Intergenerational Mobility in Iran

Ali Bahrami Sani[*], Mohammad Hoseini[†]

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Abstract

This study measures intergenerational correlation in consumption expenditures using an administrative dataset of more than Five million Iranian people. The study consists of two parts. Firstly, we characterize the joint distribution of parents' and sons' consumption expenditure from the point of sale (POS) data at the national level in Iran. The administrative data used in this study allows us to use non-co-resident pairs in our estimations. The conditional expectation of son expenditures given parent expenditures is almost linear in percentile rank. On average, a 10-percentile increase in a parent's expenditures is associated with a 2.3-percentile increase in a son's expenditures. Besides, We provide evidence regarding the validity of consumption as a measure of intergenerational mobility. We also address the influence of life-cycle bias on estimations, with particular emphasis on the techniques employed to mitigate this bias. In the second part of the paper, we present quasi-experimental evidence that immigration across provinces affect intergenerational mobility during 2015-2021. The outcomes of children whose families move to a better province – as measured by the outcomes of children already living there – will improve conditional on the child's age. The effect is non-zero and positive for children who migrated at ages 26-32.

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[*]Department of Economics, Tehran Institute for Advanced Studies at Khatam University, East Daneshvar St., Tehran, Iran. Email: Ali.Bahrami.Sani@gmail.com.

[†]Department of Economics, Tehran Institute for Advanced Studies at Khatam University, East Daneshvar St., Tehran, Iran. Email: mo.hoseini@imps.ac.ir.

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1 Introduction

It is common among developed countries to research different kinds of mobility. This is because they can access rich panel datasets to link parents and children in various cohorts. Mobility, however, has attracted more scholars' attention in the last two decades because of improvements in methodologies and access to better datasets (Blanden, 2013).

We characterize intergenerational consumption mobility using the administrative dataset of the *Iran's ministry of labor, cooperatives, and social welfare*. Using such a comprehensive dataset allows us to link non-co-resident pairs to have an estimate without co-residency bias. This problem is one of the most critical challenges economists have had to calculate mobility so far in the developing countries (Emran et al., 2018). We organize our analysis into two parts.

First, our baseline analysis focuses on Iranian citizen sons born before 1997 whose fathers or mothers as their household heads were alive between 2019-2021. We considered their consumption as the mean consumption of each person in the years 2019-2021. Here, the paper goes into two subparts.

In the first subpart, we are trying to justify using consumption instead of income as a measure of mobility. Using PSID, we justify that consumption has better properties to be a valid proxy for lifetime achievement rather than income.

The following subpart addresses the life cycle bias. We address this problem from two channels. The rank-rank method has properties that yield more robust estimates instead of log-log specification (Vogel, 2006; Dahl and DeLeire, 2008; Eshaghnia et al., 2022). In the other channel, consumption smoothing behavior of individuals in their life course and risk sharing behavior between families could offset the effect of life cycle bias from our estimates (Charles et al., 2014; Bruze, 2018).

In the second part of the paper, we scrutinize the impact of migration in Iran between 2015-2021 on intergenerational mobility. Iran's economy has experienced massive shocks in the last decade. These shocks made many people migrate from their place of birth. We could use admin data to find people who migrated with their parents to provinces other than their province of birth. By comparing the consumption rank of these people and those who are permanent residents[1] we could find the impact of provinces on mobility. The impact suggests that going to a province with higher mobility will affect the child's rank in the national distribution, which could rise in the national distribution ranking of consumption. Moreover, we also find that this effect is persistent in those who migrate between the ages of 26 to 32.

The paper is organized as follows. We begin with section 2 to discuss related literature, then introduce our data, samples, and variables used in this study in section 3. In section 4, we discuss our results and try to address potential issues regarding our estimates and our strategy to exploit the impact of migration

[1]Those who still live in their province of birth.

and the causal effect of the place. Section 5 concludes.

2 Related Literature

The relationship between parents' socioeconomic characteristics (origins) and those of their adult offspring is used to quantify intergenerational mobility (destinations). A poor intergenerational relationship suggests everyone has a nearly equal chance of success regardless of socioeconomic origins. So, the study of mobility needs accurate data on parents and children, which is not exist for all countries for different types of mobility. This issue is more significant in developing than developed countries (Atkinson and Bourguignon, 2000).

Three kinds of datasets are prevalent in studying mobility in developed countries. These include (a) cross-sectional samples of adult populations with retrospective information about the parental generation, (b) panel surveys that span enough time to cover the socioeconomic attainment of two generations, and (c) administrative/registry datasets with linked information for parents and adult children. (Some data, such as linked survey and social security administration data in the United States, utilized a combination.)(Chetty et al., 2014b). Open access to long-term panels and administrative records is still unavailable in underdeveloped nations. This problem results in many people only focusing on the datasets containing retrospective information, especially using educational and occupational mobility (Hnatkovska et al., 2013; Asher et al., 2020). This matters because measurements using retrospective information are inaccurate without precise data such as exact income. This low-quality data problem leads even to contradicting estimations of the same measure of mobility in a country (Emran and Shilpi, 2015).

Estimating mobility in developing countries needs a comprehensive dataset and requires coping with apparent biases like life-cycle bias, attenuation bias, and co-residency bias. Life-cycle and attenuation biases were discussed more due to the lack of accurate data in the US (Haider and Solon, 2006). To cope with such biases, researchers proposed restricting the samples of parent-child pairs to specific cohorts and ages (Chetty et al., 2014b). Moreover, co-residency bias is still one of the significant issues to have a robust estimate of mobility in some countries (Emran et al., 2018). To handle co-residency bias, Ahsan and Chatterjee (2017) used a probability framework to weigh the observations to balance co-residents' weight with those not co-reside with their parents.

Regressing log child income on log parent income is a widely accepted method to estimate intergenerational elasticity of income (Solon, 1999). Unfortunately, this specification yields volatile estimates of mobility because the relationship between log child income and log parent income is non-linear, and the estimates are sensitive to the children with zero or minimal incomes (Chetty et al., 2014a). This issue will be neglected using rank-rank specification (Dahl and DeLeire, 2008).

While life cycle bias is substantial in estimating income mobility, it has less impact on consumption mobility estimates. Families' consumption smoothing and risk-sharing behavior are the main reasons Mulligan (1997); Charles et al. (2014). Other reasons related to the labor market have also reduced the severity of life cycle bias, like the homogeneous wage growth between different jobs (Vogel, 2006).

Furthermore, Eshaghnia et al. (2022) developed and estimated measures of lifetime resources (income and wealth) motivated by economic theory that account for generational differences in life-cycle trajectories, uncertainty, and credit constraints. They found that consumption is closer than income and earnings to their mobility estimates. Consistently, Bruze (2018) finds that consumption persists more across generations than earnings and income, consistent with intergenerational consumption smoothing.

Another tool that helps us have an unbiased estimate of mobility is a method in which we regress child rank on parent rank, called rank-rank estimation. This method has properties that reduce the impact of life cycle bias on accurate estimates (Dahl and DeLeire, 2008). This method is also used by genuine work of Chetty et al. (2014b) with life cycle problems in their estimates (Mazumder, 2016).

One of the most important questions yet to be addressed in the developing world is the causal effect of place on intergenerational mobility. On the other hand, there have been many attempts to find the causal impact of place on mobility in the developed world, mostly in finding the causal effect of neighborhoods (Black and Devereux, 2010; Chetty and Hendren, 2018).

3 Data

This analysis uses data from "*Iran's ministry of labor, cooperatives, and social welfare (MLCS)*." This dataset comes from an administrative database gathered by the "*Iranian Welfare Database (IWD)*" in the MLCS. The IWD contains all Iranian socioeconomic features as their yearly expenditure. Moreover, for the first time in Iran, we could link parents and children who are non-co-residents using IWD.

Iranian Welfare Database (IWD). The main goal of the existing IWD is to measure Iranian welfare to implement social assistance programs that transform indirect subsidies into direct cash transfer subsidies. This genuine administrative dataset encompasses almost all data centers in different Iranian institutions with various information from Iranian people. Variables such as wage (for those working in the formal sector), place of residency, place of birth, household structure, consumption, etc., are examples of information in this dataset. "*Iran Central Bank (ICB)*" and "*Iran Social Security Organization (ISSO)*" are examples of such institutions that we use their data in IWD.

Furthermore, Since this dataset includes all other datasets from other organizations in Iran, there exist family structures from 2015 to 2022. Thus, we could link children to their parents using this dataset to minimize co-residency bias. The bias that almost many studies in developing countries suffer from that (Emran et al., 2018).

3.1 Sample Definitions

Our base dataset of children consists of all individuals who (1) are sons who were born before 1997, (2) their parents were alive in the years 2019-2021, and (3) their parents worked in the formal sector for at least one month in 2015.

We could only link parents and sons whose sons did not marry before 2015 since there is no family structure dataset in which we could link the present dataset to that before 2015.

To construct our sample using two datasets of ISSO and IWD, we tracked the son(s) of parent we had their information in ISSO 2015 to IWD 2021. Some parents passed away in 2021, which is unimportant since we do not use their economic numbers in 2021. Plausibly, some sons co-reside with their parents, and some are not co-reside with their parents in the sample.

Our primary analysis sample, which we refer to as the *core sample*, includes all sons in the IWD dataset (1) whose parents have ages below 60 years old,(2) whom we can identify their parents, (3) whose mean parent expenditures between 2019-2021 is strictly positive. Moreover, for some robustness analysis, we use the *aged sample*, which imposes the same restrictions as the core sample but includes parents of all ages.

3.2 Variable Definitions and Summary Statistics

This subsection defines the key variables we use to measure intergenerational mobility. We measure all expenditure variables in the 2021 rials, adjusting for inflation using the consumer price index (CPI).

Expenditures. The expenditure we use comes from ICB, linked to other socioeconomic features of a family by IWD. These expenditures consist of all purchases of a person from everywhere where they could use their credit card to buy a good or service and pay the fee using POS devices. Thus, we can also refer to it as consumption. The expenditure data is available from 2019 to 2021 on an annual frequency.

Summary Statistics. Table 1 reports summary statistics for the *core sample*, *aged sample*, and *base sample*[2]. As we mentioned before, our sample includes both co-resident and non-co-resident pairs. 53% of pairs are non-co-residents. 88% of parents are fathers, and 12% are mothers. One important attribute of our dataset is that in 2015 we only have the household head and their son economic features, and we do not have the data for other members in this year. Thus, we do not know whether a son had a mother or a father who was not a household head. Another important feature is the family sizes of parents and children. The family size of parents is almost 0.2 people higher than that of children.

To construct expenditures, we averaged three years' expenditures of parents and children. We ex-

[2]Total

cluded those years when the expenditures were not positive[3]. As you can see, in the core sample, the differences between the mean expenditure of parents and children are not too much, while this difference is much higher in the aged sample and total dataset (base sample) than in the core sample.

Table 1: Summary Statistics

	Mean	Median	SD	Number of Pairs
Aged Sample				
Coresident Pairs	0.54	1	0.50	1,454,577
Parent Gender	0.88	1	0.32	1,454,577
Parent Age	67.59	66	5.75	1,454,577
Son age	34.08	34	4.64	1,454,577
Parent Family Size	3.35	3	1.32	1,454,577
Son Family Size	3.26	3	1.31	1,454,577
Mean Son Expenditures over 3 Years (Million Rials)	2,638.49	1,191	5,122.62	1,454,577
Mean Parent Expenditures over 3 Years (Million Rials)	1,433.60	645	3,550.52	1,454,577
Core Sample				
Coresident Pairs	0.52	1	0.50	1,095,388
Parent Gender	0.88	1	0.32	1,095,388
Parent Age	55.89	56	3.15	1,095,388
Son age	30.00	30	2.78	1,095,388
Parent Family Size	3.49	3	1.22	1,095,388
Son Family Size	3.30	3	1.25	1,095,388
Mean Son Expenditures over 3 Years (Million Rials)	2,128.84	976	4,261.07	1,095,388
Mean Parent Expenditures over 3 Years (Million Rials)	2,010.34	920	4,294.75	1,095,388
Base Sample (Total)				
Coresident Pairs	0.53	1	0.50	2,549,965
Parent Gender	0.88	1	0.32	2,549,965
Parent Age	62.56	62	7.53	2,549,965
Son age	32.33	32	4.43	2,549,965
Parent Family Size	3.41	3	1.28	2,549,965
Son Family Size	3.28	3	1.29	2,549,965
Mean Son Expenditures over 3 Years (Million Rials)	2,419.56	1,090	4,778.28	2,549,965
Mean Parent Expenditures over 3 Years (Million Rials)	1,681.35	748	3,898.19	2,549,965

Note: All currencies are deflated to 2021 rials.

4 Empirical Framework

We begin our empirical analysis by characterizing the relationship between parent and son expenditures at the national level. We first present a set of baseline estimates of relative mobility and then evaluate the robustness of our estimates to alternative samples to investigate the validity of using consumption instead of income. Finally, we will discuss life cycle bias and present reasons why our choice of consumption in estimating mobility will handle this issue.

[3]This is because individuals with zero expenditures died in that year or a year before.

4.1 Baseline Estimates

Our baseline analysis used two approaches to estimate consumption mobility: (1) log-log specification and (2) rank-rank specification. We found quite different results from these two approaches, which will be discussed in the following parts.

log-log specification. To estimate intergenerational elasticity we use equation (1) on our core sample. $log(\bar{C}_s)$ and $log(\bar{C}_p)$ are the logarithm of sons' consumption, and parents' consumption averaged over three years of 2019 to 2021, respectively. X_{sp} is a vector of controls, including parents' and sons' age, family size, and the gender of the parent whose household head.

$$log(\bar{C}_s) = \alpha + \beta log(\bar{C}_p) + \gamma X_{sp} + \varepsilon_i \tag{1}$$

The results are in Table 2. The estimation leads to intergenerational elasticity (IGE) of 0.247 for all pairs and 0.223 for non-co-residents which is an expected result. The results suggest that for one unit increase in the parent's expenditures, the son's expenditures will be increased by 24.7%.

Table 2: Estimations of Intergenerational Elasticity

	(1)	(2)
	All Pairs	Non-Co-Resident Pairs
dependent variable: Log. of Son Expenditure		
Log. of Parent Expenditure	0.247***	0.223***
	(0.000)	(0.000)
Constant	12.27***	15.81***
	(0.000)	(0.000)
Parent and Children Age	Yes	Yes
Parent and Children Family Size	Yes	Yes
Head Gender	Yes	Yes
N	1,095,388	523,295
r2	0.09	0.08

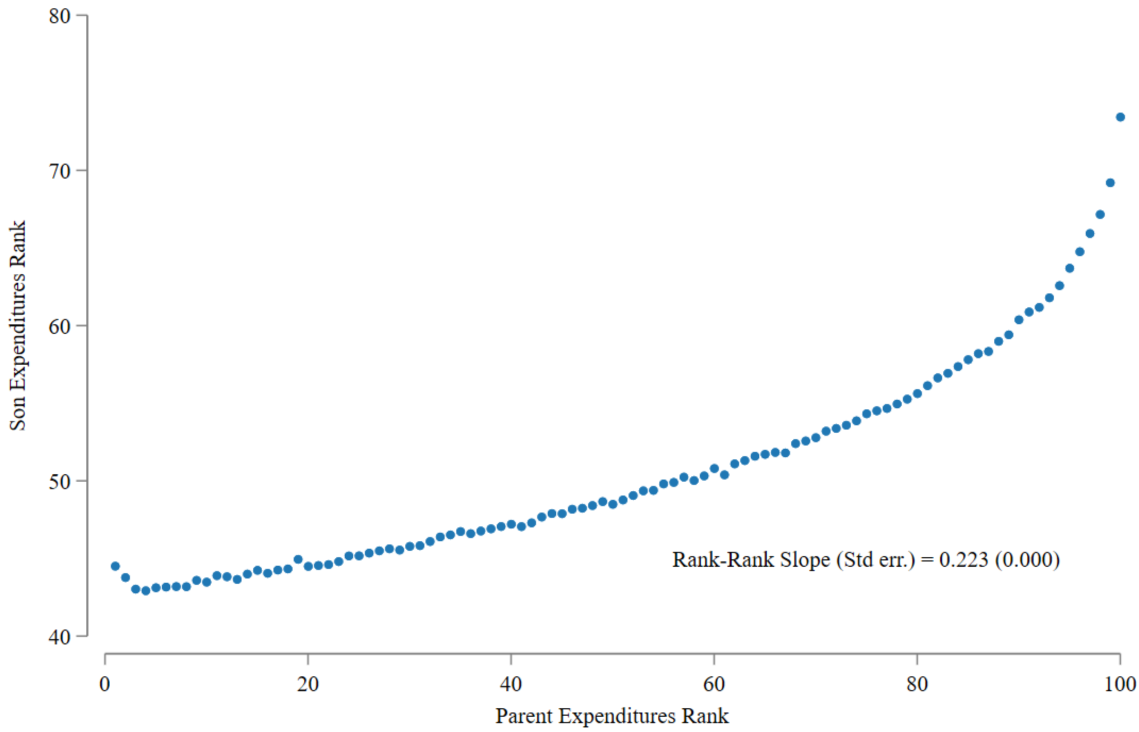
p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Unfortunately, this estimate is highly sensitive to changes in the regression specification. Moreover, using rank-rank instead of log-log specifications is statistically more suitable for comparing areas because they are robust across specifications. We will discuss this matter later in the following parts.

Rank-Rank Estimates. Figure 1 presents a binned scatter plot of children's mean consumption rank versus their fathers' mean consumption rank. To construct this figure, we regress the log of parental and child expenditures on their age-cubic polynomial and family size dummies and then rank the resulting regression residuals into percentiles.

Figure 1: Mean Son Expenditures Rank vs. Parent Expenditures Rank in Iran.



The rank-rank estimates are shown in Table 3. Using an OLS regression, we estimate that a one percentage point increase in the parent's rank is associated with a 0.223 percentage point increase in the son's mean rank. This value is 0.213 for non-co-resident pairs.

Table 3: Estimation of Intergenerational Rank-Rank Correlation.

	(1)	(2)
	All Pairs	Non-Co-Resident Pairs
dependent variable: Child Expenditures Rank		
Parent Expenditure Rank	0.223***	0.213***
	(0.000)	(0.000)
Constant	36.78	39.29
	(0.180)	(0.126)
Parent and Children Age	Yes	Yes
Parent and Children Family Size	Yes	Yes
Head Gender	Yes	Yes
N	1,095,388	523,295
r2	0.06	0.06

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.2 Robustness of Baseline Estimates

In this subsection, we try to justify our consumption usage as the measure for estimating mobility instead of income. We also discuss life-cycle bias and our choice of method to estimate mobility.

Several economists have argued (e.g., Mulligan (1997)) that an ideal measure of intergenerational mobility would be lifetime consumption across both generations since consumption is perhaps the closest measure to the utility economists are interested in.

Charles et al. (2014) asserts that families share risk or smooth consumption across generations due to unobserved or mismeasured inter vivos transfers, which is perhaps one of the main reasons why consumption expenditures have a systematically different correlation than other measures of material well-being. Even if different generations of a family experience radically different income or wealth shocks, the intergenerational expenditure correlation should be equal to 1, even with complete intra-family risk-sharing. There might also be factors underlying intergenerational correlations in expenditures, such as particular preferences in family utility functions, that do not seem to be reflected in income and wealth correlations.

Bruze (2018) also finds that consumption persists more across generations than earnings and income, consistent with intergenerational consumption smoothing. Further, Eshaghnia et al. (2022) derived and estimated lifetime resource measures that consider generational differences in life-cycle trajectories, uncertainty, and credit constraints. They found that consumption is closer than income and earnings to their estimate of intergenerational mobility.

4.2.1 Estimations

Now, we try to link intergenerational correlations derived from income and expenditure using PSID. Then, compute expenditure mobility for Iran based on the IWD.

PSID- Consumption [1999-2019]. Using PSID and IRS (tax data used by Chetty et al. (2014b)), estimates of IGE vary between 0.34-0.60. However, the rank-rank correlation estimates are around 0.28-0.38 (Mazumder, 2016, 2018). The first estimate of expenditure mobility using PSID was done by (Charles et al., 2014) for non-co-resident pairs. They used the average of three years consumption of parents and their offspring in the same years[4]. While their estimation suffered from life-cycle bias, they derived the rank-rank correlation of 0.3. The income rank-rank correlation for the same pairs was 0.26.

To compare new results from those of Charles et al. (2014), we are trying to re-estimate the findings of Charles et al. (2014). We use consumption data of all pairs in 2 periods. First, we use the mean of three years of parents' consumption in 1999, 2001, and 2003. These years for children are 2015, 2017, and 2019 (Table 4). Second, we calculate the expenditure mobility using three years of 2015, 2017, and

[4] 2005, 2007, and 2009.

2019 expenditures for non-co-resident pairs[5] (Table 5). The first set of estimates has less impact of the life-cycle bias, while the second one suffers from life-cycle bias.

Table 4: Intergenerational Expenditure Mobility using PSID Expenditures of children at 2015-2019 and parents at 1999-2003.

	(1)	(2)	(3)	(4)	(5)	(6)
	Children Expenditure Rank	Children Expenditure Rank	Children Expenditure Rank	log. of Children Expenditure	log. of Children Expenditure	log. of Children Expenditure
Parent Expenditure Rank	0.402^{***}	0.400^{***}	0.400^{***}			
	(0.000)	(0.000)	(0.000)			
log. of Parent Expenditure				0.371^{***}	0.367^{***}	0.361^{***}
				(0.000)	(0.000)	(0.000)
Constant	31.65^{***}	32.80^{***}	32.77^{***}	6.659^{***}	6.730^{***}	6.787^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Parent and Children Gender	No	Yes	No	No	Yes	No
Observations	25699	25699	5276	30461	30461	6333
R^2	0.163	0.164	0.157	0.139	0.142	0.125

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Using long-years-distance of expenditures between parents and children in PSID, we can estimate expenditure mobility with less life-cycle bias. To do so, we regressed the log of children and parent expenditures on a third-order polynomial of their age, then ranked the residuals. Finally, we regressed ranks on each other to estimate rank-rank correlation (Charles et al., 2014). The first three columns end with almost the same results in both Table 4 and Table 5. We used all pairs without any control covariate in the first column of Table 4. In the second column, we controlled for the interaction of pairs' genders and used only father-son pairs in the third column.

Table 5: Intergenerational Expenditure Mobility using PSID Expenditures of children at 2015-2019 and parents at 2015-2019.

	(1)	(2)	(3)	(4)	(5)	(6)
	Children Expenditure Rank	Children Expenditure Rank	Children Expenditure Rank	log. of Children Expenditure	log. of Children Expenditure	log. of Children Expenditure
Parent Expenditure Rank	0.406^{***}	0.409^{***}	0.391^{***}			
	(0.000)	(0.000)	(0.000)			
log. of Parent Expenditure				0.274^{***}	0.321^{***}	0.267^{***}
				(0.000)	(0.000)	(0.000)
Constant	32.42^{***}	31.73^{***}	32.62^{***}	7.647^{***}	7.207^{***}	7.726^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Parent and Children Gender	No	Yes	No	No	Yes	No
Observations	7523	7523	1436	10230	6656	2031
R^2	0.175	0.176	0.154	0.104	0.101	0.095

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[5] I only used non-co-residents to keep the consistency of estimations since there were not any co-resident pair in the sample of the first set of estimations.

However, in Table 5, we only used all pairs' expenditures in the same three years for non-co-resident pairs. Similar to columns of Table 4, in this table, we estimate rank-rank correlation in three conditions. The results of both tables using rank-rank correlation are almost the same. While the results in rank-rank correlation are the same in both tables, the results for log-log specifications have meaningful differences.

PSID- Consumption [2005-2019]. Now, we shortened the distance between years so we could measure both income and expenditure mobility. We do this since the earliest years we can calculate income and expenditure for estimating mobility in the same time begins by 2005. In Table 6, we calculated expenditure mobility in which parents' expenditures were measured in 2005-2009 and children's expenditures in 2015-2019. We used only non-co-resident pairs in Table 6. As you can see, there is a little difference between rank-rank correlations and those of Table 4 and Table 5.

Table 6: Intergenerational Expenditure Mobility using PSID Expenditures of children in 2015-2019 and parents in 2005-2009.

	(1) Children Expenditure Rank	(2) Children Expenditure Rank	(3) Children Expenditure Rank	(4) log. of Children Expenditure	(5) log. of Children Expenditure	(6) log. of Children Expenditure
Parent Expenditure Rank	0.388***	0.391***	0.371***			
	(0.000)	(0.000)	(0.000)			
log. of Parent Expenditure				0.373***	0.256***	0.227***
				(0.000)	(0.000)	(0.000)
Constant	31.67***	30.44***	31.49***	6.590***	7.799***	8.107***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Parent and Children Gender	No	Yes	No	No	Yes	No
Observations	10896	10896	2248	29347	13118	2740
R^2	0.153	0.155	0.128	0.163	0.097	0.072

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

PSID- Income [2005-2019]. Following previous estimates using PSID, we estimate income mobility for the years equivalent to the years we have estimated expenditures mobility. The results are in Table 7. To compare the results of Table 6 and Table 7, we put their rank-rank results in Table 8. All pairs are non-co-residents. As you can see, results of expenditure mobility are closer than income mobility[6], with life cycle bias, to unbiased estimates of income mobility, without life cycle bias, of Mazumder (2018); Chetty et al. (2014b). Thus, consumption is a more robust measure for estimating mobility.

[6]Estimates of income were derived by sample weights which increased the size up to 1,500 observations.

Table 7: Intergenerational Income Mobility using PSID income of children in 2015-2019 and parents in 2005-2009.

	(1)	(2)	(3)	(4)	(5)	(6)
	Children Income Rank	Children Income Rank	Children Income Rank	log. of Children Income	log. of Children Income	log. of Children Income
Parent Income Rank	0.214**	0.225**	0.240*			
	(0.045)	(0.029)	(0.091)			
log. of Parent Income				0.149**	0.161**	0.0951
				(0.047)	(0.035)	(0.500)
Constant	37.13***	31.45***	41.64	6.726***	6.484***	7.055***
	(0.000)	(0.000)	(.)	(0.000)	(0.000)	(0.000)
Parent and Children Gender	No	Yes	Yes	No	Yes	No
Observations	123	123	44	211	211	60
R^2	0.046	0.101	0.062	0.016	0.030	0.007

p-values in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Table 8: Intergenerational Income and Expenditure Mobility using PSID income and expenditure of children in 2015-2019 and parents in 2005-2009

	(1)	(2)	(3)	(4)	(5)	(6)
	Children Income Rank	Children Income Rank	Children Income Rank	Children Expenditure Rank	Children Expenditure Rank	Children Expenditure Rank
Parent Income Rank	0.214**	0.225**	0.240*			
	(0.045)	(0.029)	(0.091)			
Parent Expenditure Rank				0.388***	0.391***	0.371***
				(0.000)	(0.000)	(0.000)
Constant	37.13***	31.45***	41.64	31.67***	30.44***	31.49***
	(0.000)	(0.000)	(.)	(0.000)	(0.000)	(0.000)
Parent and Children Gender	No	Yes	Yes	No	Yes	No
Observations	123	123	44	10896	10896	2248
R^2	0.046	0.101	0.062	0.153	0.155	0.128

p-values in parentheses

* p<0.10, ** p<0.05, *** p<0.01

4.2.2 Life Cycle Bias

Eventually, we will justify our results in Table 3 so that life cycle bias does not have a meaningful impact on rank-rank estimates of expenditure mobility. Our explanation goes to two branches; first, by consumption smoothing and risk sharing, and second, by rank-rank estimation method.

Consumption Behavior. According to Mulligan (1997), consumption is a closer measure to utility rather than income. Besides, mobility estimates in the literature are all estimated in the same years for pairs. Scholars measure consumption for both generations in the same years but at different points in the life cycle. In each case, the estimates are only slighter higher than comparable estimates of income persistence (Mulligan, 1997; Aughinbaugh, 2000; Charles et al., 2014). Moreover, consistent with intergenerational consumption smoothing, the persistence of consumption across generations is higher than earnings and income (Bruze, 2018). This shows that consumption smoothing behavior makes consumption at any age a valid proxy for the lifetime output of a person. On the other hand, while risk sharing could be a potential reason why the correlation in consumption differs from other measures of material well-being, Charles et al. (2014) found that the intergenerational correlation in expenditure is not substantially greater than that in income, implying limited intergenerational risk sharing.

Furthermore, Charles et al. (2014) found that even controlling for the correlation in income, expenditures remained correlated across generations, suggesting other factors, such as preferences, access to credit, and non-pecuniary inter vivos transfers, potentially played a role in consumption smoothing across generations within a family. In contrast, in IWD, by controlling for the income of people working in the formal sector, the coefficients of rank-rank correlations do not change dramatically (Table 9), which is a consistent result with Bruze (2018) and in opposing with Charles et al. (2014). Consequently, risk sharing and consumption smoothing could be possible sources that can validate our mobility estimate with minimal impact of life cycle bias.

Table 9: Estimation of Intergenerational Rank-Rank Correlation.

	(1)	(2)
	All Pairs	Non-Co-Resident Pairs
dependent variable: Child Expenditures Rank		
Parent Expenditure Rank	0.227***	0.214***
	(0.000)	(0.000)
Constant	40.30	40.03
	(0.140)	(0.119)
Parent and Children Age	Yes	Yes
Parent and Children Family Size	Yes	Yes
Head Gender	Yes	Yes
Income Status	Yes	Yes
N	1,095,387	523,294
r2	0.06	0.06

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Estimation Methods. Following the previous part, we compare the rank-rank (IRA) method versus the log-log (IGE) method. Besides, we will discuss under which conditions we can imply that life-cycle bias has a minor impact on the mobility coefficient.

Estimates based on earnings of children in their 20s appear substantially downward biased. Estimates of the IGE are sensitive to the age spans over which father's earnings are averaged, while the estimates of the IRA are less sensitive. Estimates of the IGE are also sensitive to the number of years of fathers' earnings used, while estimates of the IRA, remarkably, are not sensitive (Dahl and DeLeire, 2008). This is why the log-log estimates in Table 4 and Table 5 are not identical to rank-rank results.

Dahl and DeLeire (2008) also find that both the estimates of the IGE in earnings and the IRA in earnings require measuring children's earnings in their 30s. However, using consumption allows us to widen the range of ages to estimate mobility to working age to minimize life-cycle bias (Charles et al., 2014; Chetty et al., 2014b).

Furthermore, Vogel (2006) by comparing the impact of life-cycle bias in the estimation of mobility between Germany and the US, find that the impact of life-cycle bias in the US is more modest compared to Germany because the correlation of wage growth and wages is not significant in the US rather than Germany. Accordingly, using Iran Household Expenditures and Income Survey, we could not find a significant correlation between earnings growth and earnings between different jobs in Iran.

4.3 Impacts of Migration

In this section, we assess how much of the differences in observed outcomes across provinces in Iran reflect the causal effects of place. We begin by characterizing the consumption behavior of permanent residents across provinces. We then turn to the immigrants sample that move between provinces to estimate the causal effect of provinces on intergenerational mobility in Iran.

4.3.1 Geographical Variation in Outcomes of Permanent Residents

We begin by characterizing spatial variation in the outcomes of children who grew up and still living in their province of birth. Our permanent residents are those that live in the same province that they lived in 2015, now in 2021. To be clear, we define the immigrant sample as individuals who migrated from their previous location in 2015 to a new one in 2021. By this definition, we first compute the consumption mobility across provinces in Iran.

As another restriction, we focus on the sample of movers who migrate with their parents and stay in the destination for at least one year. Consequently, to estimate the causal effect of a province, we implement the fixed-effect regression of equation (2):

$$y_i = \alpha_{poa} + \beta \Delta_{poda} + \epsilon_i \tag{2}$$

where α_{poa} is the fixed effect for origin o by parent consumption percentile p and age a. $\Delta_{poda} = \bar{y}_{pda} - \bar{y}_{poa}$ is the difference in the predicted outcomes of permanent residents in the destination d versus origin o for the given age a and parent consumption percentile p.

Figure 2: Movers' Outcomes vs. Predicted Outcomes Based on Residents in Destination.

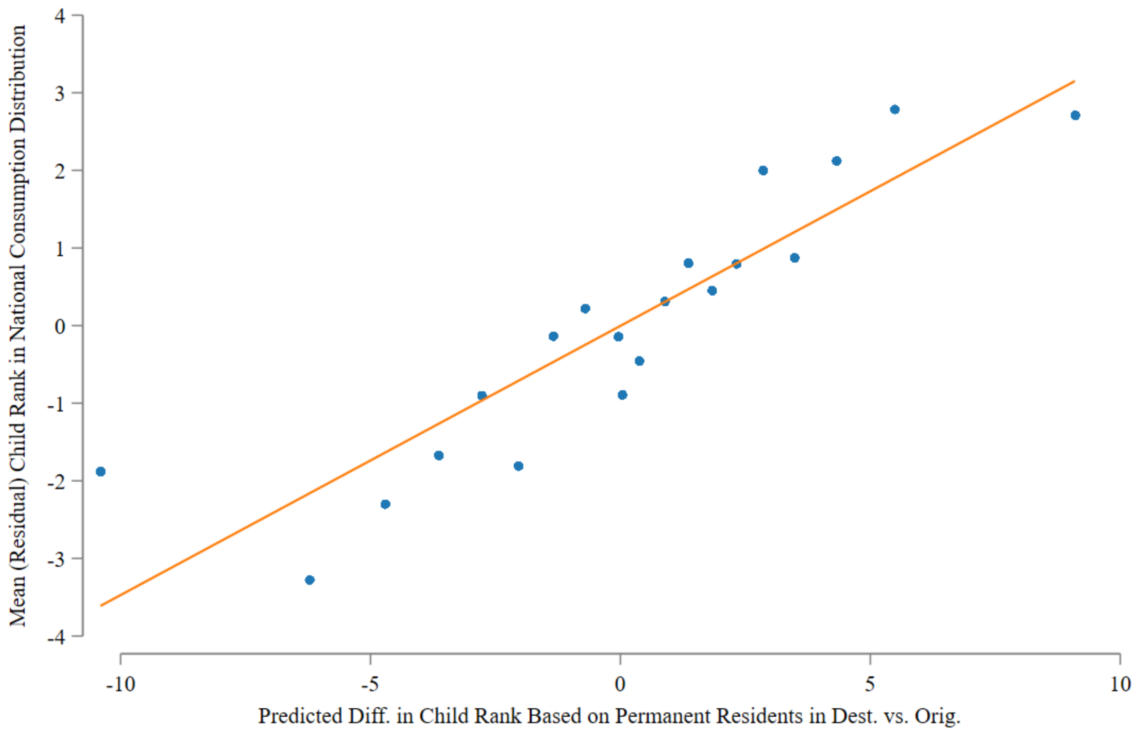


Figure 2 presents a non-parametric analog of the regression in equation (2). To construct this binned scatter plot, we first demeaned both y_i and Δ_{poda} within the parent percentile p by origin o and age a in the sample of movers to construct residuals: $y_i^r = y_i - \mathbb{E}[y_i|p,o,d,s]$ and $\Delta_{poda}^r = \Delta_{poda} - \mathbb{E}[\Delta_{poda}|p,o,d,s]$. We then divide the Δ_{poda}^r residuals into twenty-two equal-size groups and plot the mean value of y_i^r vs. the mean value of Δ_{poda}^r in each bin. The results are also shown in Table 10.

Table 10: Exposure Effect Estimates.

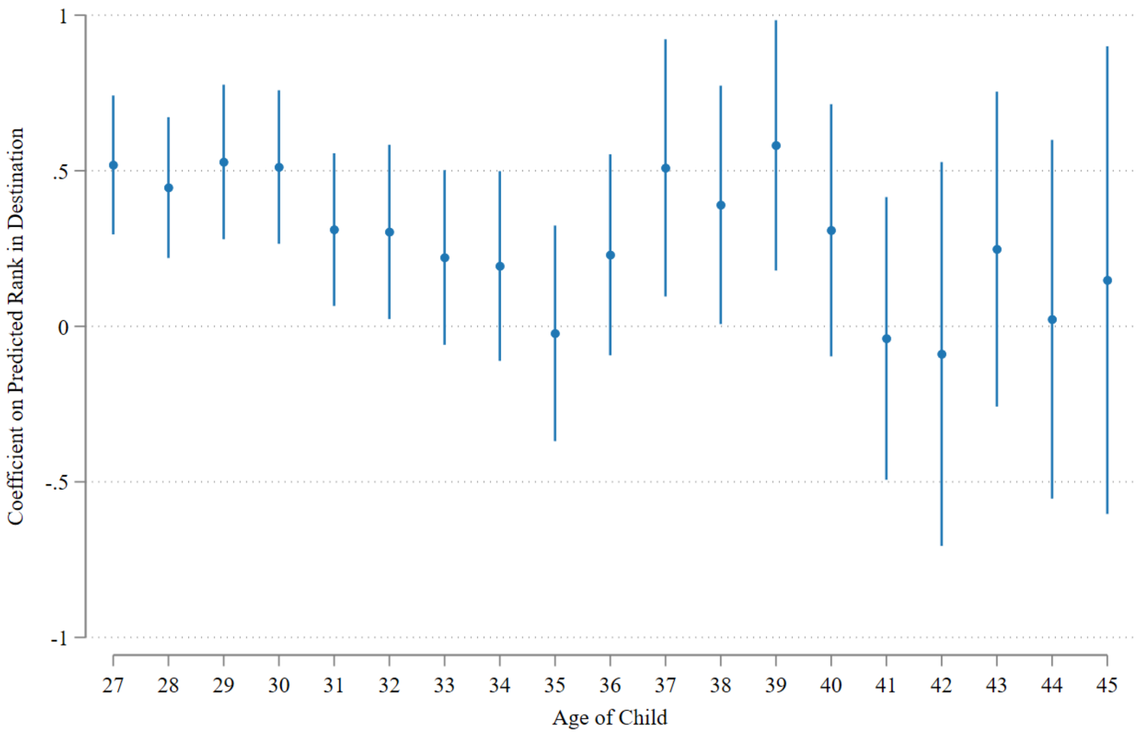
	(1)
	Children Expenditure Rank
Exposure Effect	0.382***
	(0.000)
Constant	47.01***
	(0.000)
Observations	29758
R^2	0.376

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The *exposure effect* coefficient in Table 10 implies that a one percentile increase in $\bar{y}_{pda}$ is associated with a 0.382 percentile increase in y_i for the children who moved between 2015 and 2021. To decompose the impacts of migration in different ages, we exploit the impact of migration in different ages depicted in Figure 3. The baseline is those who are at age 26. The impact is positive and significant until age 32. However, after that, the impact begins to fade.

Figure 3: Exposure Effect Estimates for Children Consumption Rank in Different Ages.



5 conclusion

This paper has used population data to understand intergenerational mobility in Iran. Using the consumption data of parent-son pairs, we could estimate consumption mobility. The data allow us to have non-co-resident pairs in our estimations for Iran for the first time. The data also allowed us to use admin data of individuals' consumption, their place of birth, and their place of residency.

This analysis showed that consumption could be a better proxy for lifetime utility in estimating intergenerational mobility. Using PSID, we showed that consumption mobility is a better measure of intergenerational mobility than income mobility when we have life cycle bias. However, we addressed life cycle bias using the rank-rank method as our econometric framework to estimate mobility. Moreover, consumption reduces the degree of life cycle bias because of consumption smoothing behavior of individuals during their life course.

Furthermore, this study shed light on the impact of where people grow up on their mobility. Findings suggest that migrating to a place with higher intergenerational mobility will increase the consumption rank of children in the national distribution. This impact is significant for sons who have migrated from ages 27 to 32.

The main lesson of our analysis is that intergenerational mobility is a local problem that could potentially be tackled using place-based policies. Since Iran experienced numerous shocks in the last decade, in the future, a key question is the causal effect of such shocks on intergenerational mobility. We hope scholars can answer these questions by using the mobility statistics constructed here to evaluate the performance of local policies.

References

Ahsan, R. N. and Chatterjee, A. (2017). Trade liberalization and intergenerational occupational mobility in urban india. *Journal of International Economics*, 109:138–152.

Asher, S., Novosad, P., and Rafkin, C. (2020). Intergenerational mobility in india: New methods and estimates across time, space, and communities. *Unpublished manuscript. Available at: https://paulnovosad.com/pdf/anr-india-mobility. pdf*.

Atkinson, A. B. and Bourguignon, F. (2000). Introduction: Income distribution and economics. *Handbook of income distribution*, 1:1–58.

Aughinbaugh, A. (2000). Reapplication and extension: Intergenerational mobility in the united states. *Labour Economics*, 7(6):785–796.

Black, S. E. and Devereux, P. J. (2010). Recent developments in intergenerational mobility. Technical report, National Bureau of Economic Research.

Blanden, J. (2013). Cross-country rankings in intergenerational mobility: a comparison of approaches from economics and sociology. *Journal of Economic Surveys*, 27(1):38–73.

Bruze, G. (2018). Intergenerational mobility: New evidence from consumption data. *Journal of Applied Econometrics*, 33(4):580–593.

Charles, K. K., Danziger, S., Li, G., and Schoeni, R. (2014). The intergenerational correlation of consumption expenditures. *American Economic Review*, 104(5):136–140.

Chetty, R., Friedman, J. N., and Rockoff, J. E. (2014a). Measuring the impacts of teachers ii: Teacher value-added and student outcomes in adulthood. *American economic review*, 104(9):2633–79.

Chetty, R. and Hendren, N. (2018). The impacts of neighborhoods on intergenerational mobility i: Childhood exposure effects. *The Quarterly Journal of Economics*, 133(3):1107–1162.

Chetty, R., Hendren, N., Kline, P., and Saez, E. (2014b). Where is the land of opportunity? the geography of intergenerational mobility in the united states. *The Quarterly Journal of Economics*, 129(4):1553–1623.

Dahl, M. W. and DeLeire, T. (2008). *The association between children's earnings and fathers' lifetime earnings: estimates using administrative data*. University of Wisconsin-Madison, Institute for Research on Poverty Madison ....

Emran, M. S., Greene, W., and Shilpi, F. (2018). When measure matters coresidency, truncation bias, and intergenerational mobility in developing countries. *Journal of Human Resources*, 53(3):589–607.

Emran, M. S. and Shilpi, F. (2015). Gender, geography, and generations: Intergenerational educational mobility in post-reform india. *World Development*, 72:362–380.

Eshaghnia, S., Heckman, J. J., Landersø, R., and Qureshi, R. (2022). Intergenerational transmission of family influence. Technical report, National Bureau of Economic Research.

Haider, S. and Solon, G. (2006). Life-cycle variation in the association between current and lifetime earnings. *American economic review*, 96(4):1308–1320.

Hnatkovska, V., Lahiri, A., and Paul, S. B. (2013). Breaking the caste barrier intergenerational mobility in india. *Journal of Human Resources*, 48(2):435–473.

Mazumder, B. (2016). Estimating the intergenerational elasticity and rank association in the united states: Overcoming the current limitations of tax data. In *Inequality: Causes and consequences*, volume 43, pages 83–129. Emerald group publishing limited.

Mazumder, B. (2018). Intergenerational mobility in the united states: What we have learned from the psid. *The Annals of the American Academy of Political and Social Science*, 680(1):213–234.

Mulligan, C. B. (1997). *Parental priorities and economic inequality*. University of Chicago Press.

Solon, G. (1999). Intergenerational mobility in the labor market. In *Handbook of labor economics*, volume 3, pages 1761–1800. Elsevier.

Vogel, T. (2006). Reassessing intergenerational mobility in germany and the united states: the impact of differences in lifecycle earnings patterns. Technical report, SFB 649 Discussion Paper.