Labor Economics
Intergenerational Mobility

Black et al. (2015) – Swedish Adoptions

Black et al. (2015) **NBER (forthcoming in ReStud)**
Poor Little Rich Kids? The Role of Nature versus Nurture in Wealth and Other Economic Outcomes and Behaviors

This paper aims to advance the intergenerational mobility literature in a key way: by focusing on the effect of wealth. Past papers have focused on the intergenerational transmission of income and education, but wealth has not been studied extensively. Wealth is certainly an important factor - possibly even more so than income and education. It affects consumption and investment decision, and there is even more wealth inequality than income inequality.[1] Wealth is also highly correlated across generations, but how much of this is because of biology and genetic differences (nature) and how much of is because of environment and parental investments (nurture)?

Usually, it is hard to distinguish between nature and nurture since most children are raised by their biological parents. To separate these effects, the authors focus on adopted children. Adoptees usually have no genetic relationship with their adoptive parents. Therefore, if we compare the children to their *adoptive* parents, we can attribute all of this to the *nurture* channel. Similarly, adoptees are not raised by their biological parents. Therefore, if we compare the children to their *biological* parents, we can attribute all of this to the *nature* channel.

To do such a study requires a very extensive dataset. We would need something that allows you to link children to parents (both adoptive and biological) and you would need to be able to observe the wealth status of both the parents and children (once they reach adulthood). Fortunately for the authors, Swedish data can do just that! Sweden has a multigenerational register that allows the linkages between parents and children (however, only 50% of biological fathers are identified for adoptees). Moreover, Sweden had a wealth tax until 2007, and so by linking this to tax data, the authors can observe wealth from 1999-2006. Other than foreign assets (which made up a small fraction of total household assets), this was reported by various financial institutions so we do not have to worry about measurement error. They are also able to observe the highest educational degree that a person has receiving as well as annual labor earnings and income.

The paper focuses on adopted children born between 1950 and 1970, with all parents (adoptive and biological) alive in 1999 (at the start of the data). Because of the time window for their data, they observe the children at around age 45 and the parents at around age 65. This is definitely a limitation because wealth is changing over one's lifetime, but we are only seeing a slight snapshot of it (but given how amazing this data is in almost every respect, I think we can cut the authors some slack here). In their final sample, they have 2,598 adopted children as well as over 1.2 million children who were raised by their biological parents.

One concern could be that adopted children could be quite different to the general population. This would be an issue for external validity (i.e. how do we generalize these results?) but not for internal validity.

[1] The difference between income and wealth is that income is a "flow", while wealth is a "stock". Income is how much you earn in a time period (e.g. your annual salary), but wealth is how much you own at a particular point in time (e.g. how much is in your bank account right now).

Tables 1 and 2 compares adopted children to those raised by their biological parents. They tend to look fairly similar on a few of dimensions, such as age and gender. However, adopted children have slightly lower wealth, income, education and much lower consumption. The differences are even starker if we look at their parents. The biological parents of adoptees are much less wealthy and have fewer years of schooling. Another comparison is between the adoptive parents and the biological parents. The adoptive parents are much older, wealthier, and better educated than the biological parents of their children. However, in comparison to the biological parents of the own-birth children, the differences are not as large. However, it is certainly the case that adoptive parents are positively selected relative to the general population. This makes sense because there were government requirements on adoption (e.g. the father had to have a steady income and the mother was expected to stay at home for some time).

Table 1: Comparison of Adopted and Own-Birth Children

	Own-birth children		Adopted children	
	Mean	SD	Mean	SD
	Children			
Net Wealth Rank	0.50	0.29	0.48	0.30
Net Wealth*	634,413	3,138,855	610,218	1,650,647
Age in 2006	43.96	5.59	43.48	4.74
Years of Schooling	12.57	2.38	12.19	2.23
Female	0.51	0.50	0.53	0.50
Earnings	215,490	134,889	197,700	132,695
Income	225,433	492,036	207,098	157,081
Market Participation	0.57	0.49	0.50	0.50
Risky Share	0.29	0.34	0.24	0.33
Mean Saving rate	0.06	0.583	0.07	0.496
Mean Consumption	341,786	375,149	192,713	136,602
Observations	1,219,014		2,598	

Source: Black et al. (2015), *Table 1a*

Table 2: Comparison of Adopted and Own-Birth Children

	Own-birth children		Adopted children		Adopted children	
	Mean	SD	Mean	SD	Mean	SD
	Biological parents		Biological parents		Adoptive parents	
Net Wealth Rank	0.50	0.29	0.34	0.27	0.55	0.28
Net Wealth	1,297,127	4,063,940	499,808	1,332,740	1,660,851	4,415,320
Average Age in 1999	64.16	7.46	60,04	6.69	68.94	6.43
Average Years of Schooling	10.12	2.62	9.63	2.08	10.50	2.79
Earnings, Father	235,539	112,483	189,810	75,505	264,142	134,326
Income, Father	237,750	140,266	194,663	80,754	271,755	146,856
Market Participation	0.75	0.43	0.57	0.50	0.80	0.40
Risky Share	0.40	0.35	0.27	0.33	0.45	0.35
Mean Saving rate	0.06	0.683	0.115	0.559	0.05	0.728
Mean Consumption	302,342	268,370	236,662	171,694	325,667	287,940

Source: Black et al. (2015), *Table 1a*

The authors estimate the following equation for a person with biological family i and adoptive family j:

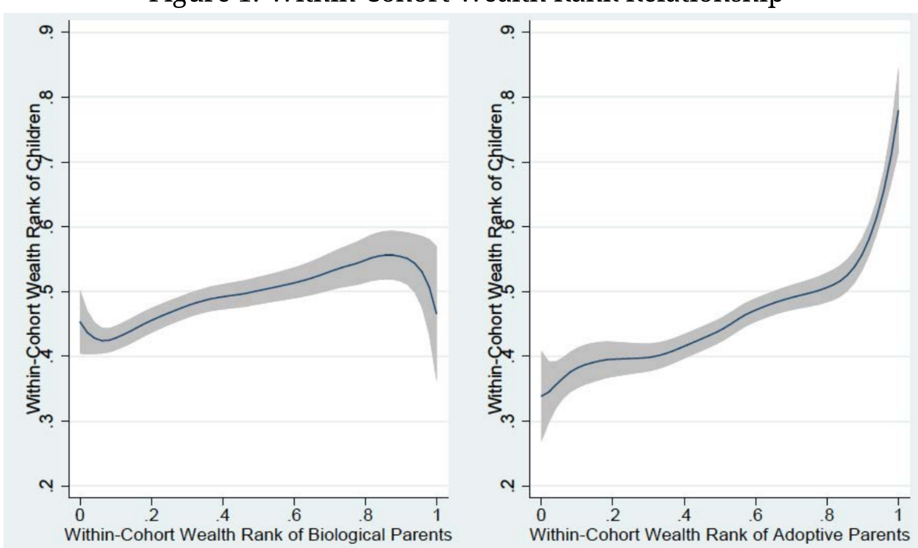
$$W_{ij} = \beta_0 + \beta_1 W_i + \beta_2 W_j + X\beta_3 + \varepsilon_{ij}$$

where W is the *rank* of net wealth and X are a set of demographic controls (e.g. gender dummy, region, year of birth). Child wealth is how much wealth the child has in 2006. The family wealth is the total parental wealth (mother and father) in 1999. We don't look at the actual value of wealth, but rather the rank of the person in the wealth distribution *within* their birth cohort (for family, they take the average cohort of the parents). This gives a number between 0 to 1, where 0 is the bottom of the distribution and 1 is the top of the distribution.

The identification strategy here relies on the assumption that adoptees are randomly assigned to their adoptive families at birth. In that case, we can attribute β_1 as the effect of pre-birth factors on adult outcomes and β_2 as the effect of post-birth factors. Note that this isn't quite the nature and nurture split that the paper's motivation started out with. Biological parents still make investments into the child during pregnancy (e.g. the biological mother decides whether or not to smoke while pregnant) that can impact the child. Also, adoptions do not occur immediately after birth; however, about 80% of children were adopted within their first year of life.

As a first pass, they look at the relationship between the within-cohort wealth rank of adopted children in comparison to their adoptive and biological parents. This is shown in Figure 1. We can see that this is generally trending upwards in a fairly linear pattern (which matches the general population). The grey shaded areas represent the 95% confidence intervals, and we can see that these become wider at the tails. This is because it is less likely to have biological parents at the top of the wealth distribution and to have adoptive parents at the bottom of the wealth distribution. Another interesting aspect is that the slope of the lines are different: it seems steeper for the adoptive parents, which suggests that this may have a stronger impact on the child's outcomes.

Figure 1: Within-Cohort Wealth Rank Relationship



Source: Black et al. (2015), *Figure 2*

The next step is to actually run the regression. The results from estimating the equation are shown in Table 3. In the paper they try a number of specifications given complications on how to define certain variables and the distributions of the variables. The regressions are also run separately for the own-birth children (those raised by their biological parents) and the adopted children. Obviously for the own-birth children, there is only one parental wealth variable. For now, just focus on column 1. The coefficient for own-birth is about 0.35. We can interpret this as meaning that a one percentile increase in the parent's position in the wealth distribution is associated with about a one-third increase in the child's position (this is just a correlation). For the adopted children, the coefficient β_1 is estimated as 0.11 and β_2 is estimated as 0.27. This indicates that the nurture (post-birth) effects are stronger than the nature (pre-birth) effects.

The authors try excluding parents in the top and bottom 5% of the distribution (as we saw in Figure 1, things get quite noisy around the tails) in column (2). Then they try re-defining wealth to include pensions in column (3), since it's not clear whether pensions matter (they cannot be passed on to children but it does indicate how wealthy a person is). Then they try again with including pensions but trimming the extremes in column (4). Overall, we get the same general result that there is a substantial role for environment and a much smaller role for pre-birth factors.

Table 3: Intergenerational Wealth Relationships

	Net Wealth w/o Pensions	Net Wealth w/o Pensions Trimmed	Net Wealth with Pensions	Net Wealth with Pensions Trimmed
Own-birth Children				
Rank Parental Net Wealth	0.344	0.328	0.219	0.191
	(0.001)***	(0.001)***	(0.001)***	(0.001)***
Observations	1,219,014	1,097,191	1,117,636	1,008,984
R-squared	0.152	0.124	0.100	0.083
Adopted Children				
Rank Biological Parents' Net Wealth	0.109	0.130	0.047	0.038
	(0.022)***	(0.026)***	(0.024)**	(0.028)
Rank Adoptive Parents' Net Wealth	0.273	0.227	0.237	0.192
	(0.021)***	(0.027)***	(0.024)***	(0.029)***
Sum Biological & Adoptive Parents	0.382	0.357	0.284	0.230
	(0.028)***	(0.035)***	(0.033)***	(0.039)***
Observations	2,598	2,027	2,059	1,684
R-squared	0.128	0.112	0.116	0.107

Source: Black et al. (2015), Table 2

The authors motivate this paper by speaking about the importance of wealth. And they can answer this because they actually can observe wealth. However, given this dataset, there's nothing necessarily special about wealth and so they can do the exact same analysis over a different number of variables. For example, we could let W be education of the child/parent or their within-cohort *income* rank. This is exactly what they do, and a some of these results are shown in Table 4. A few interesting results come out from this. First, we see that the child education is more closely related to that of their biological parents than their adoptive parents. This supports the idea that nature is more important for human capital accumulation. In terms of income, they find a much stronger effect through the nurture channel (but noticeably it is a much smaller relationship than in the wealth regression). These two outcomes have been studied in the literature; the authors can also look at saving and consumption behavior, which no other paper has done so far. This is important because savings rates may play a role in explaining wealth inequality. Savings may be driven by individual preferences and characteristics (e.g. risk aversion), but we do not know if these are genetic or shaped by our environment. The analysis here suggests it is entirely a nurture effect as we only find an effect for the adoptive parents. Finally, consumption is a good way to summarize the overall economic well-being of a person. While there seems to be some scope for nature, once again it seems that nurture has the overwhelming effect.

Table 4: Intergenerational Relationships for Other Outcomes

	(1) Years of Schooling	(3) Income Rank	(6) Saving Rate Rank	(7) Consumption Rank
Own-birth Children				
Biological Parents	0.341	0.193	0.098	0.177
	(0.001)***	(0.001)***	(0.001)***	(0.001)***
Observations	1,219,014	1,202,401	1,161,161	1,161,161
R-squared	0.172	0.236	0.023	0.385
Adopted Children				
Biological Parents	0.184	0.064	0.007	0.085
	(0.022)***	(0.020)***	(0.030)	(0.021)***
Adoptive Parents	0.143	0.108	0.129	0.134
	(0.016)***	(0.018)***	(0.023)***	(0.023)***
Sum Biological & Adoptive Parents	0.327	0.172	0.135	0.220
	(0.025)***	(0.025)***	(0.038)***	(0.031)***
Observations	2598	2534	2,363	2,363
R-squared	0.138	0.179	0.070	0.405

Source: Black et al. (2015), Table 7

Chyn (2018) – Public Housing

Chyn (2018) **AER**
Moved to Opportunity: The Long-Run Effects of Public Housing Demolition on Children

Public housing demolitions involves demolishing houses in high-poverty areas and provide housing vouchers for those who have lost there home. The rationale for this is that the residents would move into better neighborhoods and therefore result in better outcomes for the children. This paper aims to study the long-run impact of public housing demolitions in children.

The paper looks at public housing demolitions in Chicago during the 1990s. The Chicago Housing Authority (CHA) decided to demolish public houses because they were in poor shape, and instead offer housing vouchers. In general, CHA aimed to demolish the buildings that had the most severe issues. Some buildings however were chosen after a sudden crisis, e.g. pipes bursting, weather damage.

The author looks at families with children who were aged 7 to 18 in year of the demolition. Because of the date range in the data, the author can look at the outcomes for when these children turn 21 (for the youngest children) up to 34 (for the oldest children). The sample contains 5,250 children from 2,767 households.

The empirical strategy compares children in buildings that were demolished (treatment) to children in non-demolished buildings in the same public housing project (control). One may worry that since the worst houses were demolished, this could cause selection bias. However, public housing was high in demand and so typically families spent years on waiting lists and then accepted the first unit that was offered to them. There is also little opportunity to transfer within units once you are in the system. The identification assumption is that that the treatment and control groups were randomly assigned *within* the same project. Therefore, any differences in outcomes must be due to demolition and subsequent relocation. To support this, the author shows that the treatment and control groups look very similar on observable characteristics, prior to demolition (Table 5).

The author estimates the following regression for a person i at time t who lived in building b in project p:

$$y_{ibpt} = \alpha + \beta \cdot Demolish_b + \delta_p + \varepsilon_{ibpt}$$

where $Demolish_b$ is an indicator for whether a building b is slated for demolition and δ_p are project fixed effects. We can let y be various outcomes and the estimate of β will tell us the difference between the treated and control groups. Given the identification strategy, we can interpret this as the causal effect of the public housing demolition.

The first thing to check is that families who receive the housing vouchers actually move to better neighborhoods. Here, we think about "better" neighborhoods as those with lower poverty rates (defined as the fraction of people in a census tract that are below the federal poverty line). The poverty rate for the Chicago public housing was 78%, far higher than the 40% threshold that categorizes census tracts as having extreme poverty. So we let y be the poverty rate of the tract that person i lives in at time t. Indeed, the author finds that families in demolished houses move to better neighborhoods. Three years after demolition, the treated group lived in census tracts that had an average of 50% poverty rate, while the control group lived in places with a 64% poverty rate. This represents a 21% drop in poverty rate of the neighborhood (and the difference is highly significant). However, looking even further out to 8 years after the demolition, the difference becomes much smaller. Both groups are in better neighborhoods (treated: 38%;

Table 5: Comparison of Displaced and Non-Displaced People (Prior to Demolition)

	All children		Male children		Female children		Adults	
	Control mean (1)	Difference: treated–control, within estimate (2)	Control mean (3)	Difference: treated–control, within estimate (4)	Control mean (5)	Difference: treated–control, within estimate (6)	Control mean (7)	Difference: treated–control, within estimate (8)
Demographics								
Age	11.714	0.035 (0.159)	11.548	0.145 (0.196)	11.873	−0.070 (0.186)	28.851	0.810 (0.312)
Male (= 1)	0.489	−0.008 (0.017)					0.128	−0.001 (0.011)
Teen mom (= 1)†							0.371	−0.018 (0.024)
Past arrests (#)								
Violent	0.015	0.005 (0.007)	0.028	0.011 (0.014)	0.004	−0.003 (0.009)	0.185	−0.017 (0.032)
Property	0.011	0.010 (0.009)	0.018	0.015 (0.014)	0.004	0.004 (0.010)	0.156	0.016 (0.020)
Drugs	0.025	0.000 (0.013)	0.054	0.017 (0.023)	0.000	−0.018 (0.012)	0.166	0.031 (0.022)
School outcomes								
Enrolled (= 1)	0.948	0.003 (0.015)	0.946	−0.009 (0.017)	0.949	0.014 (0.016)		
Reading score (SD)	−0.443	0.024 (0.074)	−0.477	−0.045 (0.087)	−0.410	0.074 (0.074)		
Math score (SD)	−0.449	0.048 (0.061)	−0.509	0.007 (0.077)	−0.393	0.073 (0.065)		
Economic activity								
Employed (= 1)							0.173	0.006 (0.016)
Earnings‡							\$1,493.75	−\$45.91 (193.358)
Observations (individuals)		5,250		2,547		2,703		4,331

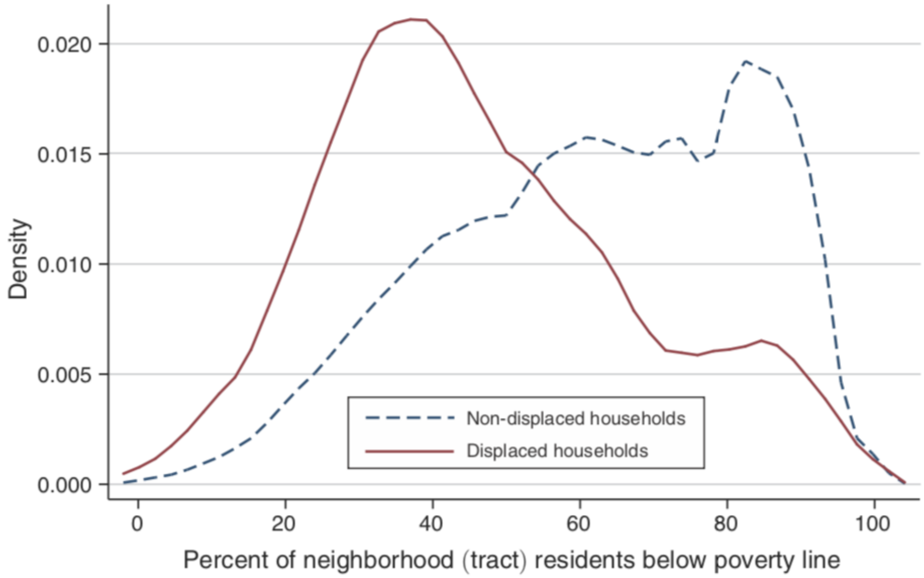
Source: Chyn (2018), Table 1

control: 41%), but the difference is not significant. The key point is that families do move to better neighborhoods. We see this clearly in Figure 2, where we can see that the distribution of neighborhood poverty rates has shifted to the left, indicating that the treated group lives in better neighborhoods.

Next, we want to look at y being labor market outcomes. This is shown in Table 6. Here, we look at labor market outcomes when the children become adults (age > 18). The treated group is more likely to be employed (4 percentage points) and having higher earnings ($600 more in annual earnings, representing a 16% increase over the control group). The author also does further specifications and finds that most of these effects are being driven by girls. Since the ages of the children at the time of the demolition vary substantially, the author also checks for heterogeneity by age. The sample is divided into those who were young (ages 7-12) and old (ages 13-18) at the time of demolition and finds positive effects for both groups, which is contrast to past estimates in the literature.

Given the nature of this experiment, one concern is that the control group may also be affected during the treatment. In particular, the demolition of a nearby building could have a negative effect on the non-displaced children (e.g. noise and dust from the demolitions). If that is the case, then the control group is going to look worse than they actually should be, which would make the impact of the treatment be larger

Figure 2: Distribution of Neighborhood Poverty after Demolition



Source: Chyn (2018), Figure 1

than it should (i.e. it is biased upwards). But if this spatial spillovers story is true then it should be the case that the children in the buildings *closest* to the demolished one should be the *most* affected. The author adds an indicator for this in the regression (which should pick up differences in the control group), but finds no evidence of these spillovers.

Does this suggest that housing vouchers are a good policy? Under a few assumptions, in particular that the 16% increase in income remains constant over time, the author estimates that this policy increased lifetime income by $45,000 ($12,000 in present value). For a family with two children, this would mean that the policy increases lifetime earnings by $24,000. From the government's perspective, this is good because it raises tax revenue. If there is a 10% increase in tax revenue, then this policy generates an extra revenue of $2,400 in present value for the government. The cost of moving this family is only $1,100, which means that this policy has a net benefit of $1,300 per family. Obviously there are a number of assumptions and simplifications, but this back-of-the-envelope calculation suggests that this is an effective policy tool.

Table 6: Impact of Demolition on Adult Labor Market Outcomes

	Control mean (1)	Difference: treated–control, within estimate (2)
Employed (= 1)	0.419	0.040
		(0.014)
Employed full-time (= 1)	0.099	0.013
		(0.006)
Earnings	\$3,713.00	\$602.27
		(153.915)
Earnings (> 0)	\$8,856.91	\$587.56
		(222.595)
Observations		35,382
Individuals		5,246

Source: Chyn (2018), Table 3

References

Black, Sandra E, Paul J Devereux, Petter Lundborg, and Kaveh Majlesi. 2015. "Poor Little Rich Kids? The Role of Nature versus Nurture in Wealth and Other Economic Outcomes and Behaviors." *NBER Working Paper*.

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