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Intragenerational Income Mobility between 1999 and 2020 in Iran

Ali Reza Oryoie[a,*]

a. Faculty of Economics, University of Tehran, Tehran, Iran.
* Corresponding Author, E-mail: Oryoie@ut.ac.ir

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ABSTRACT

This study analyzes absolute and conditional income mobility in Iran using pseudo-panel data constructed from 22 cross-sectional Household Surveys of Income and Expenditures conducted by the Statistical Center of Iran between 1999 and 2020. The findings indicate that households with below-average income experienced faster income growth than households with above-average income, suggesting income convergence over the past two decades. However, it is important to note that some of this convergence may be attributed to international sanctions imposed between 2007 and 2014. These sanctions resulted in reduced income across all income groups, particularly affecting the top-income groups. Consequently, there was a significant decrease in income disparity between the wealthy and the poor, potentially leading to an inflation of measured income mobility. Absolute mobility is found to be high in both total income and total expenditures. Individuals displayed considerable mobility around their fixed effects, demonstrating a quick recovery from negative income shocks and low initial income endowments. Urban areas exhibited higher income mobility than rural areas.

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1. Introduction

In the literature on income distribution, most papers focus on the static aspects of income distribution. For example, they measure income inequality at a specific point in time. However, static measures of inequality alone cannot accurately reflect people's well-being. To assess well-being, it is crucial to examine the dynamic aspects of income distribution, specifically income mobility. Income mobility is important because it can help to reduce inequality and promote economic growth. Income mobility explores the evolution of an individual's income between two specific points in time (intragenerational mobility) or the changes in income between different generations (intergenerational mobility). In essence, income mobility measures the degree of movement individuals experience across different parts of the income distribution, shedding light on the relationship between short-term and long-term inequalities. Higher income mobility mitigates the negative consequences of high short-term inequalities. As mobility increases, individuals can more easily traverse the income distribution, resulting in reduced lifetime inequality. Moreover, this mobility may lead people to believe that their position on the income ladder is determined by their efforts and hard work. For instance, consider two countries with the same level of inequality but different degrees of income mobility. The country with higher mobility creates greater incentives for individuals to work harder, thereby increasing productivity and economic growth.

This study focuses on examining income mobility in Iran. Iran holds the second-largest economy in the MENA region based on GDP (current US $) between 1978 and 2019[1], and it is the second-largest holder of natural gas reserves and the fourth-largest holder of crude oil reserves in the world. Therefore, investigating various aspects of Iran's economy holds significant importance. Cross-sectional income inequality is high in

1. Iran held the position of the largest economy in the MENA region between 1960 and 1977. However, it currently ranks as the fifth largest economy in the region.

Iran[1], and the country has experienced numerous negative shocks that likely affected income inequality and mobility. One notable shock in the past three decades was the extensive economic sanctions imposed by the United Nations Security Council (UNSC), the European Union (EU), and the United States (US). In 2012, the US implemented sanctions on the Central Bank of Iran to prevent dollar transfers from Iranian exports, while the EU banned imports of Iranian crude oil and prohibited its members from investing in Iran's gas and oil industries. The UNSC imposed comprehensive trade and financial sanctions on Iran from 2007 to 2014, with some easing in 2016.

To analyze income mobility, it is necessary to track individuals surveyed over time, which requires a well-collected panel dataset. Unfortunately, such panel data is not available in Iran. In this scenario, constructing cohorts based on time-invariant characteristics such as gender or birth year can form a pseudo-panel dataset. The pseudo-panel approach, initially proposed by Deaton (1985) and increasingly employed across various fields of study (for example, Cutanda et al., 2021), enables the analysis of income mobility.

Pseudo-panel data is a useful tool for analyzing income mobility. It has several advantages over panel data, but it also has some disadvantages. Employing pseudo-panel data to analyze income mobility has at least four advantages over panel data: 1- Less sample attrition. In panel data, individuals may drop out of the study over time. This is less of a problem with pseudo-panel data, as the data is constructed by averaging groups of individuals. 2- Less measurement error. Measurement error can occur when the data is collected, such as when respondents make mistakes or when the data is not recorded accurately. Pseudo-panel data is less affected by measurement error, as the data is averaged over groups of individuals. 3- Ability to analyze income mobility over a longer period. Panel data is typically collected over a shorter period than cross-

1. For example, in 2018, the Gini coefficient based on household total income was 0.61, while the Gini coefficient based on household total expenditures was 0.43 (**Source:** Research finding).

sectional data. Pseudo-panel data can be used to analyze income mobility over a longer period, as it is constructed by combining cross-sectional data from different periods. 4- Ability to control for age-group effects. Cross-sectional data and panel data do not control for age-group effects. Pseudo-panel data can be used to control for age-group effects, as it is constructed by grouping individuals based on their birth year.

There is a trade-off between the number of observations in each cohort and the total number of cohorts. This trade-off is the main disadvantage of the pseudo-panel data over the panel data. The more cohorts there are, the more precise the estimates will be. However, the more cohorts there are, the less individuals there will be in each cohort. This can lead to more deviation from the true cohort population mean and increased sampling error (Deaton, 1985).

Note that there is ongoing debate in the literature regarding income mobility, as there are various concepts and measures used to study it. The most commonly used measure of income mobility is the slope coefficient in a regression of the logarithm of income on its lagged value. This coefficient can indicate absolute mobility if individual fixed effects are not controlled, or conditional mobility if they are. In our analysis, we use this method to measure income mobility. Antman and McKenzie (2007) have shown that, in the presence of measurement error, pseudo-panel estimates of the coefficient can provide consistent estimates of both absolute and conditional mobility, while estimates based on true panel data may be biased.

Few English-language papers have studied income mobility in Iran. Salehi-Isfahani and Majbouri (2013) analyze the dynamics of poverty using a panel dataset covering 1992-1995 in Iran, focusing on positional mobility and finding relatively high short-term income mobility. Raghfar and Babapour (2016) investigate poverty, inequality, and income mobility issues from 1984 to 2014, which we will discuss further later.

The rest of the paper is organized as follows: Section 2 describes the raw and pseudo-panel data. Section 3 explains our methodological approach for measuring income mobility. Section 4 presents the empirical results, and finally, section 5 concludes.

2. Data

We construct the pseudo panel data using 22 household surveys of income and expenditures conducted by the Statistical Center of Iran (SCI) between 1999 and 2020. The surveys are nationally representative and have been collected annually in both urban and rural areas since 1963, but the data are publicly accessible from 1984 onwards. All surveys use probability weights, and these weights are used in all calculations throughout this study. All surveys ask about each individual's income, employment status, and demographic information. They also ask about each household's assets and expenditures. Data on incomes are self-reported, and the focus of the surveys is on households' expenditures. Information on more than 600 items is collected, and the recall period is generally one month, but the recall period of a few items is one year (e.g. education, durables, travel, etc.).

In terms of income measures, we extracted four different variables from the data. First, we used total expenditures as a proxy for income, encompassing all household consumption expenditures, including expenditures on durables and home-produced consumption items. Second, we considered wage income. Third, we included monetary income, which accounts for all household cash incomes derived from primary jobs, non-primary jobs, transfers, interest, rent, and pensions. Fourth, we calculated total income, which combines monetary income with the value of goods received as transfers and the value of all home-produced consumption items. To account for inflation, we deflated these variables using the Consumer Price Indices[1] provided by the SCI. Additionally; we converted the deflated variables to adult equivalent incomes using the well-known OECD[2] equivalence scale.

1. The base year is 2016.
2. With the coefficients of 1 for the first adult, 0.7 for additional adults, and 0.5 for children.

The pseudo panel data are constructed based on the household head's education level (illiterate, 1 to 6 years of education, and above 6 years of education) and birth year (one-year cohorts). For example, all heads born in 1970 with 6 years of education form a cohort, all heads born in 1970 with 10 years of education form another cohort, and all heads born in 1971 with 10 years of education form a separate cohort. In this approach, we create distinct cohorts by combining the household head's education level and birth year. Our sample is limited to cohorts with more than 100 observations because Verbeek and Nijman (1992, 1993) have demonstrated that if the size of each cohort is sufficiently large (i.e., beyond 100 observations per cohort), the results will be unbiased.

Table 1. Descriptive Statistics in Iranian Rials (1999-2020), Iran

Variable	**N**	**Mean**	**Std. dev.**	**Min**	**Max**
Wage income	404,312	1.38E+08	1.35E+08	12,633	1.83E+10
Monetary income	763,089	2.63E+08	1.48E+09	14	6.51E+11
Total income	760,920	2.69E+08	1.49E+09	14	6.51E+11
Total expenditures	764,493	2.76E+08	3.31E+08	580,785	2.76E+10

Source: Research finding.

Note: All variables are at the household level, deflated by CPI, and converted to adult equivalent incomes by the OECD equivalence scale. The base year is 2016.

3. Empirical Methodology

There are many different concepts of income mobility in the literature. The term "income mobility" means different things to different researchers. For example, the definition of absolute income mobility in Berman (2022) is different from that in Antman and McKenzie (2007). To read about different concepts and measures of income mobility, refer to Asher et al. (2020), Fields (2008), and Jantti and Jenkins (2015). Note that we may see higher mobility based on some concepts and lower mobility based on others.

Our methodology for measuring income mobility is the same as that of Antman and McKenzie (2007). They convert their cross-sectional data to pseudo panel data and then regress the logarithm of income on its first lag. The slope coefficient in a regression of the logarithm of income on its lagged value is a commonly used standard measure of income mobility in the literature. This measure of income mobility was first introduced by Lillard and Willis (1976). Fields (2006) calls it time-dependence mobility, and Antman and McKenzie (2007) call it absolute mobility.

We believe that the estimation of all measures/concepts of income mobility using pseudo-panel data may not always be accurate. The variation of variables may be lower in pseudo-panel data than in panel data because the number of observations is much smaller in pseudo-panel data. Therefore, we may expect the magnitude of the actual mobility to be larger than what is calculated by the pseudo-panel data. However, Antman and McKenzie (2007) have shown that the pseudo-panel estimates of the regression of the logarithm of income on its lagged values are consistent estimates of the absolute mobility even in the presence of measurement error, while estimations based on true panel data are biased in the presence of measurement error. That is why our focus is only on this measure of income mobility and we do not estimate other measures/concepts of mobility.

Suppose $y_{i,t}$ denotes the income of individual i at time t. The slope coefficient of the following equation measures the absolute mobility:

$$y_{i,t} = \alpha + \beta y_{i,t-1} + \epsilon_{i,t} \tag{1}$$

To see why the coefficient β measures absolute income mobility, consider two different individuals i and j in year $t-1$ such that $y_{j,t-1} - y_{i,t-1} = 1\$$. In year t, we have $y_{j,t} - y_{i,t} = \beta$. Therefore, when $0 < \beta < 1$, the poorer individuals experience faster income growth than the richer individuals; that is, income converges and income growth is pro-poor. When $\beta < 0$, the richer individuals experience a fall in their incomes, while the poorer ones experience a rise in their incomes. When $\beta > 1$, the income gap between i and i'increases over time; that is, income diverges and when $\beta = 0$, the current income gaps do not depend on the past income gaps, and this situation is called “full origin independence”. Therefore, we understand that β can show us how much income mobility might reduce lifetime inequality.

When the data generating process of $y_{i,t}$ includes individual fixed effects, we need to add the fixed effects to equation 1 as follows:

$$y_{i,t} = \alpha_i + \beta y_{i,t-1} + \epsilon_{i,t} \tag{2}$$

where α_i controls for innate abilities and opportunities that individual i face with. The coefficient β in equation 2 is a measure of "conditional mobility". The lower the coefficient is, the higher the conditional mobility is. To understand the interpretation of β, we need to mention three points[1]. First, consider two individuals i and i' in year $t-1$ that their individual fixed effects are the same (i.e. $\alpha_{i'} = \alpha_i$) and $y_{i',t-1} - y_{i,t-1} = 1\$$. In fact, they are the same persons but in two different parallel worlds with this difference that he/she earn 1 dollar more in world i'. In year t, we have $y_{i',t} - y_{i,t} = \beta$. When $0 < \beta < 1$, an individual who is below his/her own mean income grows more rapid. Therefore, from this point of view, β shows how much an individual is mobile around his/her mean income.

Second, it can be shown from equation 2 that:

$$y_{i,t} = \beta^t y_{i,0} + \alpha_i \left(\frac{1-\beta^t}{1-\beta}\right) + \sum_{k=0}^{t-1} \beta^k \epsilon_{i,t-k} \tag{3}$$

If we subtract the current incomes of two different individuals i and j from each other, we get:

$$y_{j,t} - y_{i,t} = \beta^t \left(y_{j,0} - y_{i,0}\right) + \left(\alpha_j - \alpha_i\right) \left(\frac{1-\beta^t}{1-\beta}\right) + \sum_{k=0}^{t-1} \beta^k (\epsilon_{j,t-k} - \epsilon_{i,t-k}) \tag{4}$$

Suppose the current income gap between j and i is positive (i.e. $y_{j,t} - y_{i,t} > 0$) because the initial income of individual j is higher than that of i (i.e. $y_{j,0} - y_{i,0} > 0$), and i experiences a series of negative shocks to income (i.e. $\sum_{k=0}^{t-1} \beta^k (\epsilon_{j,t-k} - \epsilon_{i,t-k}) > 0$). Equation 4 demonstrates that as the value of β decreases, the impact of the negative shocks and differences in initial incomes on the current income gap diminishes. In other words, individual i experiences faster income growth compared to individual j as conditional mobility increases. Additionally, it is evident

1. Refer to Antman and McKenzie (2007).

that the current income gap decreases over time. However, if the fixed effects of individual j are larger than those of individual i, and $0< \beta <1$, then the income gap widens as time progresses. In such cases, a high degree of conditional mobility can only reduce the income gap when it is primarily driven by differences in initial incomes and negative shocks, rather than by disparities in fixed effects. Income differences resulting from fixed effects are likely to persist over many years.

Third, by taking the variance of Equation 3, we get:

$$Var(y_{i,t}) = \beta^{2t} Var(y_{i,0}) + \left(\frac{1-\beta^t}{1-\beta}\right)^2 Var(\alpha_i) + Var\left(\sum_{k=0}^{t-1} \beta^k \epsilon_{i,t-k}\right) \qquad (5)$$

Equation 5 illustrates that income inequality is influenced by disparities in initial incomes, individual fixed effects, and income shocks. A lower value of β decreases the impact of inequality in initial incomes on cross-sectional income inequality. It is important to note that $Var(\alpha_i)$ captures differences in opportunities and innate abilities[1], representing inequality of opportunity. Therefore, Equation 5 suggests that as conditional mobility increases, the impact of inequality of opportunity on income inequality decreases. However, it is worth noting that the impact still remains significant when inequality of opportunity is high.

From these three points, we can deduce that β in equation 2 reflects the level of efficiency and freedom in the labor market. It indicates the speed at which individuals who earn less (or more) than their income level determined by their abilities and opportunities converge towards their mean income. Additionally, it demonstrates how quickly individuals can recover from low initial income endowments and negative income shocks.

The last point is that Equations 1 and 2 estimate income mobility without controlling for other covariates. If we control for other covariates, such as education, job skills, and work experience, in addition to the lagged income to explain current income, the mobility measures estimated from Equations 1 and 2 are called conditional. For brevity, we

1. It shows inequality in health and education. It also shows discrimination in the labor market.

do not control for other covariates in this analysis; that is, we estimate income mobility unconditionally.

4. Empirical Results

The pseudo-panel data estimates of equations 1 and 2 between 1999 and 2022 are reported in Table 2. We combine every two consecutive years into a single period to increase the number of observations per cohort. For instance, we merge the years 1999 and 2000 into one period, while the years 2003 and 2004 are combined into another period. The estimation of equations is conducted for four different dependent variables in panels A through D. These variables include the natural logarithm of total income, monetary income, wages, and total expenditures. Additionally, we have performed regression analyses using the level of income as the dependent variable to further ensure the robustness of our findings. The results for these analyses can be obtained upon request. In Table 2, columns 1-3 display the estimates of absolute mobility over 1-year, 2-year, and 3-year time frames[1]. Columns 4-6, on the other hand, present the estimates of conditional mobility over the same periods.

Regarding absolute mobility, the results suggest the following: first, the mobility increases slightly with time intervals. For example, as can be seen in panel A, in terms of total income, a 10% income gap between two different families is expected to be reduced to 7.5% after one year, 7.4% after two years, and 7.2% after three years. Second, the families with below-mean incomes experience more rapid income growth than those with above-mean incomes, since $0 < \beta < 1$. Third, the degree of absolute mobility in total income, monetary income, and total expenditures is high, while the degree of mobility in wage income is low. For example, as can be seen in column (3) of Table 2, the coefficient is

1. In regressions conducted within 3-year time frames, the time distance between periods is three years. For example, the first period is 1999-2000, the second period is 2003-2004, the third period is 2007-2008, and so forth. In regressions carried out within 2-year time frames, the time distance between periods is two years; that is, the first period is 1999-2000, the second period is 2001-2002, the third period is 2003-2004, and so on.

0.73 based on the log of total income, 0.72 based on the log of monetary income, 0.74 based on the log of total expenditures, and 0.94 based on the log of wage income.

The lower mobility in wage income can be attributed to the fact that many wage earners in Iran work for the government, where wages are typically not based on employee efficiency. The wage determination rules are outdated and inflexible. Among the various measures of income, the measure based on total income provides a more comprehensive depiction of income mobility for our specific analysis.

Upon initial examination, the finding that families with below-mean incomes experience faster income growth than those with above-mean incomes may appear surprising, considering the high-income inequality prevalent in Iran. Typically, countries with high-income inequality exhibit income growth patterns that disproportionately benefit the wealthy while lagging behind for the poor. However, it is crucial to consider several factors in this context:

Firstly, our calculation of average income within each cohort causes high incomes to blend within the cohort means, while the same applies to very low-income individuals. Additionally, the sample collected by the SCI may not include extremely wealthy families. Therefore, our analysis does not compare the income growth rates of the poor with those of the very rich. So instead of saying that the poor families’ income grow faster than the rich ones, we say that our findings suggest that families with below-mean incomes experience more rapid income growth than families with above-average incomes.

Secondly, our focus is specifically on income growth rates, rather than income levels. For instance, a poor family of three with an income of 10 million Rials per month in 2008 would experience a 15% income growth when the government provides a 1.5 million Rials subsidy to families of three, while the income of the rich may grow by nearly zero percent due to the subsidy.

Thirdly, when the poor or the below-mean income groups experience faster income growth compared to the average income growth, it is expected to contribute to a reduction in income inequality. This observation aligns with the data provided by the World Bank, which indicates a decreasing trend in the Gini coefficient in Iran. Specifically, the Gini coefficient stood at approximately 0.435 in 1998, but it declined to 0.374 in 2013, and slightly increased to 0.409 in 2019. These figures demonstrate a diminishing level of income inequality in the country over the past decades. Furthermore, the research conducted by Oryoie and Abbasinejad (2017) reveals that the imposition of sanctions on Iran reduced significantly both the concentration of income within the top income groups and the income share of these top groups. Their findings further support the notion of decreasing inequality in Iran. Considering these factors, our results align with the overall trend of decreasing income inequality in the country.

Fourthly, it is important to acknowledge that the extent of pro-poor growth can vary over time within a country, due to factors such as political or economic changes and shocks. Iran, in particular, has undergone significant structural transformations in recent decades, which can lead to periods of pro-poor income growth as well as deviations from this pattern. It is crucial to consider the dynamic nature of these factors when interpreting our findings. Our results indicate income convergence in Iran between the years 1999 and 2020, which aligns with discussions around pro-poor growth. This suggests that, at least in a relative sense, there have been positive opportunities for upward mobility for families with below-mean incomes during this period. However, it is vital to continue monitoring and analyzing these trends to develop a comprehensive understanding of income dynamics and their implications for different income groups in Iran. Continued research will contribute to a deeper understanding of the factors driving income convergence and the potential policy interventions needed to foster sustained pro-poor growth.

Regarding conditional mobility, our findings indicate a substantial degree of conditional mobility in Iran. The coefficient associated with the log of wage income reveals that a 10% income gap between two families with the same fixed effects is anticipated to decrease to 3.1% after one year and further decline to 2.7% after three years. The coefficients related to the other income variables are either statistically insignificant or negative. For instance, the coefficient associated with the log of total expenditures suggests that a 10% income gap is reduced to 1.4% after one year, reaches zero[1] percent after two years, and eventually becomes negative after three years.

In the subsequent analysis, we have computed the estimates of absolute and conditional mobility for 2-year intervals in both rural and urban areas. The corresponding results are presented in Table 3. Concerning absolute mobility, the estimates for rural areas are as follows: 0.634 (total income), 0.979 (wage income), and 0.618 (total expenditures). In urban areas, the estimates are 0.566 (total income), 0.898 (wage income), and 0.704 (total expenditures). Hence, the results suggest the following: Firstly, total expenditures in rural areas display greater mobility compared to urban areas. However, wage income (total income) in rural areas exhibits lower mobility in contrast to wage income (total income) in urban areas. Secondly, the degree of mobility in wage income is generally low, particularly in rural areas, while total income shows higher mobility, particularly in urban areas. Regarding conditional mobility, the estimates for rural areas are zero (total income), 0.324 (wage income), and 0.136 (total expenditures). In urban areas, the estimates are -0.157 (total income), 0.233 (wage income), and zero (total expenditures). Consequently, the degree of conditional mobility in all three-resource measures is higher in urban areas compared to rural areas.

1. By zero, we mean the coefficient is statistically insignificant at 5% level.

Table 2. Conditional and Absolute Mobility over Different Time Intervals, Pseudo Panel Estimates, 1999-2020, Iran

	Absolute mobility			**Conditional mobility**		
	(1) 1-year intervals	**(2) 2-year intervals**	**(3) 3-year intervals**	**(4) 1-year intervals**	**(5) 2-year intervals**	**(6) 3-year intervals**
Panel A: Dependent variable is Log of total income						
Lag of dependent variable	0.753**	0.732**	0.732**	-0.041	-0.115*	-0.166**
	(0.023)	(0.030)	(0.026)	(0.042)	(0.046)	(0.048)
N	678	540	432	678	540	432
R^2	0.616	0.598	0.607	0.807	0.827	0.854
Panel B: Dependent variable is Log of monetary income						
Lag of dependent variable	0.751**	0.737**	0.717**	-0.110**	-0.026	-0.124**
	(0.021)	(0.025)	(0.025)	(0.040)	(0.039)	(0.041)
N	678	540	432	678	540	432
R^2	0.645	0.664	0.640	0.850	0.868	0.890
Panel C: Dependent variable is Log of wage income						
Lag of dependent variable	0.956**	0.929**	0.943**	0.310**	0.233**	0.273**
	(0.019)	(0.024)	(0.023)	(0.049)	(0.053)	(0.056)
N	678	540	432	678	540	432
R^2	0.833	0.781	0.791	0.892	0.874	0.884
Panel D: Dependent variable is Log of Total expenditures						
Lag of dependent variable	0.849**	0.799**	0.742**	0.143**	0.057	-0.096**
	(0.018)	(0.023)	(0.021)	(0.039)	(0.030)	(0.035)
N	678	540	432	678	540	432
R^2	0.793	0.733	0.655	0.882	0.883	0.880

Source: Research finding.

Note: *Denotes significance at 5%, **at 1%. Robust standard errors in parentheses. N shows the number of cohorts. Balanced pseudo panels.

Our findings indicate that income mobility is high in Iran. However, it is crucial to consider the context in which our analysis took place. Between 2007 and 2015, Iran faced significant international economic sanctions, which had a profound impact on the country's economy. As a result, all income groups experienced a substantial reduction in income. We calculated income growth for three classes: poor, middle, and rich[1].

1. The boundaries used for classifying individuals are 75% and 125% of the median income in each year. A household is considered middle-class if its income falls between 75% and 125% of the median. Conversely, it is categorized as poor or rich if its income is lower or higher than 75% or 125% of the median, respectively.

The reduction in real income for the poor, middle, and rich classes was -7%, -14%, and -31% between 2007 and 2015, respectively. This means that the top-income groups experienced a greater reduction in income than the low-income groups, leading to a decrease in the income gap between the rich and the poor. Oryoie and Abbasinejad (2017), from another perspective and using a different methodology, have also shown that the gap has decreased between 2007 and 2015. As the gap decreases, the estimated coefficient in equation 1 decreases; that is, the measured mobility increases. It is important to note that some of the high degree of income mobility found in this research may be related to the fact that the rich experienced a larger income reduction than the poor. Therefore, the small coefficients found through equation 1 do not necessarily mean that Iran's economy is as mobile as the estimated coefficients suggest. Further research is needed to determine the impact of sanctions on income mobility in Iran.

At the end of our study, we compared our estimates of absolute and conditional mobility with those of other similar studies. Raghfar and Babapour (2016) employed a pseudo-panel approach to examine the dynamics of income distribution in Iran from 1984 to 2014. Their estimates suggested that the absolute (conditional) mobility was 0.93 (0.91) in two-year intervals, signifying a very low degree of mobility in Iran. In contrast, our study, utilizing up-to-date data, discovered higher levels of mobility. This discrepancy might be attributed to the international sanctions imposed between 2007 and 2014. We discussed how these sanctions could have reduced the income gap between the poor and rich (i.e., increased income mobility). Alternatively, it could be due to other factors, such as the quality of data provided by the SCI in earlier years and the number of cohorts used in the analysis. Raghfar and Babapour's study was based on data from earlier years when data quality was lower, and their number of cohorts was limited because they only employed one criterion, the year of birth, to construct the cohorts. In addition, they built their cohorts in five-year bands. In comparison, our study used two criteria and defined our cohorts in one-year bands.

Antman and McKenzie (2007) estimated income mobility for the period 1987-2001 in Mexico using a pseudo-panel approach. They found that the absolute (conditional) mobility was 0.936 (zero) in 2-year intervals. Cuesta et al. (2011) estimated income mobility for the period 1992-2003 for 14 countries in the Latin American region. Their estimations suggested that the absolute mobility was around 0.97. Therefore, our findings suggest that income mobility is higher in Iran than in Latin American countries in terms of absolute/conditional mobility.

Table 3. Mobility in Income, Wage, and Expenditures: Pseudo panel estimates, 2-year intervals, 1999-2020, Iran

	Rural			**Urban**		
	(1) Log Total Income	**(2) Log Wage Income**	**(3) Log Total Expenditures**	**(4) Log Total Income**	**(5) Log Wage Income**	**(6) Log Total Expenditures**
Panel A: Absolute Mobility						
Lag of dependent variable	0.634**	0.979**	0.618**	0.566**	0.898**	0.704**
	(0.042)	(0.032)	(0.032)	(0.046)	(0.034)	(0.037)
N	395	395	395	330	330	330
R^2	0.377	0.766	0.430	0.363	0.686	0.574
Panel B: Conditional Mobility						
Lag of dependent variable	0.009	0.324**	0.136**	-0.157**	0.233**	0.001
	(0.055)	(0.068)	(0.040)	(0.059)	(0.072)	(0.045)
N	395	395	395	330	330	330
R^2	0.673	0.848	0.664	0.692	0.810	0.793

Source: Research finding.

Note: *Denotes significance at 5%, **at 1%. Robust standard errors in parentheses. N shows the number of cohorts. Balanced pseudo panels.

5. Conclusion

We conducted a parametric analysis of absolute and conditional income mobility using pseudo-panel data spanning from 1999 to 2020. Our findings revealed that households with below-average income experienced faster income growth compared to those with above-average income. The level of absolute mobility in wage income was relatively low, particularly in rural areas, but exhibited higher rates in monetary income, total expenditures, and particularly in total income within urban areas. The results indicated a significant degree of conditional mobility, particularly in urban settings.

The observed high degree of conditional mobility suggests that families can quickly recover from initial disparities in household income and adverse income shocks. In other words, negative shocks do not have a long-term impact on income inequality. Therefore, the substantial income inequality observed in Iran is likely attributed to household fixed effects. While these fixed effects have a greater influence on inequality than adverse shocks and low initial income endowments, their impact does not persist due to the high levels of absolute income mobility in Iran.

The fixed effects encompass various factors such as gender, ethnicity, race, language, disability status, socioeconomic status, household demographic characteristics, educational background, religion and political beliefs, institutions, and social abilities. To address the disparities arising from these fixed effects, we suggest implementing policies that target inequality in education, ethnicity and race, healthcare, and women's participation in the labor market. Future studies should focus on analyzing the impact of these fixed effects on income mobility in Iran.

Finally, it is important to acknowledge that the high degree of mobility observed in this research may not accurately reflect the true extent of mobility in Iran. In other words, the high mobility observed does not necessarily indicate a society with equal opportunities for all individuals. We have provided clarification that the sanctions imposed between 2007 and 2015 resulted in a decrease in income across all income groups, with a particular impact on the top-income groups. As a result, there was a significant reduction in income disparity between the wealthy and the poor. This reduction in the income gap is likely to affect the estimated coefficients in the regression analyses, potentially inflating the measured income mobility. To gain a more comprehensive understanding of mobility in Iran, further research is required to explore the impact of sanctions on income mobility.

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