median income in the children's place of residence (municipality) in childhood. Our estimates suggest the effect of being raised by wealthier parents is not operating through its correlation with parents' education and household income or children's sibship size and place of residence in childhood.

To help interpret the magnitude of the effects of being assigned to wealthier families, the fourth and fifth columns reports the intergenerational associations for the sample of non-adoptees (born in the same years as the adoptees). This enables us to compare the predictive influence of parental wealth when there is and is not a genetic link between children and the parents raising them. We find that wealth shows much less transmission from parents to adoptees (point estimate of 0.225) as compared to non-adoptees (point estimate of 0.575). Comparing columns 3 and 5, we find that this conclusion holds if we control for observable characteristics of the childhood rearing environment other than parental wealth. In column 6, we weight the sample of non-adoptees to match the sample of non-adoptees in terms of the pre-determined observable characteristics. This matching procedure is discussed in more detail in Section 5.2. Comparing columns 5 and 6, we find that the matching

Table 3. Intergenerational links in wealth

	Korean-Norwegian adoptees			Non-adoptees			Families with both Adopted and Non-adopted Child	
	(1)	(2)	(3)	(4)	(5)	(6)	(7) Adoptees	(8) Non-adoptees
Child-parent net wealth relation	0.225***	0.225***	0.204***	0.575***	0.547***	0.548***	0.276**	0.468***
	(0.041)	(0.041)	(0.042)	(0.011)	(0.011)	(0.018)	(0.139)	(0.122)
Adoption year indicators	Yes	Yes	Yes				Yes	
Birth year ind. of child & parents	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Gender		Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adoption age (in days)		Yes	Yes				Yes	
Family characteristics			Yes		Yes	Yes		
Matched sample (prop. score)						Yes		
Observations		2,254			1,206,650		515	1,105

Notes: The Korean-Norwegian adoptees are born in South Korea between 1965 and 1986, and adopted at infancy by Norwegian parents. The non-adoptees are born in Norway between 1965 and 1986, and raised by their biological parents. Family characteristics include education (in years) of the mother and father, the number of siblings, the (log of) parents income and the (log of) the median income in parents' municipality of residence, all measured at the time of birth of the child. In column 6 the observations in the sample of non-adoptees are weighted by the propensity score for being an adoptee (based on pre-determined characteristics, see Section 5.2 and Appendix Table B.9). In columns 7 and 8, we restrict the sample to families with both a Korean-Norwegian adopted child and a non-adopted child. Using this restricted sample, we then estimate the intergenerational wealth transmission separately for the 515 adopted children (column 7) and for the 1,105 non-adopted children (column 8). The sample restriction ensures that we are comparing adoptees and non-adoptees with exactly the same set of parents. Standard errors (in parentheses) are clustered at the mother. ***p<.01, **p<.05, *p<.10.

results are nearly identical to those we obtain from the OLS regressions with controls.

In the last two columns of Table 3, we address the concern that there might be unobserved dimensions along which adoptive parents are different. This is done by restricting the sample to families with both a Korean-Norewegian adopted child and a non-adopted child. Within this sample of families, we then estimate the intergenerational wealth transmission separately for the adopted children in column 7 and for the non-adopted children in column 8. The sample restriction ensures that we are comparing adoptees and non-adoptees with exactly the same set of parents. Thus, we are drawing inferences about the intergenerational wealth associations of adoptees and non-adoptees with identical distributions of not only observed but also unobserved family characteristics. Our findings do not materially change if we restrict the sample to families with both an adopted child and an non-adopted child. We still find that wealth shows much stronger transmission when there is a genetic link between children and the parents raising them (point estimate of 0.468 for non-adoptees) as compared to when no such link exists (point estimate of 0.276 for adoptees).

4.3 Robustness checks

Before turning to the interpretation of our findings, we present results from several robustness checks, all of which are reported in Appendix Tables B.4-B.5.

Age of wealth measurement. In the above analysis, we take the average of parental wealth for the three year period, 1994-1996 and the average of child wealth for the three year period, 2012-2014. This means that the average (median) age of wealth measurement is 48.0 (48) for parents and 35.8 (36) for children. In our baseline specification, we followed previous studies of intergenerational wealth correlations in pooling the cohorts in our estimation sample while flexibly controlling for birth years of children and parents. This specification produces an estimate of intergenerational wealth transmission of 0.225 for adoptees and 0.575 for non-adoptees. Since this parameter estimate is a weighted average of potentially heterogeneous effects across different ages, a natural concern is the issue of life-cycle variation in the intergenerational transmission of wealth. To address this concern, we examine the sensitivity of our results with respect to i) age of wealth measurement of the child, and ii) the age gap in measurement of wealth across generations.

Appendix Table B.4 shows the sensitivity of the intergenerational transmission to the age of wealth measurement of the child. We perform this robustness check for our sample of Korean-Norwegian adoptees (Panel A) and the sample of non-adoptees (Panel B). Both samples of children are born between 1965 and 1986. The results show that the intergenerational wealth transmission does not vary dramatically with the age at which we measure the children's wealth. Moreover, the intergenerational transmission is about twice as large for non-adoptees as compared to adoptees, at all ages. Given our data, however, we are unable to look at children older than 49 years. Thus, we cannot rule out that both the wealth transmission and the importance of inheritance are higher at older ages.

Appendix Figure B.1 presents estimates of intergenerational wealth transmission when we align the ages of measurement of the wealth variables across generations. As above, we use the samples of Korean-Norwegian adoptees and non-adoptees. For each sample, we estimate the intergenerational wealth transmission separately according to differences in the ages of wealth measurement between parents and children. To maintain a reasonable size for the subsamples of adoptees, we use data on wealth for the entire period 1994-2014. For adoptees, we find that the wealth transmissions do not materially change across the subsamples as the age gap closes from 15 to 8 years. Unfortunately, the relatively small number of adoptees prevent us from further aligning the ages of measurement. For non-adoptees, however, the sample sizes are sufficiently large for us to perfectly align the age of measurement. It is reassuring to find that the intergenerational wealth transmission remains similar if there are large, small or no differences in ages of wealth measurement across generations

Other specification checks.
In Appendix Table B.5, we present results from a battery of specification checks. In columns 1 and 2, we examine the sensitivity to outliers. When performing a median regression, which is less sensitive to extreme values (column 1), we find that the effects on the median of child net wealth are significant and close to the baseline estimates in Table 3. In the baseline specification, we winsorize the top and bottom 0.1 % of the wealth data. In column 2, we drop this winsorizing, finding that the estimates do not change appreciably.

In column 3, we investigate the sensitivity of the results to whether children's net wealth is measured at the household or the individual level. We find that the intergenerational transmission is robust to whether we use measures of individual versus household wealth. Column 4 examines how the estimates change if we use annual data on wealth (1994 for parents and 2014 for children) instead of taking three year averages of wealth (1994-1996 for parents and 2012-2014 for children). The estimates do not change appreciably.

In the last two columns of Appendix Table B.5, we examine the robustness to two alternative specifications to describe intergenerational transmission, namely rank-rank (column 5) and log-log (column 6). The estimates from both specifications suggest that adoptees who were assigned to wealthier parents tend to become significantly richer themselves, and that the intergenerational wealth transmission is not driven by observable characteristics of the childhood rearing environment other than parental wealth. We measure the percentile rank of parents based on their positions in the entire distribution of parental wealth, pooling parents of the non-adoptees and the Korean-Norwegian adoptees. Similarly, we define children's percentile ranks based on their positions in the entire distribution of child wealth, including both the non-adoptees and adoptees. To adjust for differences in age across children and parents, we condition on a full set of indicator variables for child and parent birth year. Then, we estimate the rank correlations across generations in net wealth. We find a rank correlation in net wealth of 0.17, conditional on gender and year of adoption. Thus, on average, a ten percentile increase in the position of the adoptive parents in the wealth distribution is associated with a 1.7 percentile increase in the average position of the adoptees. When using a log-log specification, the child-parent wealth elasticity is 0.18.[12] However, this estimate must be interpreted with caution as the log-log specification requires that we exclude a significant number of children and parents with zero or negative net wealth.

5 Mechanisms and generalizability

This section explores mechanisms and examines the generalizability of the lessons from the adoptees.

5.1 Mediation analysis of mechanisms

Standard models of wealth accumulation suggest that wealth levels depend on individuals incomes, their propensity to save and choice of investment portfolio, and the amount and timing of gifts and bequests. These models point to several reasons why parent and child wealth would be similar, even after removing the genetic connection between children and the parents raising them: Wealthy parents may invest more in children's human capital, raising their income levels; wealthy parents may directly transfer wealth, inter vivos or through inheritance; and wealthy parents may shape the attitudes or traits that influence children's savings propensity or investor behavior.

The ideal experiment for quantifying the relative importance of these inputs to wealth accumulation would have two layers of randomization. First, there would be random assignment of children to families of different wealth. Then, a second

[12]The corresponding log-log estimate for the sample of non-adoptees is 0.23. This estimate is similar to the results reported by Boserup et al. (2014) for Denmark.

experiment would be implemented in both rich and poorer families, such that measured inputs vary through a randomization protocol conditional on parental wealth. Admittedly, we do not have access to such an ideal experiment. We are able to quasi-randomly assign adoptees to richer and poorer families, but we do not randomize inputs conditional on parental wealth. Thus, additional assumptions are needed. In particular, we follow Heckman et al. (2013) and Heckman and Pinto (2015) in using a model of mediation to quantify the mechanisms.[13] The goal of this analysis is to disentangle the average causal effect on outcomes that operate through two types of inputs or channels: a) Indirect effects arising from the effect of treatment on measured mediators, and b) direct effects that operate through channels other than changes in the measured mediators (including changes in mediators that are not observed by the analyst and changes in the mapping between mediators and outcomes).

Measured mediators.
Our mediation analysis considers four observable mediators: children's education, children's income, children's financial literacy, and inter vivos transfer of wealth from the parents. Using our data for the period 1994-2014, we construct measures of direct transfers of wealth over this time period. In each year, we observe both gifts and bequests (in cash or in kind) from friends, parents and other family members.[14] Our measures of gifts and bequests should include any transfer to an individual, either directly or indirectly, where full consideration (measured in money or money's worth) is not received in return. The general rule is that both the donor and the recipient must report any gift or bequest to the tax administration (even in cases where it is not taxable).[15] Child education is measured as years of schooling, child income is measured as the average over the years 2012-2014, and we proxy financial literacy with a dummy variable for whether the child has a college degree in finance, business or economics.

Model of mediation.
Our specification of the model of mediation builds on Heckman et al. (2013) and Heckman and Pinto (2015). For simplicity we suppress the individual and family

[13] We thank the editor for suggesting that we use mediation analysis to explore mechanisms.

[14] Norwegian law states that in kind transfers are counted at the full fair market value, which is the price at which the property would change hands between a willing buyer and a willing seller. The law also limits the possibilities of parents to differentiate between children (own-birth or adopted) through bequests, as only a certain fraction can be transferred according to parents' preferences. The remainder is reserved for equal sharing between children. The same regulations apply to gifts that are advancements of inheritance.

[15] There are exceptions to this rule. For instance, individuals do not have to report gifts or bequests if their value, in total, do not exceed a relatively low annual threshold.

index. Let D denote parental wealth, the multi-valued treatment variable. Let Y_d denote the potential wealth of the adoptee if she is assigned to a family with parental wealth $D = d$.

Our analysis is based on the following linear model:

$$\begin{aligned} Y_d &= \kappa_d + \underbrace{\sum_{j\in\mathcal{J}_p} \alpha_d^j \theta_d^j}_{\text{measured mediators}} + \underbrace{\sum_{j\in\mathcal{J}\setminus\mathcal{J}_p} \alpha_d^j \theta_d^j}_{\text{unmeasured mediators}} + \boldsymbol{X'\beta_d} + \tilde{\epsilon}_d \\ &= \tau_d + \sum_{j\in\mathcal{J}_p} \alpha_d^j \theta_d^j + \boldsymbol{X'\beta_d} + \epsilon_d \end{aligned} \tag{2}$$

where $\mathcal{J}$ is an index set for mediator variables, κ_d is a treatment-specific intercept, $\boldsymbol{X}$ is a vector of pre-assignment variables (gender, age at adoption, birth cohort of child and parents, year of adoption) and $\tilde{\epsilon}_d$ is an error term assumed to be uncorrelated with $\boldsymbol{X}$ and the vector of mediator variables $\boldsymbol{\theta_d} = (\theta_d^j : j \in \mathcal{J})$. While the background variables $\boldsymbol{X}$ are not affected by the treatment, their effect on Y can be affected by the treatment as captured by the treatment-specific coefficients $\boldsymbol{\beta_d}$. Equation (2) decomposes the vector of mediator variables $\boldsymbol{\theta_d}$ into components we can measure, $\boldsymbol{\theta_d^p} = (\theta_d^j : j \in \mathcal{J}_p)$, and components we do not observe, $\boldsymbol{\theta_d^u} = (\theta_d^j : j \in \mathcal{J} \setminus \mathcal{J}_p)$. The second equality of equation (2) moves the components we do not observe to an intercept and a mean-zero error term, $\tau_d = \kappa_d + \sum_{j\in\mathcal{J}\setminus\mathcal{J}_p} \alpha_d^j E[\theta_d^j]$ and $\epsilon_d = \tilde{\epsilon}_d + \sum_{j\in\mathcal{J}\setminus\mathcal{J}_p} \alpha_d^j(\theta_d^j - E[\theta_d^j])$. Any difference in the error terms if the adoptee is assigned to one type of family versus another can be attributed to differences in the mediator variables we do not observe.

We specify linear models for the observed mediators $\boldsymbol{\alpha_d^p}$, the background variables $\boldsymbol{\beta_d}$, and the treatment-specific intercept τ_d:

$$\boldsymbol{\alpha_d^p} = \boldsymbol{\alpha_0^p} + \boldsymbol{\alpha^p} d \qquad \boldsymbol{\beta_d} = \boldsymbol{\beta_0} + \boldsymbol{\beta} d \qquad \tau_d = \tau_0 + \tau d \tag{3}$$

We also use a linear model for each observed mediator variable:

$$\theta_d^j = \mu_{0,j} + \boldsymbol{X'\mu_{1,j}} + \mu_{2,j} d + \eta_j, \qquad j \in \mathcal{J}_p \tag{4}$$

where η_j is a mean-zero error term.

If we allow the mediators variables we do not observe to be correlated with $\boldsymbol{X}$ or with the measured mediator variables, we cannot identify the parameters $(\boldsymbol{\alpha_0^p}, \boldsymbol{\alpha^p}, \boldsymbol{\beta_0}, \boldsymbol{\beta})$. To achieve identification, we therefore assume that the mediators we do not observe are uncorrelated with both $\boldsymbol{X}$ and the measured mediators for all values of D. Under this uncorrelatedness assumption, it is possible to identify the parameters $(\boldsymbol{\alpha_0^p}, \boldsymbol{\alpha^p}, \boldsymbol{\beta_0}, \boldsymbol{\beta})$, as shown in Heckman and Pinto (2015). It is important to observe, however, that any correlation between observable and unobservable mediators would bias our estimates of the coefficients on the mediators.[16]

The model of mediation can be simplified if treatment affects the mediator variables, but not the impact of these variables and the background variables on outcomes, i.e. $\boldsymbol{\alpha^p} = \mathbf{0}$ and $\boldsymbol{\beta} = \mathbf{0}$. Under the uncorrelatedness assumption, it is possible to test these hypotheses (Heckman and Pinto, 2015). We perform this test, failing to reject both hypotheses at conventional significance levels (p-value of 0.22 for the null hypothesis that $\boldsymbol{\alpha^p} = \mathbf{0}$ and $\boldsymbol{\beta} = \mathbf{0}$).[17] In our main analysis, we will therefore impose the assumption that $\boldsymbol{\alpha^p} = \mathbf{0}$ and $\boldsymbol{\beta} = \mathbf{0}$. With these restrictions, equations (2)-(4) give the mediation model:

$$\begin{aligned} Y_d &= \tau_0 + \tau d + \sum_{j \in \mathcal{J}_p} \alpha_0^j \theta_d^j + \boldsymbol{X'}\boldsymbol{\beta_0} + \epsilon_d \\ &= \tau_0 + \tau d + \sum_{j \in \mathcal{J}_p} \alpha_0^j (\mu_{0,j} + \boldsymbol{X'}\boldsymbol{\mu_{1,j}} + \mu_{2,j} d + \eta_j) + \boldsymbol{X'}\boldsymbol{\beta_0} + \epsilon_d \end{aligned} \tag{5}$$

where the second equality of equation (5) comes from substituting the linear expressions for each observed θ_d^j from equation (4). Based on (5), we can decompose the average treatment effect associated with being assigned to a family with parental wealth level *d'* instead of a family with parental wealth level *d*:

$$\begin{aligned} E[Y_{d'} - Y_d] &= (d' - d)\tau + \sum_{j \in \mathcal{J}_p} \alpha_0^j E[\theta_{d'}^j - \theta_d^j] \\ &= \underbrace{(d' - d)\tau}_{\text{Direct Effect}} + \underbrace{\sum_{j \in \mathcal{J}_p} \alpha_0^j (d' - d)\mu_{2,j}}_{\text{Indirect Effect}} \end{aligned} \tag{6}$$

Our primary goal is to disentangle the indirect effect arising from the effect of treatment on measured mediators and the direct effect operating through channels other than changes in the observed mediators. A secondary goal is to quantify the

[16] It is possible to relax the uncorrelatedness assumption and allow for dependence between unmeasured and measured mediators among children assigned to *wealthy* parents. However, we would then have to both invoke the restrictions $\boldsymbol{\alpha^p} = \mathbf{0}$ and $\boldsymbol{\beta} = \mathbf{0}$ and maintain the assumption of uncorrelatedness among children assigned to *poorer* parents. We decided against this for two reasons. First, we find it difficult to think of an argument for why independence will hold in poor families but not in rich families. Second, it is reasonable to expect (or at least allow for, as we do) parental wealth to affect the relation between the mediators and the children's wealth.

[17] To perform this test, we estimate an extended version of the model in equation (7), interacting the treatment variable D with the observed mediators $\boldsymbol{\theta_d^p}$ and with the background variables X. Testing the null-hypothesis that $\boldsymbol{\alpha^p} = \mathbf{0}$ and $\boldsymbol{\beta} = \mathbf{0}$ correspond to testing that the coefficients on these interactions are equal to zero. See Heckman et al. (2013) and Heckman and Pinto (2015) for more details.

relative importance of the different observed mediators.

Estimation proceeds in two steps. The first step consists of the estimating equation given by:

$$Y = \tau_0 + D\tau + \sum_{j \in \mathcal{J}_p} \alpha_0^j \theta^j + \boldsymbol{X}'\boldsymbol{\beta_0} + \epsilon \tag{7}$$

OLS of equation (7) produces consistent estimates of the parameters of interest $(\tau_0, \tau, \boldsymbol{\alpha_0^p}, \boldsymbol{\beta_0})$ under the assumptions that lead to equation (5). The second step involves estimating the linear model for the observed mediator variables. For each observed mediator $j \in \mathcal{J}_p$, this can be done by OLS estimation of a linear regression model with θ^j as dependent variable and $\boldsymbol{X}$ and D as regressors. These regressions produce estimates of the parameters in equation (4), necessary to derive the direct and indirect effects.

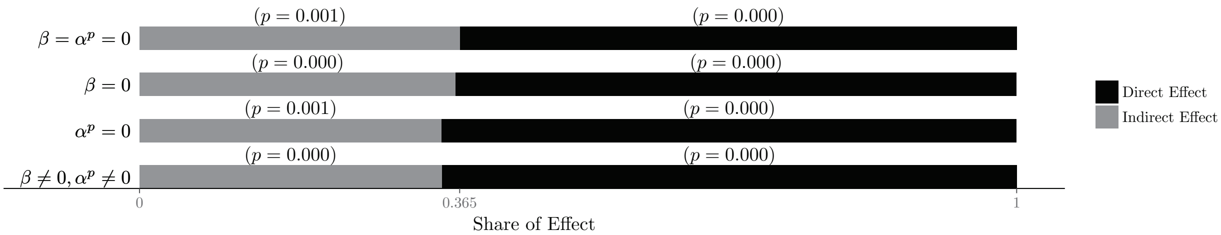
Findings from mediation analysis.
Treatment effects are generated through changes in mediators if mediators affect outcomes and mediators are affected by treatment. Before decomposing the average treatment effects into direct and indirect effects, we therefore examine how assignment to wealthier parents affect observed mediators and how the observed mediators affect children's accumulation of wealth.

Appendix Table B.6 presents estimates from equation (7) of the effects of parental wealth and the observed mediators on children's accumulation of wealth. The results show that parental wealth, children's income and parental transfer of wealth have statistically significant and economically meaningful impact on children's accumulation of wealth. Holding these variables fixed, there is no evidence of significant effects of children's education and financial literacy. We also estimate the effect from assignment to wealthier families on each observed mediator variables. We find statistically significant effects of being assigned to wealthier parents on children's education and parental transfer of wealth. However, the impact on education is small. On average, the adoptees accrue an additional 0.01 years of schooling and an extra USD 1,480 of wealth transfer if she is assigned to an adoptive family with USD 10,000 of additional wealth. The estimated effects of parental wealth on child financial literacy or income are small and not statistically distinguishable from zero.

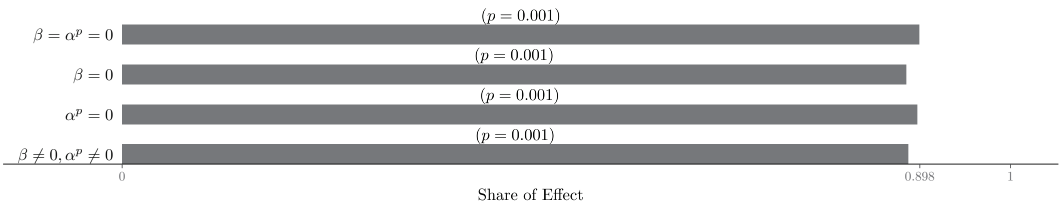
In Figure 5, we decompose the average treatment effect, as described in equation (6). In the top graph, we decompose the average causal effect of being assigned to wealthier parents into the indirect and direct effects. The bottom graph shows how much of the indirect effect that can be attributed to the key observable mediator variable, parental wealth transfers. We find that the indirect effects arising from

Figure 5. Decomposition of average treatment effects of parental wealth on child wealth

(a) Share of the average treatment effect attributable to direct and indirect effects



(b) Share of the indirect effect attributable to wealth transfers



Notes: This figure decomposes the average treatment effect, as described in equation (6). In the top graph, we decompose the average causal effect of being assigned to wealthier parents into the indirect and direct effects. The bottom graph shows how much of the indirect effect that can be attributed to the key observable mediator variable, parental wealth transfers. In each graph, we report results with and without restrictions on the coefficients α^p and/or β. P-values correspond to two-tailed tests for non-zero coefficients. The average treatment effect is a comparison between being assigned to a family at the 75th percentile versus 25th percentile of the parental wealth distribution (USD 151,603 vs 34,393).

changes in the observed mediator variables explain about 37 percent of the average causal effect from assignment to wealthier parents on children's accumulation of wealth. Direct transfers of wealth is the most important mediator variable, accounting for almost 90 percent of the indirect effect. This reflects, in part, that being assigned to wealthier families has a strong impact on parental wealth transfers, but also that parental wealth transfers has a sizable effect on children's accumulation of wealth.

Although we cannot reject that $\boldsymbol{\alpha^p} = \mathbf{0}$ and $\boldsymbol{\beta} = \mathbf{0}$, one may be worried that the estimates are sensitive to allowing these coefficients to be non-zero. To examine this, we have also estimated the model of mediation without any restrictions on $\boldsymbol{\alpha^p}$ and $\boldsymbol{\beta}$, i.e. allowing parental wealth to change the mappings between child wealth and the mediator variables $\boldsymbol{\theta_d}$ and the background variables $\boldsymbol{X}$ (see Heckman et al. (2013) and Heckman and Pinto (2015) for a detailed description of resulting model of mediation). As shown in Figure 5, relaxing the restriction that $\boldsymbol{\alpha^p} = \mathbf{0}$ or $\boldsymbol{\beta} = \mathbf{0}$ does not change the estimates of the indirect and direct appreciably. Moreover parental wealth transfers remain the most important mediator variable, accounting for nearly 90 percent of the indirect effect.

5.2 External validity and comparability of adoptees and non-adoptees

The quasi-random assignment of adoptees to pre-approved adoptive families provides a unique opportunity to identify the effects of being raised in different family environments on children's outcomes. At the same time, the specificity of the setting raises questions about whether the effects we identify are unique to adoptive parents and their adopted children, or if they are likely to generalize to a larger population of parents and children.

Comparability of adoptees and non-adoptees.
As discussed in Holmlund et al. (2011), there are several possible reasons why the external validity of adoption results may be limited. The first is that adoptive parents may be different from other parents, either due to self-selection or because parents had to meet pre-specified criteria to be eligible to adopt. Section 3 discusses these criteria and Table 1 in Section 2 compares the outcomes and characteristics of the parents who adopted from Korean to the parents who did not adopt. While similar in many dimensions, the adoptive parents have, on average, higher income and net wealth than parents who do not adopt. However, these differences are to a large extent because the adoptive parents in our sample are, on average, a few years older than the parents of the non-adoptees. As shown in Appendix Table B.7, the socio-economic characteristics of the adoptive parents are quite comparable to those of other parents once we condition on their year birth years (as we do in the empirical analyses). By way of comparison, parents who adopt native-born children are much less comparable to parents who do not adopt (last column of Appendix Table B.7), and controlling for birth year do not eliminate the large differences in outcomes and socio-economic characteristics across the two groups.

A second possible concern for external validity is that adoptees may be different from other children. This could either be due to selection in the type of children adopted from Korea or because of the pre-adoption environment in Korea may affect child development. The first wave of adoption from Korea consisted mainly of war orphans and abandoned children from poverty stricken families. During the period we study, however, most of the children adopted from Korea were born out-of-wedlock, with working or middle class mothers. Prior to adoption, these children were typically placed with foster families (as opposed to orphanages which were common in the first wave of adoption from Korea). As shown in Table 1 in section 2, the outcomes and characteristics of our sample of Korean-Norwegian adoptees tend to be similar to that of other children.

Consistent with adoptees (and their parents) being relatively comparable to non-adoptees (and their parents), adding controls for family characteristics does not materially affect the size of the intergenerational wealth transmission for the non-adoptees as compared to the adoptees. (see columns 3 and 5 in Table 3). These controls include the education of the mother and the father, the number of siblings, parental income, and information about place of residence, all measured at time of birth of the child. One might, however, be worried that these OLS estimates suffer from bias due to the functional form assumptions that are invoked. Thus, we have also examined the sensitivity of our results to a less restrictive approach for making the non-adoptees more comparable to the adoptees. In particular, we first use a probit specification to estimate the propensity score; that is, the conditional probability of being a Korean-Norwegian adoptee given the set of observed (predetermined) child and parental characteristics. No observations are off support in our sample, and, therefore, it is not necessary to disregarded any of the observations of adoptees. After estimating the propensity score, we weigh the observations of non-adoptees to balance the distributions of characteristics as compared to the Korean-Norwegian adoptees.

A description of the balancing between the treatment (Korean-Norwegian adoptees) and the control group (non-adoptees) is given in Appendix Table B.9. For each variable used to calculate the propensity score, we report the averages across the two samples before (columns 1 and 2) and after (column 3) the weighting procedure. We then check the balancing by comparing (column 4) and testing (column 5) the differences that remain after weighting the non-adoptees. The normalized differences are contrasts in average covariate values by treatment status, scaled by a measure of the standard deviation of the covariates. The normalized differences are useful in that they provide a scale and sample size free way of assessing overlap. It is reassuring to find that the differences between the adoptees and non-adoptees are economically modest and statistically insignificant once we weight the non-adoptees.

Using the weighted sample of the non-adoptees, we then re-estimate the baseline regression model, given in equation (1). The results are reported in column 6 of Table 3. These estimates are nearly identical to those we obtain from the OLS regressions with controls (reported in column 5 of Table 3). This finding lends further support to the conclusion that differences in intergenerational wealth transmission between adoptees and non-adoptees are not primarily driven by the groups being difficult to compare.

In the last two columns of Table 3, we address the concern that there might be unobserved dimensions along which adoptive parents are different. This is done by restricting the sample to families with both a Korean-Norewegian adopted child and a non-adopted child. Using this restricted sample, we then estimate the intergenerational wealth transmission separately for the adopted children in column 7 and for the non-adopted children in column 8. The sample restriction ensures that we are comparing adoptees and non-adoptees with exactly the same set of parents. It is reassuring to find that this sample restriction does not materially affect the differences in intergenerational wealth transmission between adoptees and non-adoptees.

Differential investments.
Even though the Korean-Norwegian adoptees and their adoptive parents are broadly similar to that of other children and parents, the external validity of adoption results may be limited because parents may invest differently in adopted children as compared to genetically related ones. Different theories make different predictions about how parents treat adopted and own-birth children (see e.g. Hamilton et al., 2007). On the one hand, the kin selection theory in evolutionary science predicts that parents are genetically predisposed to invest in own-birth children. Other theories, however, highlight compensatory mechanisms, predicting that adoptive parents may invest more in adopted children than in biological ones.

Since we do not have data on parental investments, we cannot directly assess whether parents invest more or less in adoptees as compared to own-birth children. However, if parents treats adoptive children differently from biological ones, we would expect the transmission of parental wealth to children to depend on whether these children has an adopted or non-adopted sibling. Using the subsample of Korean-Norwegian adoptees with siblings, we extend equation (1) to include an indicator variable taking the value one if the sibling is adopted (from Korea) and zero if not adopted (hence is biologically linked to the parents) and an interaction term between parental wealth and the indicator variable for having an adopted sibling. The results are reported in Appendix Table B.8. The estimates in the first column suggest the transmission of parental wealth to adoptive children do not differ appreciably depending on whether the adoptee has an adopted or non-adopted sibling. The second column shows that this conclusion holds also if we control for observable characteristics of the family and the children.

The results reported in the last two columns in Appendix Table B.8 complement this analysis. Here, we follow the same procedure as used in the first two columns, but now for the sample of own birth children with siblings. Using this sample, we extend equation (1) to include an indicator variable for having an adopted sibling (and zero if non-adopted sibling) and an interaction term between parental wealth and this indicator variable. This allows us to examine whether parental transmission of wealth differ for own-birth children with adopted siblings as compared to own-birth children with non-adopted siblings. We find no evidence of significant differences in the transmission of parental wealth to own-birth children depending on whether these children have adopted or non-adopted siblings. It is important to observe, however, the relatively large standard errors on the interaction coefficients in Appendix Table B.8. Thus, these estimates need to interpreted with caution.

Taken together, we view the descriptive statistics and the estimation results (in Table 3 and Appendix Table B.8) as suggestive evidence in support of the external validity of our findings based on the Korean-Norwegian adoptees. The estimation results in Appendix Table B.8 are consistent with survey evidence presented in Hamilton et al. (2007), showing that two-adoptive-parent families invest at similar levels as two-biological-parent families once one control for observable family characteristics such as education and income. In contrast, Gibson (2009) present descriptive evidence suggesting that parents invest more in adopted children than in genetically related ones. Because his sample of adoptees experience more negative outcomes, he does not interpret the results as suggesting that parents favor adoptive children. Instead, he argues, that parents invest more in adoptees because they are more likely than own birth children to need help. In our setting, however, the outcomes and characteristics of the Korean-Norwegian adoptees are broadly similar to that of other children. Thus, even if compensatory mechanisms guide parental investment, we would not necessarily expect that parents invest more in the Korean-Norwegian adoptees as compared to genetically related ones.

6 Intergenerational links in financial wealth and investor behavior

So far, we have focused on intergenerational transmission of net wealth. In Table 4, we turn attention to intergenerational links in financial wealth and investor behavior. Each column reports estimates from equation (1) with controls for year of adoption, birth years of the adoptees and their adoptive parents, and the adoptee's age at adoption and gender.

In the first panel of Table 4, we regress the financial wealth of the adoptee on the financial wealth of the adoptive family. In the first column, we find an intergenerational association of 0.247 with a standard error of 0.049. On average, the adoptees accrue an extra USD 2,470 of financial wealth if she is assigned to an adoptive family with USD 10,000 of additional financial wealth. Comparing the results in Table 4 to those in Table 3, it is clear that the estimates of intergenerational wealth transmission are very similar if we use imperfect measures of net wealth or high quality measures of financial wealth. This is reassuring since measuring net wealth is challenging and reliable measures requires accessing and linking data other than the tax records.

The second column investigates whether the intergenerational transmission of financial wealth is not really due to wealth per se, but to the effect of parent's stock market participation and portfolio risk. Our estimates show that if we control for these variables, the intergenerational wealth transmission barely changes. As shown in the third column, the same holds true if we control for observable characteristics of the childhood rearing environment other than parental wealth. This suggest the effect of being raised by parents with more financial wealth is not operating through parents' education and household income or children's sibship size and place of residence in childhood.

The second and third panel turn to intergenerational links in investor behavior, as measured by stock market participation and the proportion of financial wealth invested in risky assets. The first column shows that adoptees' stock market participation and risky share are increasing in adoptive parents' stock market participation and risky share. However, as evident from the second column, other aspects of family background play a significant role for children's asset allocation and the riskiness of chosen portfolios. In particular, an adoptee's financial risk taking is increasing significantly in the proportion of financial wealth that their adoptive parents invested in risky assets. The same holds true if we control for parents' education and income, children's sibship size, and place of residence in childhood.

Since the variables in Table 4 are measured in different units, it is difficult to directly compare the magnitude of the coefficients. In Appendix Figures B.2 and B.3, we assess the relative importance of the different aspects of family background for the adoptees. These figures point to the importance of parental wealth for children's accumulation of financial wealth, and indicate that children's financial decision making is relatively strongly affected by parents' financial risk taking.

Appendix Figure B.2 displays standardized coefficients for the regression models of column 3 in Table 4. Each variable (outcomes and regressors) is standardized by subtracting its mean from each of its values and then dividing these new values by the standard deviation of the variable. The standardized coefficients show how many standard deviations the outcome variable of the child is expected to change, per standard deviation change in the characteristic of the parents. We find that a one standard deviation difference in parental financial wealth produces more of a change in children's financial wealth levels than a one standard deviation difference in parental risky share or stock market participation. By comparison, a one standard deviation difference in parental risky share is estimated to have a stronger impact on children's financial risk taking as compared to a one standard deviation difference in parental financial wealth or stock market participation.

Appendix Figure B.3 complements by comparing the explanatory power of parental financial wealth, stock market participation, and risky share from the regressions reported in column 3 of Table 4; we normalize the partial R-squared values to sum to one, so the reported values can be directly interpreted as the fraction of the explained variability that is attributable to an observable aspect of family background. We find that parental financial wealth is most important in explaining the variation in adoptees' accumulation of wealth. By comparison, parents' risky share accounts for most of the explained variability in the financial decision making of the adoptees.

Table 4. Intergenerational links in wealth and investor behavior

	Korean-Norwegian adoptees		
A. Dep. variable: Child fin. wealth (in 10,000 USD)			
Parental:			
financial wealth (in 10,000 USD)	0.247***	0.238***	0.232***
	(0.049)	(0.049)	(0.049)
participation		-0.563*	-0.576*
		(0.339)	(0.336)
risky share		1.372	1.322
		(0.990)	(0.974)
B. Dep. variable: Child participation			
Parental:			
financial wealth (in 10,000 USD)		0.005*	0.005*
		(0.003)	(0.003)
participation	0.112***	0.058**	0.058**
	(0.022)	(0.028)	(0.028)
risky share		0.127*	0.120
		(0.072)	(0.073)
C. Dep. variable: Child risky share			
Parental:			
financial wealth (in 10,000 USD)		0.003**	0.003**
		(0.001)	(0.001)
participation		-0.012	-0.008
		(0.013)	(0.013)
risky share	0.157***	0.135***	0.133***
	(0.030)	(0.036)	(0.036)
Additional controls:			
Family char.			Yes
Number of children		2,254	

Notes: The Korean-Norwegian adoptees are born in South Korea between 1965 and 1986, and adopted at infancy by Norwegian parents. All specifications include controls for birth year, mother birth year, father birth year, gender, adoption year, and adoption age. Family characteristics include education (in years) of the mother and father, the number of siblings, the (log of) parents income and the (log of) the median income in parents' municipality of residence, all measured at the time of birth of the child (see Table 1 for further details). Standard errors (in parentheses) are clustered at the mother. ***p<.01, **p<.05, *p<.10.

7 Comparison with results from behavioral genetics decompositions

To directly compare what we find to previous evidence, we supplement the empirical analysis with an interpretation of our data through the lens of a behavioral genetics decomposition. This analysis follows much of the previous literature in applying a restrictive but commonly used ACE model, which decomposes child outcome into a linear and additive combination of genetic factors, shared family environment, and unexplained factors. One of several limitations of the standard ACE model is that it assumes independence between genes and shared environment. By exploiting that we have three sets of sibling pairs, biological-biological, adoptive-biological and adoptive-adoptive, we are able to relax this assumption.

Basic and extended ACE model.
Consider an outcome Y which is normalized so that the conditional mean among adopted and non-adopted children is zero. The basic model assumes that the outcome Y of individual i from family j is a function of three error components

$$\begin{aligned} Y_{ij} &= E[Y_{ij}] + e_{ij} \\ &= \begin{cases} \sigma_0(a_i + c_{j(i)} + e_i) & \text{if } adopt_i = 0 \\ a_i + c_{j(i)} + e_i & \text{if } adopt_i = 1 \end{cases} \end{aligned} \tag{8}$$

where $adopt_i$ equals one if sibling i is adopted (zero otherwise), and a_i captures genetic factors, $c_{j(i)}$ the shared environment in i's family $j(i)$, and e_i remaining non-shared factors that are by construction orthogonal to a_i, $c_{j(i)}$. We are interested in estimating the variances of the error components in (8); σ_a^2, σ_c^2 and σ_e^2. Note that equation (8) allows the total variance of Y_{ij} to differ across adoptees and non-adoptees through the parameter σ_0, but constrains the relative contribution of the genetic component, shared environment, and residual idiosyncratic factors to be the same.[18] This constraint is fairly standard in the literature using behavioral genetics decompositions.

In the basic version of the model, the genetic and family environmental factors are assumed to be independent: $cov(a_i, c_{j(i)}) = 0$. This implies that the variance in outcome for a non-adopted child can be expressed by the following formula:

$$Var(Y_{ij} \mid adopt_i = 0) = \sigma_0^2(\sigma_a^2 + \sigma_c^2 + \sigma_e^2) \tag{9}$$

[18] As evident from Table 1 the variation in some of our outcome variables, such as wealth, years of schooling and risky share, is somewhat larger in the sample of non-adoptees than in the sample of adoptees. This motivates the inclusion of the parameter σ_0. Note that σ_0^2 is simply the ratio between $Var(Y_{ij} \mid adopt_i = 0)$ and $Var(Y_{ij} \mid adopt_i = 1)$.

Given this framework the correlation between the outcomes of two regular siblings equals

$$corr(Y_{j1}, Y_{j2} \mid adopt_1 = 0, adopt_2 = 0) = \frac{\frac{1}{2}\sigma_a^2 + \sigma_c^2}{(\sigma_a^2 + \sigma_c^2 + \sigma_e^2)} \tag{10}$$

provided that biological siblings share half of their genetic endowment and the full common family environment. This shows that σ_a^2, σ_c^2 and σ_e^2 are not separately identified using data on biological siblings only, as we have three unknown parameters and only two moment conditions, Equation (9) and (10).

To achieve identification, we therefore follow Sacerdote (2007) and rely on adoptees to generate additional moment conditions which allow us to estimate all variances of the three error components $(\sigma_a^2, \sigma_c^2, \sigma_e^2)$. First note that

$$Var(Y_{ij} \mid adopt_i = 1) = \sigma_a^2 + \sigma_c^2 + \sigma_e^2 = 1 \tag{11}$$

where the second equality follows a normalization of Y to have variance of one among the adopted children. It also follows that

$$corr(Y_{1j}, Y_{2j} \mid adopt_1 = 1, adopt_2 = 0) = \frac{\sigma_c^2}{(\sigma_a^2 + \sigma_c^2 + \sigma_e^2)} \tag{12}$$

We now have an exactly identified system of three moment conditions and three parameters of interest $(\sigma_a^2, \sigma_c^2, \sigma_e^2)$.

This basic framework can be extended by allowing the genetic and shared environmental factors to be correlated (see e.g. Ridley, 2003; Lizzeri and Siniscalchi, 2008). A positive correlation, for example, captures the possibility that families with better genes also provide a better environment. A negative correlation, on the other hand, may suggest that parents increase investments to compensate for lower genetic endowments. Let γ be the parameter that governs how genes vary with family environment among the non-adopted:

$$cov(a_i, c_{j(i)} \mid adopt_i = 0) = \gamma \neq 0$$

Since the Korean-Norwegian adoptees are matched (quasi-)randomly to families, we assume γ to be zero for them:

$$cov(a_i, c_{j(i)} \mid adopt_i = 1) = 0$$

The variance of Y_{ij} for adoptees in equation (11) is unchanged while, in contrast, the variance of the outcome Y_i for non-adoptive siblings now becomes

$$Var(Y_{ij} \mid adopt_i = 0) = \sigma_0^2(\sigma_a^2 + \sigma_c^2 + 2\gamma + \sigma_e^2) \tag{13}$$

which depends on γ since the genetic and shared environmental factors can be correlated. To identify the last parameter, γ, we make use of sibling pairs consisting of two Korean-Norwegian adopted children adopted by the same family. The correlations in outcomes for the sibling pairs in the extended ACE model can be expressed by Equations (14), (15) and (16):

$$\begin{aligned} & corr(Y_{1j}, Y_{2j} \mid adopt_1 = 0,\, adopt_2 = 0) \\ & \quad = \frac{\sigma_0^2 \cdot (cov(a_1, a_2) + cov(c_{j(1)}, c_{j(2)}) + cov(c_{j(1)}, a_1) + cov(c_{j(2)}, a_2))}{\sqrt{var(Y_{1j} \mid adopt_1 = 0,\, adopt_2 = 0) var(Y_{2j} \mid adopt_1 = 0,\, adopt_2 = 0)}} \\ & \quad = \frac{\frac{1}{2}\sigma_a^2 + \sigma_c^2 + 2\gamma}{\sigma_a^2 + \sigma_c^2 + 2\gamma + \sigma_e^2} \end{aligned} \tag{14}$$

$$\begin{aligned} & corr(Y_{1j}, Y_{2j} \mid adopt_1 = 1,\, adopt_2 = 0) \\ & \quad = \frac{\sigma_0 \cdot (cov(c_{j(1)}, c_{j(2)}) + cov(c_{j(1)}, a_2))}{\sqrt{var(Y_{1j} \mid adopt_1 = 1,\, adopt_2 = 0) var(Y_{2j} \mid adopt_1 = 1,\, adopt_2 = 0)}} \\ & \quad = \frac{(\sigma_c^2 + \gamma)}{\sqrt{(\sigma_a^2 + \sigma_c^2 + \sigma_e^2)(\sigma_a^2 + \sigma_c^2 + 2\gamma + \sigma_e^2)}} \end{aligned} \tag{15}$$

$$\begin{aligned} & corr(Y_{1j}, Y_{2j} \mid adopt_1 = 1,\, adopt_2 = 1) \\ & \quad = \frac{cov(c_{j(1)}, c_{j(2)})}{\sqrt{var(Y_{1j} \mid adopt_1 = 1,\, adopt_2 = 1) var(Y_{2j} \mid adopt_1 = 1,\, adopt_2 = 1)}} \\ & \quad = \frac{\sigma_c^2}{\sigma_a^2 + \sigma_c^2 + \sigma_e^2} \end{aligned} \tag{16}$$

Empirical findings.

Table 5 presents the decomposition results.[19] The upper panel reports the results from the standard ACE which do not take into account the possible correlation between genes and shared environment, whereas the lower panel of the table reports

[19] We do not report results for stock market participation, as it is not clear how to apply the linear and additive ACE framework to binary outcomes.

the results from the extended ACE model where we allow shared environment to vary with genes.

The first two columns of the upper panel of Table 5 suggest that both family environment and genetics are important in explaining the variation in children's wealth accumulation. Shared environment accounts for about 16 (10) percent of the variation in net (financial) wealth accumulation. Relative to shared environment, the genetic factors explain a bigger portion (twice as much or more) of the variation in wealth accumulation (both net and financial wealth). These findings are consistent with the results in Table 3, showing significant but less wealth transmission from parents to adoptees as compared to non-adoptees.

As shown in column three of the upper panel of Table 5, shared environment is also important for explaining the variation in financial risk taking, as measured by the risky share. By comparison, genetic factors explain little of the variation in this measure of financial risk taking. In the last column of Table 5, we report results for education as measured by years of schooling. These results are close to the American study of Korean adoptees by Sacerdote (2007), who finds that 9 percent of the variation in years of schooling can be explained by shared environment while 60 percent is attributable to genes.

The results in Table 5 need to be interpreted with caution as the behavioral genetics model relies on a number of strong assumptions. The extended ACE model relaxes one of these assumptions, allowing dependence between genes and shared environment through the parameter γ. As shown in the second panel of Table 5, both family environment and genetics become more important in explaining the variation in children's wealth accumulation (both net wealth and financial wealth) when allowing dependence between genes and shared environment. Moreover, the estimated γ is negative (but only significant at the 10 percent level for net wealth), suggesting that parents compensate worse genes by providing a better environment or transferring more wealth. As compared to the results for children's accumulation of wealth, the estimated contributions of genes and shared environment change relatively little for financial risk taking and education when we allow for correlation between genes and shared environment. Furthermore, the correlation parameter is close to zero and far from significant at conventional levels.

While the extended ACE model allows for dependence between genes and shared environment, it still maintains a linear and additive structure. This structure is highly questionable. While the transmission of the genotype follows biologically determined mechanisms, the mapping of the genotype into phenotype is likely affected by the environment through epigenetic forces potentially affecting also future generations. Heckman and Mosso (2014) review the main studies in the behavioral genetics literature. They conclude that whenever the role of environmental effects in mediating genes expressions is considered, the estimates of heritability are highly impacted. For this reason, the main analysis of this paper did not rely on the ACE model. Instead, we took advantage of the quasi-random assignment of adoptees to show significant causal links between family background and individuals wealth, stock market participation and financial risk taking. The resulting causal estimates of family background does not require assumptions about gene-environment interactions.

Table 5. ACE decompositions

	(1) Net wealth	(2) Financial wealth	(3) Risky share	(2) Education
		STANDARD MODEL		
Genetic factors (a^2)	0.291***	0.333***	0.005	0.544***
	(0.090)	(0.100)	(0.114)	(0.0850)
Shared environment (c^2)	0.164***	0.096*	0.171**	0.127**
	(0.044)	(0.050)	(0.057)	(0.04325)
Unexplained factors (e^2)	0.546***	0.571***	0.824***	0.329***
	(0.047)	(0.050)	(0.057)	(0.04326)
		EXTENDED MODEL		
Genetic factors (a^2)	0.576**	0.523**	-0.055	0.492***
	(0.188)	(0.188)	(0.273)	(0.130)
Shared environment (c^2)	0.365***	0.246**	0.141**	0.05875
	(0.094)	(0.094)	(0.071)	(0.0491)
Unexplained factors (e^2)	0.058	0.231	0.914**	0.451**
	(0.270)	(0.261)	(0.315)	(0.151)
Gene-Environment	-0.249*	-0.166	0.036	0.0791
correlation (γ)	(0.129)	(0.117)	(0.111)	(0.0761)

Notes: This table uses the correlation coefficients in outcomes for the different sibling pairs (560 adoptive-biological sibling pairs, 376 adoptive-adoptive sibling pairs and 678,304 randomly drawn biological-biological sibling pairs) and decomposes the variation in the outcome variable (measured as an average of 2012-2014) into genetic factors (a^2), shared environment (c^2), unexplained factors (e^2) and gene-environment correlation (γ). The upper panel of the model reports results from the standard ACE model where we assume independence between $a^2$and c^2, whereas the lower panel reports results from the extended ACE model where we allow a^2 and c^2 to be dependent. All adoptees included in this table are adopted at infancy by Norwegian parents. Standard errors in parentheses. ***p<.01, **p<.05, *p<.10.

8 Conclusion

This paper provided novel evidence on intergenerational links in wealth accumulation and investor behavior in a setting where we can credibly control for genetic transmission of abilities and preferences. The key to our research design is that we can link Korean-born children who were adopted at infancy by Norwegian parents to a population panel data set with detailed information on disaggregated wealth portfolios and socio-economic characteristics. The mechanism by which these adoptees were assigned to adoptive families is known and effectively random. We used the quasi-random assignment to estimate the causal effects from an adoptee being raised in one type of family versus another. We found that family background matters significantly for children's accumulation of wealth and investor behavior as adults, even when removing the genetic connection between children and the parents raising them. In particular, adoptees raised by wealthy parents are more likely to be well off themselves, and adoptees' stock market participation and portfolio risk are increasing in the financial risk taking of their adoptive parents.

We view the study of Korean-born children who were adopted at infancy by Norwegian parents as a unique opportunity to learn about the causal effects of family background on children's wealth accumulation and investor behavior as adults. At the same time, the results raise a number of questions such as: What are the mechanisms through which parents influences children? What can we learn from adoptees about the population of children at large?

We took several steps to shed light on these important but difficult questions. First, we examined whether the effects of parental wealth and investor behavior operate through other observable characteristics of childhood rearing environment that may be correlated with parental wealth. Our estimates suggest the effects are not operating through parents' education and household income or children's sibship size and place of residence in childhood. Second, we applied mediation analysis to quantify the empirical importance of alternative channels. Our mediation analysis considers four observable mediators: children's education, income and financial literacy as well as direct transfers of wealth from parents. Our estimates suggest that changes in these mediator variables explain nearly 40 percent of the average causal effect on children's accumulation of wealth of being assigned to wealthier families. Inter vivos transfer of wealth is the most important mediator. Lastly, we examined possible reasons why the external validity of adoption results might be limited. We found suggestive evidence that adoptive parents do not differ significantly from other parents when it comes to intergenerational wealth transmission. Furthermore, the socio-economic characteristics of the Korean-Norwegian adoptees and their adoptive parents are broadly similar to that of other children and parents (who are born in the same period). Indeed, controlling for or matching on child and parental characteristics do not materially affect the size of the intergenerational wealth transmission for the non-adoptees as compared to the adoptees. The same is true if we restrict the sample to a set of families with both a Korean-Norwegian adoptee and a non-adopted sibling. Within these families, we still find that wealth shows much less transmission from parents to adoptees as compared to non-adoptees.

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Appendix

A. Measuring net wealth

In Norway, the tax authorities collect information on the values of the vast majority of assets at the beginning and end of the year. Nearly all components of financial wealth are third-party reported (e.g., from banks and financial intermediaries). We are therefore able to accurately measure the values of most components of financial wealth, such as bank deposits, liabilities, and most securities. As shown in Eika et al. (2020) the tax data on financial wealth are measured with little error, mirroring closely the aggregates from the Norwegian Financial Accounts.

The key challenge for constructing reliable measures of net wealth is that the tax data record the full mortgage amount but not necessarily the actual market value of the property. In principle, the Norwegian tax authorities are supposed to assess a property at a certain percentage of its fair market value.[20] Prior to 2010, however, the tax assessment values differ significantly from the actual market values, and these differences vary considerably across properties depending on a wide range of factors such as area, year of construction, and housing type. As part of a tax reform in 2010, the Norwegian Tax Administration reassessed all property values based on a price per square meter calculated by Statistics Norway (using hedonic pricing models with information on property type, size, geographic regions, last sales date, age of building). While this improved the quality of the tax assessment values on real estate, differences between tax assessments and market values for individual dwellings remain a serious concern.

Instead of relying on tax assessment values, we have obtained data from the Norwegian Land Register, which offers comprehensive information on real estate transactions. For nearly all properties in Norway, this data set contains information on the last transaction prior to 1994. In addition, it records nearly all real estate transactions during the period 1994-2014. The data set provides detailed information about the transactions, including unique identifiers for both the seller, the buyer and the property, the selling price, and characteristics of the property. Using the transaction data, we first find the market value for a given property at one or several points in time between 1986 and 2015.[21] To estimate market values in other years, we combine our data on the characteristics of the properties with house price indices

[20] In 2014, for example, the tax assessment value was supposed to be 25 percent of the property's value for a primary residence, and 60 percent of the property's value for secondary residences.

[21] We do not observe the market prices of properties that are never sold during the period 1986-2015. For these properties, we use the reassessed property values for the years 2010-2014, based on the price per square meter calculated by Statistics Norway.

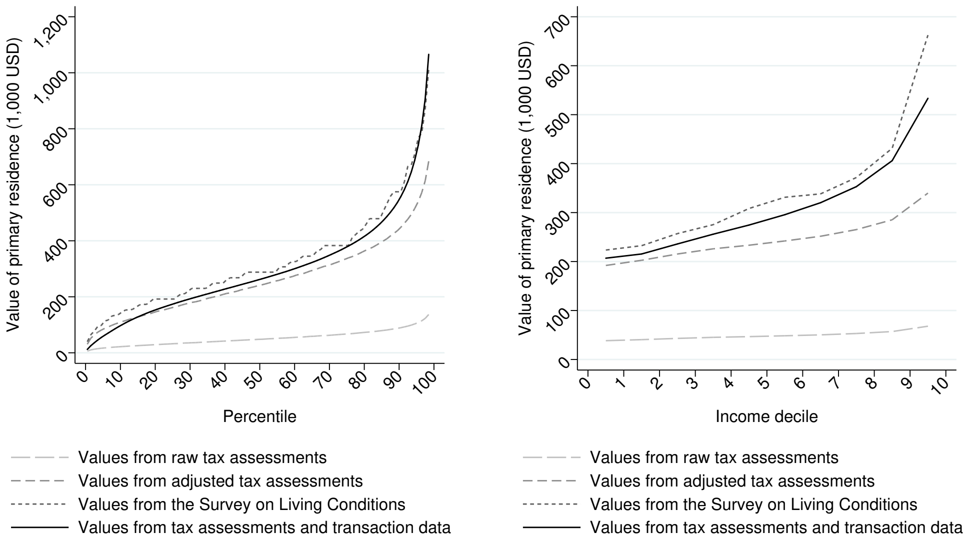
for specific regions and types of homes. We refer to Eika et al. (2020) for a detailed description of this procedure.

Appendix Figure A.1 compares our estimates of the market values of households' primary residences with those reported in the Survey on Living Conditions. In 2004 the survey asked a representative sample of households about the expected market value of their primary residence. It is reassuring to find that our estimates mirror closely the self-reported values, both across the distribution of the value of primary residences (Panel (a)) and across the disposable income distribution (Panel (b)). By comparison, tax assessment values differ significantly (even if we adjust the tax assessment values according to the aggregate differences between selling prices and tax assessments in 2004). The tax assessment values are especially inaccurate in the middle and upper parts of the income distribution.

Figure A.1. The Value of Primary Residences Based on Different Sources of Data

a) By percentile in the distribution of primary residences

b) By income decile



Notes: This figure displays the average value of primary residences; by percentile in the distribution of primary residences in Panel (a) and by income decile in Panel (b). The value of primary residences is measured based on (i) tax assessments only (raw and adjusted); (ii) the 2004 Survey on Living Conditions; and (iii) tax assessments and transactions data. "Adjusted tax assessments" are raw tax assessment values adjusted according to the aggregate ratio of selling prices to tax assessments. The percentage of households owning a residence is 72.6, 82.0, and 79.3, according to (i), (ii) and (iii), respectively. The sample includes all households owning a residence in 2004. In Panel (a), the top percentile is dropped.

Table B.1. Details about the data sources and each of the variables.

Variable:	Description:
Assets and income	Source: Income and wealth from tax returns, 1994- (unless otherwise stated)
Pensionable income	All incomes and transfers counting towards old age pensions, available since 1967
Median income at county level	Median income of working age population at county level
Financial wealth	The sum of stocks, mutual funds, money market funds, bank deposits, bonds
Risky assets	The sum of stocks and mutual funds
Risky share	The ratio of risky assets to financial wealth
Participation in risky asset markets	Indicator variable for holding a positive amount (> NOK 1,000 or USD 175) of risky assets
Net wealth	The value of non-financial and financial assets minus the value of outstanding liabilities. Sources: See Eika et al. (2020)
Education	Source: Norwegian Educational Database, 1964-
Education length	Years of schooling
Financial education	Indicator variable for college degree in finance, business or economics
Adoption	Source: Adoption Register, 1965-
ID adoptive parents	Unique individual identifier of adoptive parents
Adoption date	Date of adoption
Adoption age	Age (in days) at time of adoption
Date of birth	Date of birth
Country of origin	Country of birth
Population and family	Source: The Central Population Register, 1964-
Region	Region of residence at the end of the year
Birth date	Date of birth
Gender	Indicator variable for female
Marital status	Indicator variable for marital status
Spousal id	Unique individual identifier of spouse
Mother id	Unique individual identifier of mother
Father id	Unique individual identifier of father
# of siblings	Number of other individuals with same mother at the time of birth
Wealth transfers	Source: Register of gifts, transfers and inheritances, 1995-2013

Variable:	Description:
Wealth transfers	Sum of gifts, inter vivos transfers and inheritances
CPI and exchange rate	Asset and income variables are measured in USD, 2014 prices
Consumer price index	Source: Statistics Norway
Exchange rate	Source: Norges Bank, `https://www.norges-bank.no/en/Statistics/exchange_rates/currency/USD`

Table B.2. Testing for quasi-random assignment of domestic adoptees

	Dependent variable:			
	Age at adoption		Gender	
	Specification:			
Regressors	Bivar. reg.	Multivar. reg.	Bivar. reg.	Multivar. reg.
Parent net wealth	-0.002	0.001	-0.001	-0.000
	(0.002)	(0.002)	(0.002)	(0.003)
Mother's years of schooling	-0.012***	-0.005*	-0.003	-0.002
	(0.003)	(0.003)	(0.003)	(0.004)
Father's years of schooling	-0.013***	-0.009***	0.000	0.004
	(0.002)	(0.002)	(0.003)	(0.004)
(Log) parent income at birth	-0.160***	-0.031	-0.089	-0.121*
	(0.040)	(0.045)	(0.057)	(0.069)
Median (log) income in childhood municipality	-0.119***	-0.076**	0.013	0.039
	(0.032)	(0.034)	(0.048)	(0.051)
Dependent mean	0.55	0.55	0.50	0.50
F-stat, joint significance of regressors		6.673		1.363
[p-value]		[0.000]		[0.199]

Notes: The table contains estimates from regressions of a pre-determined characteristic of the adoptee (age at adoption or an indicator for female) on family background variables such as parental net wealth, education (in years) of the mother and father, the log of parents income and the log the median income in parents' municipality of residence, all measured at the time of birth of the child. In columns 1 and 3, we run separate regressions for each of the family background variables (conditional on a full set of indicators for adoption years of the children). In columns 2 and 4, we run multivariate regressions with all the family characteristics (conditional on a full set of indicators for adoption years of the children). The estimation sample consists of 2,393 domestic adoptees adopted at infancy (younger than 18 months when adopted) by Norwegian parents. Standard errors (in parentheses) are clustered at the mother. ***p<.01, **p<.05, *p<.10.

Table B.3. Testing for quasi-random assignment of Korean-Norwegian adoptees who were 18 months or older at time of adoption

	Dependent variable:			
	Age at adoption		Gender	
	Specification:			
Regressors	Bivar. reg.	Multivar. reg.	Bivar. reg.	Multivar. reg.
Parent net wealth	-0.0012	0.009	0.004	0.002
	(0.016)	(0.018)	(0.009)	(0.009)
Mother's years of schooling	-0.003	0.013	0.001	-0.003
of schooling	(0.017)	(0.018)	(0.004)	(0.005)
Father's years	-0.001	0.006	0.005	0.003
of schooling	(0.016)	(0.017)	(0.004)	(0.005)
(Log) parent income	-1.038***	-1.132***	0.123*	0.106
at birth	(0.268)	(0.281)	(0.063)	(0.067)
Median (log) income	-0.196	-0.010	0.065	0.046
in childhood municipality	(0.207)	(0.216)	(0.056)	(0.057)
Dependent mean	3.36	3.36	0.60	0.60
F-stat, joint significance of regressors		3.481		1.045
[p-value]		[0.004]		[0.390]

Notes: The table contains estimates from regressions of a pre-determined characteristic of the adoptee (age at adoption or an indicator for female) on family background variables such as parental net wealth, education (in years) of the mother and father, the log of parents income and the log the median income in parent's municipality of residence, all measured at the time of birth of the child. In columns 1 and 3, we run separate regressions for each of the family background variables (conditional on a full set of indicators for adoption years of the children). In columns 2 and 4, we run multivariate regressions with all the family characteristics (conditional on a full set of indicators for adoption years of the children). The estimation sample consists of 1,587 Korean-Norwegian adoptees adopted by Norwegian parents when18 months or older (at time of adoption). Standard errors (in parentheses) are clustered at the mother. ***p<.01, **p<.05, *p<.10.

Table B.4. Sensitivity of intergenerational wealth transmission to the age of wealth measurement of the child

	Child age			
	All	<=35	36-40	>40
A. Korean-Norwegian adoptees	0.225***	0.215***	0.211**	0.261***
Intergenerational wealth transmission	(0.040)	(0.035)	(0.103)	(0.100)
Number of children	2,254	1,108	649	497
B. Norwegian non-adoptees	0.575***	0.462***	0.541***	0.653***
Intergenerational wealth transmission	(0.011)	(0.018)	(0.018)	(0.015)
Number of children	1,206,650	399,384	260,476	546,790

Notes: Column 1 of panel A (panel B) repeats the baseline specification from column 1 (column 4) of Table 3 using the sample of 2,254 Korean-Norwegian adoptees (1,206,650 non-adoptees). Columns 2-4 in both panels restrict the sample according to the age of the child at the time of measurement. All specifications include a full set of indicator variables for birth year of children and parents. The specifications in panel A also control for the adoption year of the children. Standard errors (in parentheses) are clustered at the mother. ***p<.01, **p<.05, *p<.10.

Table B.5. Specification checks, intergenerational wealth transmission

	Outliers		Measuring		Specification:	
Dependent variable:	Median	No winsorizing	at ind. level	in 1994 & 2014	Rank-rank	Log-log
	(1)	(2)	(3)	(4)	(5)	(6)
Baseline:						
Parental net wealth:	0.199	0.212	0.272***	0.253***	0.167	0.181
	(0.031)***	(0.041)***	(0.059)	(0.075)	(0.021)***	(0.034)***
With family characteristics:						
Parental net wealth:	0.187	0.192	0.258***	0.235***	0.150	0.163
	(0.031)***	(0.042)***	(0.059)	(0.076)	(0.022)***	(0.034)***
Observations	2,254	2,254	2,254	2,237	2,254	1,327

Notes: The Korean-Norwegian adoptees are born in South Korea between 1965 and 1986, and adopted at infancy by Norwegian parents. All specifications include controls for birth year, mother birth year, father birth year, gender, adoption year and adoption age (in days). Panel B further includes controls for family characteristics, consisting of education (in years) of the mother and father, the number of siblings, the (log of) parents income and the (log of) the median income in parent's municipality of residence, all measured at the time of birth of the child (see Table 1 for further details). Standard errors (in parentheses) are clustered at the mother. ***p<.01, **p<.05, *p<.10.

Table B.6. Coefficients from Linear Potential Outcome Equation, assuming $\boldsymbol{\alpha^p} = \boldsymbol{\beta} = 0$

	Coefficient	Std. Error
Years of schooling, 2014	3.411	(2.029)
Transfers	0.479***	(0.088)
Child Financial Literacy	4.868	(23.580)
Mean income, 2012-2014	0.814***	(0.193)
Parental net wealth, 1994-1996	0.137***	(0.031)
N	2,254	

Notes: Wealth transfers, child income, and parental wealth are measured in thousands USD. The model includes linear controls for gender, age of adoption, child and parental birth cohorts and year of adoption. Transfers are measured as total transfers from adoptive parents between 1995 and 2013. Standard errors in parentheses and clustered at the mother. ***p<.01, **p<.05, *p<.10.

Table B.7. Comparison of socio-economic characteristics between parents who adopt and parents who do not adopt, conditional on child and parent birth year

	Parents of		Differences between parents of	
Variable	**Korean-Norwegian adoptees**	**Norwegian non-adoptees**	**Norwegian non-adoptees Korean-Norwegian adoptees**	**Norwegian non-adoptees Native-born adoptees**
Mother's years of schooling	12.06	11.82	0.24***	-0.49***
			(0.06)	(0.06)
Father's years of schooling	12.61	12.73	-0.12*	-1.21***
			(0.07)	(0.08)
Mean income, 1994-1996	39,977	43,356	-3,378***	-6,039***
			(292)	(260)
Mean net wealth, 1994-1996	93,501	97,960	-4,458	-66,797***
			(5,184)	(8,821)
Transfer	22,181	25,749	-3,567*	-37,334***
			(2,136)	(3,613)
Mean financial wealth, 1994-1996	22,034	23,188	-1,154	-8,119***
			(1,069)	(1,327)
Risky assets, 1994-1996:				
Participation	0.38	0.42	-0.04***	-0.10***
			(0.01)	(0.02)
Share	0.12	0.12	-0.00	-0.05***
			(0.01)	(0.01)
Number of children	2,254	1,206,650		

Notes: The Korean-Norwegian adoptees are born in South Korea between 1965 and 1986, and adopted at infancy by Norwegian parents. The non-adoptees are born in Norway between 1965 and 1986, and raised by their biological parents. The native-born adoptees are born in Norway between 1965 and 1986 and adopted at infancy by Norwegian parents. All monetary values are measured in USD. Income and wealth are measured at the household level. Risky assets are defined as the sum of mutual funds with a stock component and directly held stocks. Risky share is measured as the proportion of the financial wealth invested in risky assets over the three year period. Stock market participation is an indicator variable taking the value one if at least some fraction of financial wealth is invested in risky assets over the three year period. See Appendix Table B.1 for more details.

Table B.8. Intergenerational wealth transmission in different types of families

	Sample 1: Adopted children with sibling		**Sample 2: Own birth children with sibling**	
	(1)	(2)	(3)	(4)
Parent net wealth	0.256*	0.213	0.558***	0.532***
	(0.133)	(0.144)	(0.013)	(0.013)
Parent net wealth*adopted sibling	0.036	0.055	-0.030	-0.039
	(0.146)	(0.152)	(0.115)	(0.113)
Adoption year indicators	Yes	Yes		
Birth year ind. of child & parents	Yes	Yes	Yes	Yes
Gender	Yes	Yes	Yes	Yes
Adoption age (in days)	Yes	Yes		
Family characteristics		Yes		Yes
Observations	1,554		952,678	

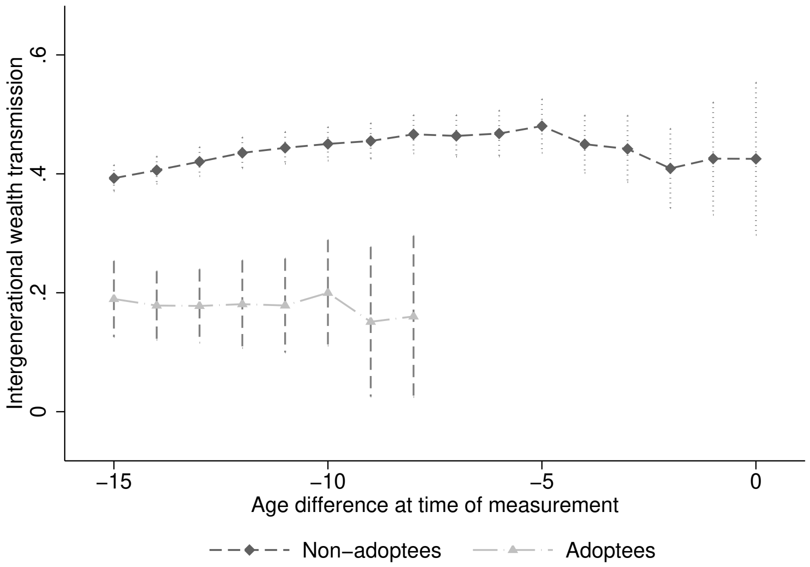
Notes: Columns 1 and 2 contain the sample of the Korean-Norwegian adoptees that were born in South Korea between 1965 and 1986, and adopted at infancy by Norwegian parents, and that have at least one sibling born in the same interval. Parental wealth is interacted with an indicator variable taking the value 1 if the sibling is adopted, and 0 if the sibling is non-adopted. Columns 3 and 4 contain the sample of non-adopted individuals (born in Norway between 1965 and 1986, and raised by their biological parents) with at least one sibling born in the same interval. Parental wealth is interacted with an indicator variable taking the value 1 if the sibling is adopted, and 0 if the sibling is non-adopted. Family characteristics include education (in years) of the mother and father, the number of siblings, the (log of) parents income and the (log of) the median income in parents' municipality of residence, all measured at the time of birth of the child (see Table 1 for further details). Standard errors (in parentheses) are clustered at the mother. ***p<.01, **p<.05, *p<.10.

Table B.9. Balancing checks

	Sample means:			Contrast between (1) and 3)	
	Korean-Norwegian	Non-adoptees		Normalized difference	Test of equality
Mean of	adoptees	Unweighted	Weighted	(percent)	(p-value)
pre-determined char.:	(1)	(2)	(3)	(4)	(5)
Mother's					
Age	46.94	45.66	47.01	-1.0	0.761
Years of schooling	12.69	12.06	12.75	-2.3	0.457
Father's					
Age	49.14	48.64	49.27	-1.7	0.594
Years of schooling	13.37	12.60	13.34	1.2	0.691
Parents'					
Number of children	1.89	2.26	1.91	-2.4	0.369
Income	46,539	39,490	46,586	0.6	0.844
Net wealth	116,933	93,388	110,691	3.0	0.329
Financial wealth	26,636	22,007	26,188	1.1	0.718
Risky assets					
Participation	0.42	0.33	0.42	0.3	0.928
Share	0.13	0.11	0.14	-1.8	0.560
Individual's					
Age	35.81	39.04	35.75	1.2	0.685
Gender	0.75	0.49	0.74	2.6	0.357
Observations	2,254	1,206,650			

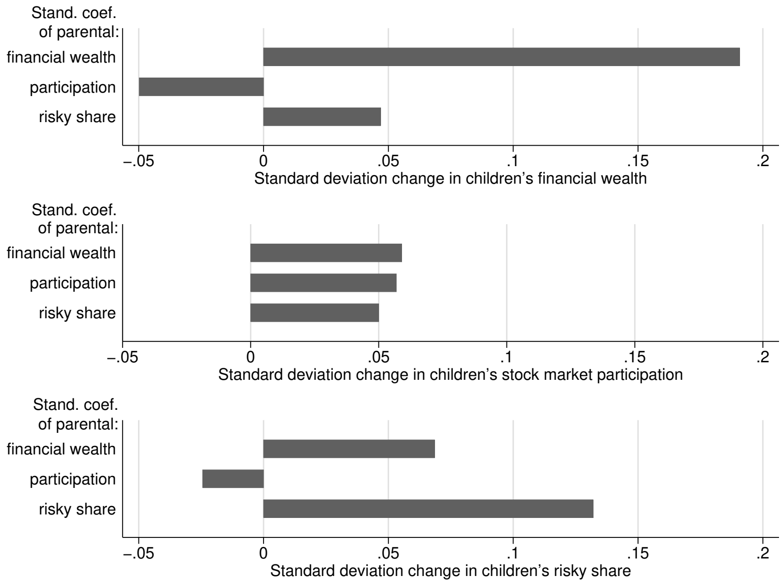
Notes: Columns 1 and 2 display the mean values of pre-determined child and parental characteristics in the sample of Korean-Norwegian adoptees (column 1) and the sample of non-adoptees (column 2). Column 3 displays the mean values of these covariates in the weighted sample of non-adoptees. Column 4 displays the normalized differences, i.e. the differences of the sample means of the adoptees and the weighted sample of non-adoptees as a percentage of the square root of the average of the sample variances in the two groups (see Rosenbaum and Rubin, 1985). Column 5 reports the p-values from t-tests for equality in means between the samples in columns 1 and 3. The Korean-Norwegian adoptees are born in South Korea between 1965 and 1986, and adopted at infancy (not older than 18 months) by Norwegian parents. The non-adoptees are born in Norway between 1965 and 1986, and raised by their biological parents. All monetary values are measured in USD, 2014 prices. Income, wealth and assets are measured at the household (per capita) level. For these variables, we take three year averages of the years 1994-1996 for parents and of the years 2012-2014 for children. Risky assets are defined as the sum of mutual funds with a stock component and directly held stocks. Risky share is measured as the proportion of the financial wealth invested in risky assets over the three year period. Stock market participation is an indicator variable taking the value one if at least some fraction of financial wealth is invested in risky assets over the three year period. Number of children of the parents includes own-birth and adopted children.

Figure B.1. Intergenerational wealth transmissions when aligning the ages of measurement of the wealth variables across parents and children



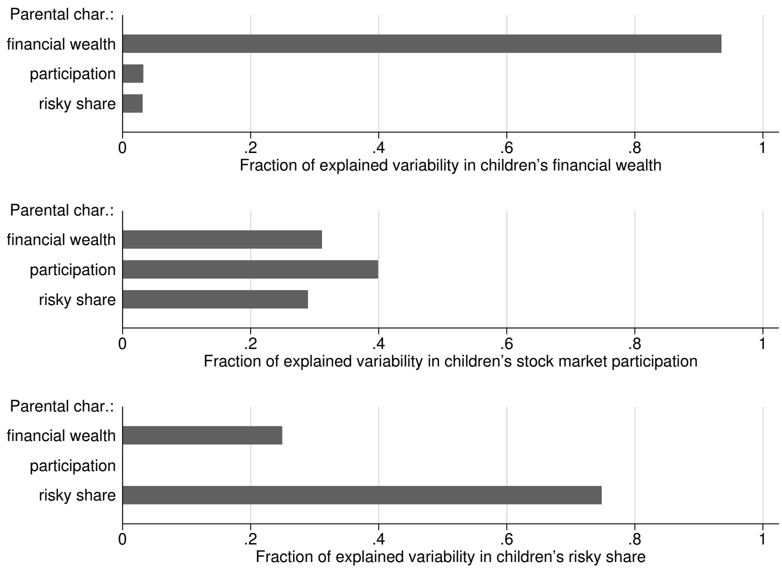
Notes: The figure displays the intergenerational wealth transmission for two different samples; 1) the sample of adoptees, N=2,254; and 2) the sample of non-adoptees, N=1,206,650, when aligning the ages of measurement of the wealth variables across parents and children. We use data on wealth for the entire period 1994-2014 for both parents and children. Regressions are run separately for each age-difference, and each child-parent pair receives the same weight. This is achieved by weighting child-parent-year observations by the inverse of the number of times a parent-child pair appears in a given regression. All specifications include controls for birth year, mother birth year, father birth year, gender and adoption year (in the adoption sample). Regressions are clustered at the level of the mother. Vertical bars indicate 95% confidence intervals.

Figure B.2. Standardized regression coefficients



Notes: This figure displays standardized coefficients for the three regression models of column 3 in Table 4, where both outcome variables and regressors are standardized with a mean of 0 and a standard deviation of 1. Each bar shows how many standard deviations the outcome variable of the child is expected to change, per standard deviation change in the characteristic of the parents (holding the other regressors fixed).

Figure B.3. Share of explained variability in children's outcomes that is attributable to specific parental characteristics



Notes: This figure displays the partial R-squared for the regressors parental financial wealth, parental participation, and parental risky share, based on the three regression models of column 3 in Table 4. For each outcome variable, we normalize the partial R-squared values to sum to one. Each bar shows the fraction of explained variability in the outcome that is attributable to a specific parental characteristic (holding the other regressors fixed).