Absolute Intragenerational Income Mobility in Iran over Three Decades*

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Abstract

Aggregate measures such as income per capita or Gini index have limitations to answer how much of households are better or worse off following booms and busts, and crises an recoveries. Intragenerational absolute income mobility defined as percent of households with higher income compared to their previous year is the answer. However, detailed panel data is needed to estimate the mobility which is not available in developing countries at least in long term. In this paper, we use copula modeling and cross sectional income data provided in Household Expenditure and Income Survey of Iran and well approximate the mobility estimated by panel data for years 2010 to 2019 and then expand expand it to three decades of 1990 to 2019 for Iran for the first time. According to our results, absolute intragenerational income mobility in Iran for urban households has been moving between around 43 to 62% with a maximum in 2007. The key macroeconomic measure that is positively associated with mobility is economic growth.

Keywords: Intragenerational Mobility, Income, Iran
JEL Codes: D31, D63, J62, O15

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1 Introduction

Aggregate measures such as income per capita or Gini index have serious limitations to show a comprehensive picture of an economy. They cannot describe *which individuals or households and how much of them are better or worse off* following booms and busts, and crises an recoveries (Berman 2018a). For a certain income growth and distribution of income, we can consider cases that major parts of people are beneficiaries, or cases that most of them are losers and lots of intermediate cases (see Table 1 for a toy example). Absolute intragenerational income mobility, defined as the fraction of households whose real income per capita is higher at the end of a period compared to the beginning of that period, can answer to this question.

Relative measures of mobility show the percent better off in income rank instead of absolute income. Intergenerational mobility studies percent of children better off compared to their parents. Relative mobilities are studied for a long time and for different countries. See for example Corak (2020) and Lee and Solon (2009) for relative intergenerational mobility and Silvia et al. (2013) and Parrado (2005) for relative intragenerational mobility. Moreover, prior to Chetty et al. (2017), the *absolute* mobility is documented in the literature in terms other than the income such as occupational status (Arrow et al. 2018) and educational attainment (Duncan and Murnane 2011). Chetty et al. (2017) for the first time show the *absolute income* mobility trend.

We need to track the households or individuals' income over the time to estimate the absolute intragenerational income mobility. Panel data surveys such as PSID[1] or administrative data sets such federal income tax records used in Chetty et al. (2014) in the United States or Australian federal income tax returns used in Deutscher and Mazumder (2020) make it possible to track the individuals and households over the time, but unfortunately similar datasets are not available for developing countries or most developed countries in a long period of time. For example, in Iran, the developing country that we study in this paper, the only available panel income data is a rotating panel survey[2] that is only available since 2010 excluding the

[1] Panel Study of Income Dynamics

[2] Household Income and Expenditure Survey provided by Statistical Center of Iran

Table 1: A toy example of cases with one percent growth and constant inequality

	Income in year 1 ($)			
Income in year 0 ($)	Case 1	Case 2	Case 3	Case 4
400	404	404	404	404
300	303	303	303	303
200	202	201	202	202
100	101	101	101	101
percent better off	100	50	75	25
percent worse off	0	50	25	75

Notes: Each color show an specific household entire the table. Cases 1 to 4 show examples of different scenarios. Income growth is 1 percent and inequality is constant for all the cases but percent of people better and worse off are different.

2012-2013 and 2017-2018 panels.

Initially to estimate the *intergenerational* income mobility, Berman (2018b) following Chetty et al. (2017) uses cross sectional income data and their copula, i.e. the joint distribution of income ranks for the parents and their children in a same age, and well approximate the detailed panel data results of Chetty et al. (2017). Next, in Berman (2018a), he uses the copula modeling and cross sectional income data for the same generations to estimate the absolute intragenerational mobility in United States for 1962-2014. His show the copula modeling results well approximates the mobility estimated from PSID panel data set.

In this paper, following the method used by Berman (2018a), we estimate the absolute intragenerational mobility for Iran over the three decades from 1990 to 2019. We do this in a few steps. First, we estimate the absolute intragenerational mobility for the years 2010 to 2019 (excluding panels 2012-13 and 2017-18) from the rotating panel data. Next, we estimate the copula parameters, for five different functional forms of copula used in Berman (2018a), using the rotating panel data from 2010 to 2019 and show that the Plackett copula has less than 5% errors (less than other copula models) in approximating the panel data results and then select it as our main copula model. In the third step, we use the Plackett copula and marginal (cross sectional) income distributions from 1990 to 2019 to estimate the absolute intragenerational mobility in Iran. Next, as a robustness check we find the Plackett copula

parameter that has the least errors in approximating the mobility estimated in Salehi-Isfahani and Majbouri (2013) using the panel data sets from 1992-95 for Iran and show that our results are not sensitive to replacing this parameter in Plackett copula instead of our original one.

The rest of the paper is organised as follows. In the next section, we describe the household expenditure and income survey data and its rotating panel structure as well as the rural and urban CPI data used to realize the nominal variables. Section 3, provides the method and results of absolute intragenerational mobility using the panel data set in the period of 2010-2019. In section 4, we introduce the copula modeling, select the best copula functional form and estimate the absolute intragenerational mobility over the three decades. Section 5 tries to study the no growth and constant inequality scenarios and also the correlations of mobility with income growth, inflation and Gini index. A final section concludes.

2 Data

The Statistical Center of Iran [3] (SCI) provide a yearly survey of income and expenditure of urban and rural households since 1984, known as Household Expenditure and Income Survey (HEIS). The main purpose of SCI for this survey is to estimate the trends of income and expenditure of households in province and country levels. We use expenditure per capita instead of income per capita as our measure of income to avoid potential under reporting the income by households [4].

Since 2010, SCI has added a rotating panel feature to HEIS so that households are re-sampled for up to three consecutive years. The first round was designed for 2010-12, then for 2013-17, and the last round has started in 2018. Then it has no rotating panel structure in years 2012-13 and 2017-18. Each round of rotating panel samples are based on the information provided in the previous Population and Housing Census[5] of Iran.

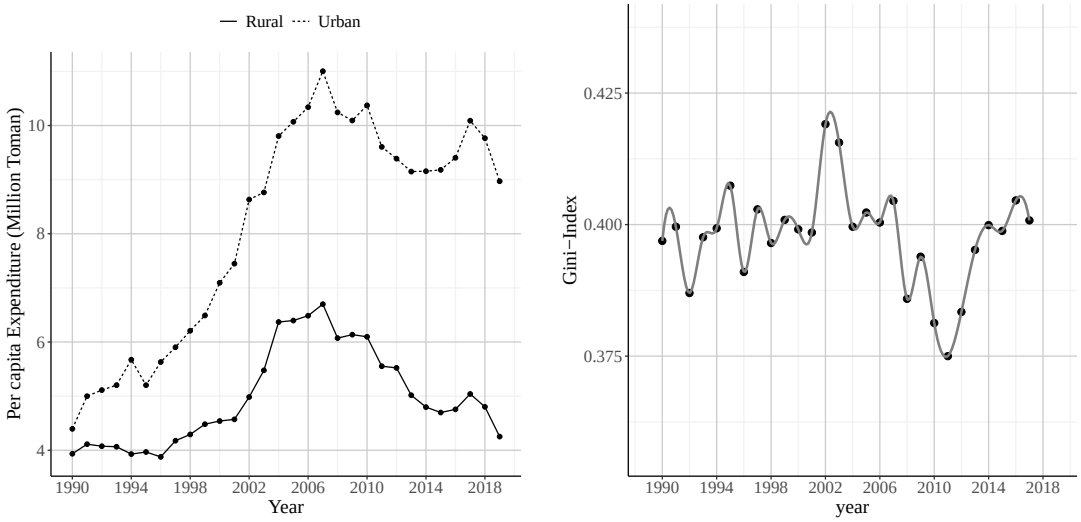
SCI initially tracks the houses not the households and assign the same address to a house-

[3] amar.org.ir

[4] see Amanzadeh et al. (2021) and Hosseini (2021) for more details on these, generally on HEIS data and its cleaning steps.

[5] Provided by SCI in 2016, 2011, and 2006

Figure 1: Evaluation of Income per capita and Gini index over last three decades



(a) Average real per capita income in 2016 prices

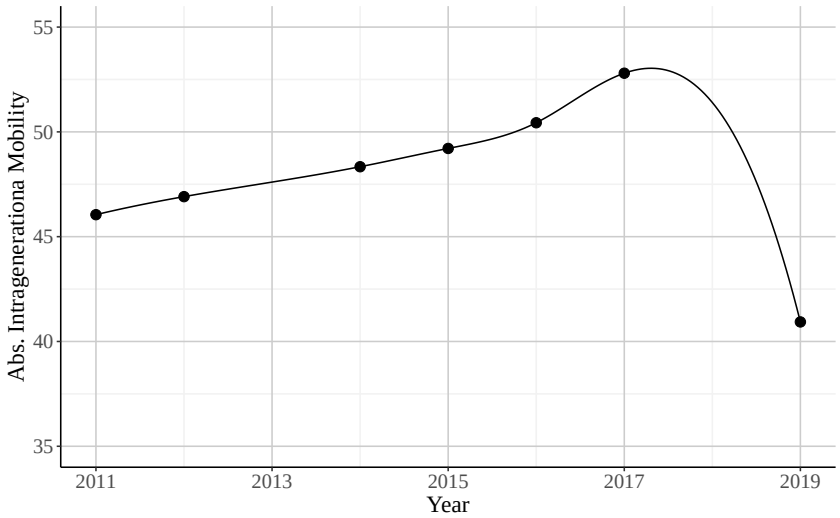
(b) Gini index

hold replaced with the previous one. However, SCI define a variable for the replacement of the household that potentially use to know that the household is not the same as previous year. But we observe that this variable is not reliable since there exist households who have been labeled as "moved" but they have the same characteristics as the last year and households who have been marked as "not-moved" but with totally different characteristic as the previous year. Therefore we defined a distance function that uses family characteristics such as average age of members, size of family, number of children, etc., to generate a distance metric between two families and used it to check if families in each panel had been replaced or not.

In order to realize the nominal variables, we use the Consumer Price Index (CPI) provided by SCI for urban and rural families in the prices of the year 2016. We also used the Gini index data provided by the the Central Bank of Iran [6] (CBI). Figure 1 shows the average real expenditure per capita for urban and rural households from 1990 to 2019 in Iran in panel A and the Gini index of Iran in panel B.

[6] cbi.ir

Figure 2: Absolute intragenerational mobility from 2011 to 2019



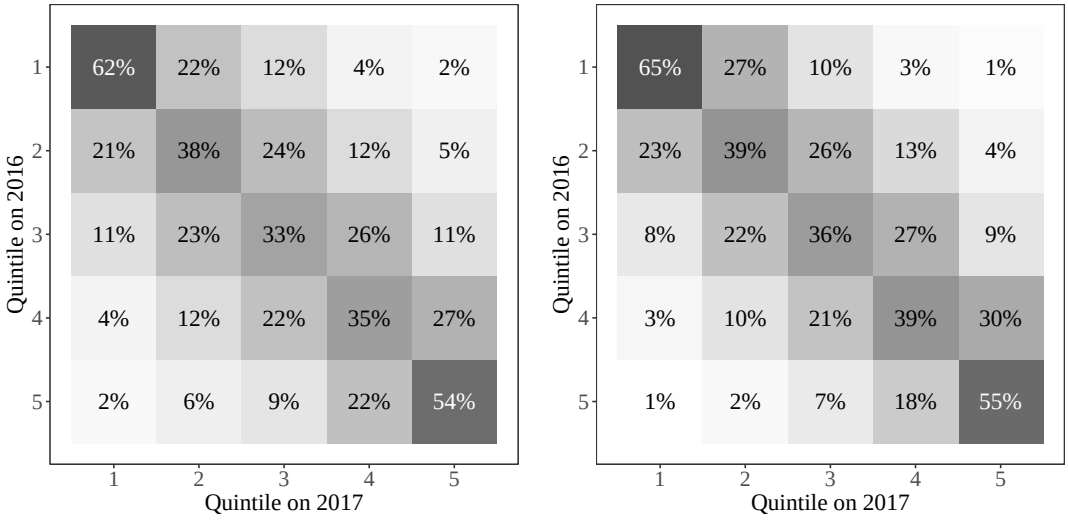
Note: Percent of urban families who had more real income per capita from the previous year. Calculated from panel data of HEIS. For rural families check figure 19 in appendix B.

3 Mobility from 2011 to 2019 using panel data

In this section, we estimate the intragenerational absolute income mobility for from 2011 to 2019 in Iran using the panel data. Here we track the same households for two years and then compare a household's real expenditure per capita with its previous year and see whether it is better or worse off. Percent of households with higher real income per capita in second year will be the absolute intragenerational income mobility. Figure 2 show the mobility for urban and rural households from 2011 to 2019. The x-axis show the second years, i.e., for each year how many percent of households have higher income compared to their previous year. Excluding years 2016 and 2017, the percent of households better off is less than 50% that is more than half of the households are worse off in each year.

to compare our results with previous studies on relative mobility and also for a methodological need that will explain in the next section, we provide the transition matrices in Figure 3. This figure shows the matrix of probabilities for quintile movements from 2016 to 2017 as an example. According to this result, 65% of urban households which were in quintile 1 (poorest quintile) in year 2016, remain there in 2017 too. They move to quintiles 2-5 with

Figure 3: Transition Matrix for HEIS Panel 2016-17



(a) Rural (b) Urban

Note: Matrix of probabilities to move between total expenditure per capita quintiles. ij element of each matrix shows the percent of families form ith quintile who end up in jth quintile in the following year. To see average transition matrices for different expenditure items check appendix A.

the probabilities 27, 10, 3, and 2 percent, respectively[7].

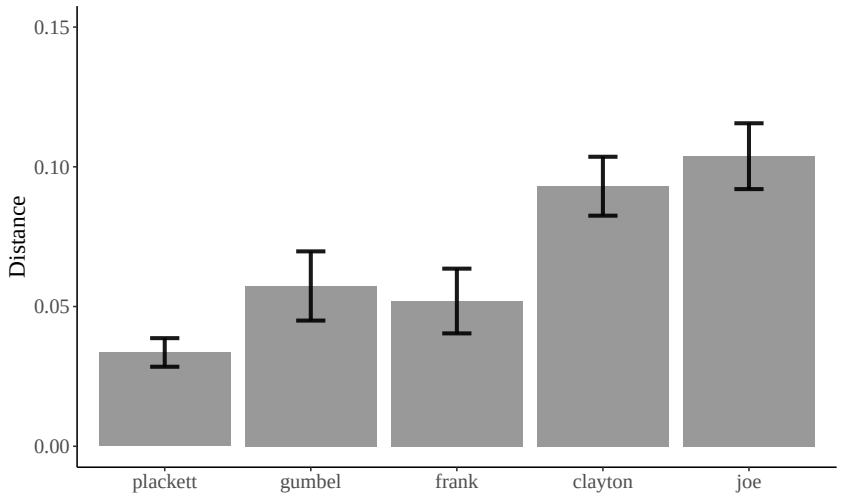
4 Mobility from 1990 to 2019 using copula modeling

As discussed in section 1, in order to calculate absolute intragenerational mobility, we need to have good quality panel data witch is not available in many developing countries. Berman (2018a) shows that if we assume the dynamic of movement in the income ladder is constant (constant transition matrix), we could use cross-sectional data and copulas to estimate absolute intragenerational mobility with good precision.

Copulas were first introduced in 1959 for estimating the joint distribution of random variables using their marginal distribution (Trivedi and Zimmer (2007)). Copula estimates the cumulative joint distribution of two or more variables using the marginal cumulative distributions and some dependence parameters. This property of copula (using CDFs) enables

[7]We also calculate these transition matrices for other years and also for different expenditure items such as food, education, etc. in appendix A.

Figure 4: Normalized Forbenius Distance



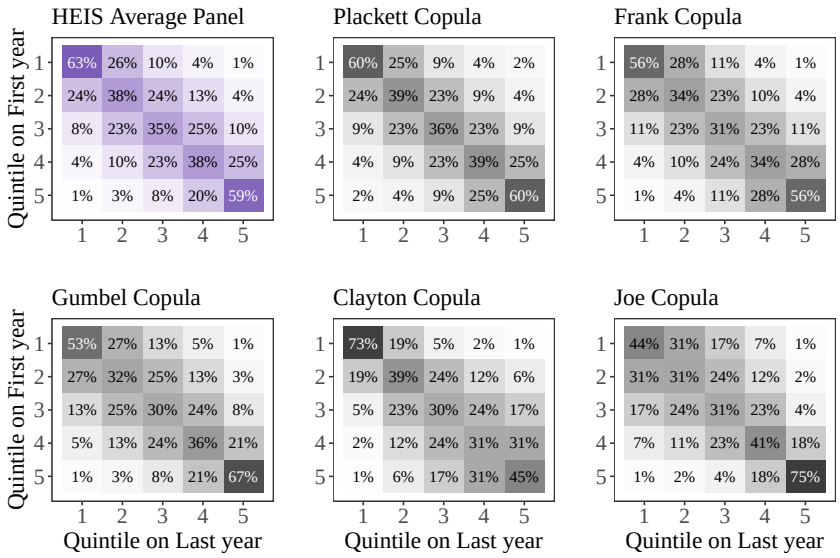
Note: Normalized Forbenius distance between estimated transition matrix for different copulas and real transition matrices calculated from HEIS panel data for urban families. Figure 5 shows the difference between different copula estimations. For rural families check figure 20 in appendix B.

us to estimate the distribution independent from the form of marginal distributions. Therefore we can represent each copula with its transition matrix and then estimate the dependence intervals with copulas.

Berman (2018a) shows that the Plackett copula would give the closest estimation to the real transition matrices calculated for PSID data in the United States. Bonhomme and Robin (2009) also shows that the Plackett copula is better than other copulas in estimating the transition matrix in France. In order to find the best copula for modeling the transition matrix in Iran, we use different copula models and calculate the average transition matrix for each one of them. Then we use normalized Forbenius distance [8] between estimated and real transition matrix as a measure of fitness and show that, as Berman (2018a) and Bonhomme and Robin (2009) conclude, the Plackett copula is the best fit for our transition matrices (Figure 4).

[8] $NFD = \frac{1}{2N}\sqrt{\sum_i \sum_j (a_{ij} - b_{ij})^2}$ where N is the matrix column/row size, a_{ij} is the ith element in the jth column of first matrix, and b_{ij} is the ith element of jth column of the second matrix.

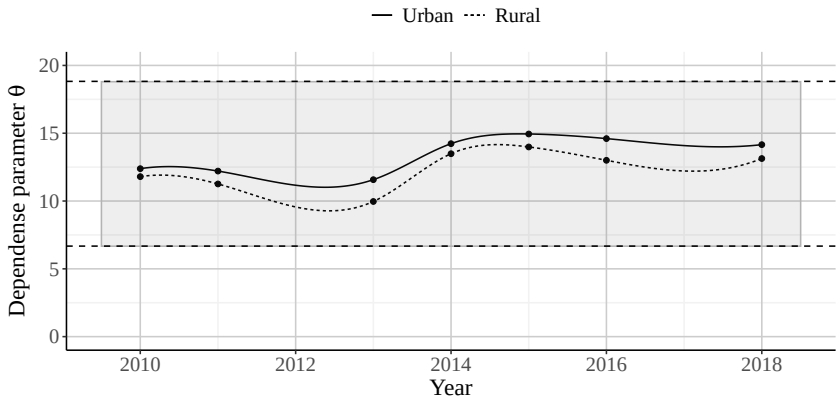
Figure 5: Estimated transition matrices



Note: Transition matrices estimated for urban families with different copulas. As we can see Plackett and Fanrk are the better estimation than other copulas. For rural families check figure 21 in appendix B.

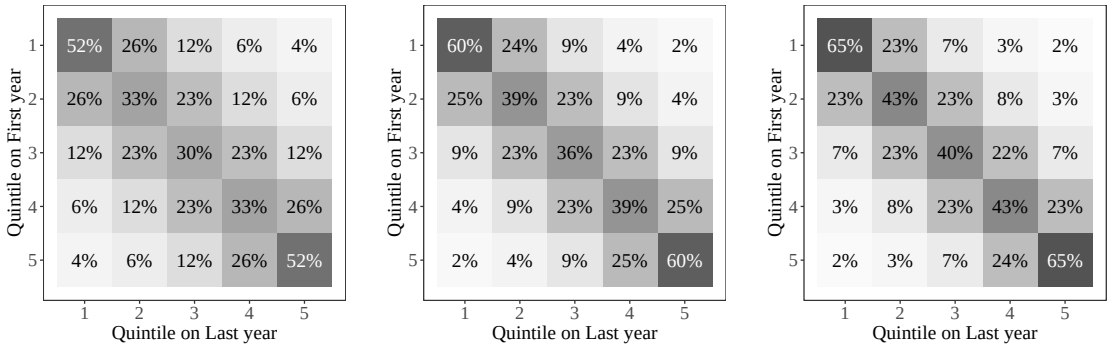
After choosing Plackett as our copula model, we estimate the dependence parameter for available panel data from 2010 to 2019 (Figure 6). We then select the average of these estimated parameters as our fixed dependence parameter and use five times standard deviation above and below the average as our robustness check. Transition matrices corresponding to each lower bound, average, and upper bound dependence parameter are shown in Figure 7.

Figure 6: Dependence Parameter for HEIS Panels



Note: Estimated placket parameter for each year in HEIS panel. Shadowed interval is representing estimation boundaries. Figure 7 shows the corresponding transition matrices for each boundary.

Figure 7: Transition Matrices corresponding to Plackett Boundaries

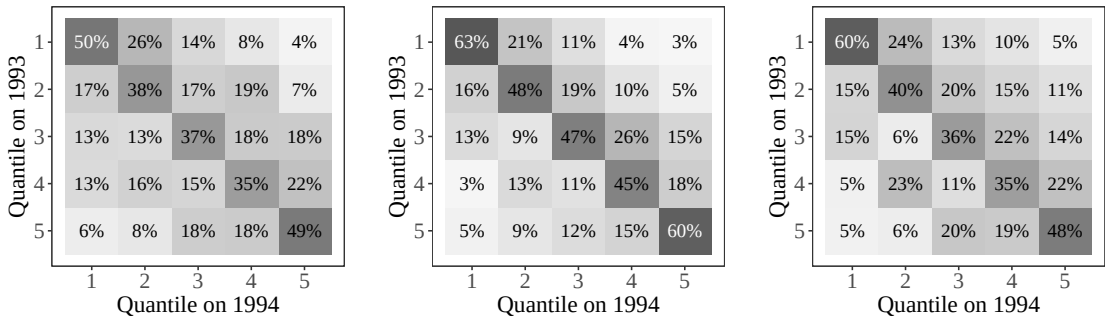


(a) Lower Bound (b) Average (c) Upper Bound

Note: Corresponding matrices of Plackett dependence parameter as plotted in figure 6.

To check whether our estimation is valid in the long run, we use transition matrices calculated by Salehi-Isfahani and Majbouri (2013) (Figure 8) to estimate the Placket dependence parameter for 1993-94. We use the normalized Forbenius distance to find the best dependence parameter that is the parameter that provide a transition matrix with the least Forbenius distance compared to original matrices in Salehi-Isfahani and Majbouri (2013) (Figure 9). We selected 5 standard deviations above and below as our upper and lower bounds to include this best parameter for Salehi-Isfahani and Majbouri (2013)'s work in our interval.

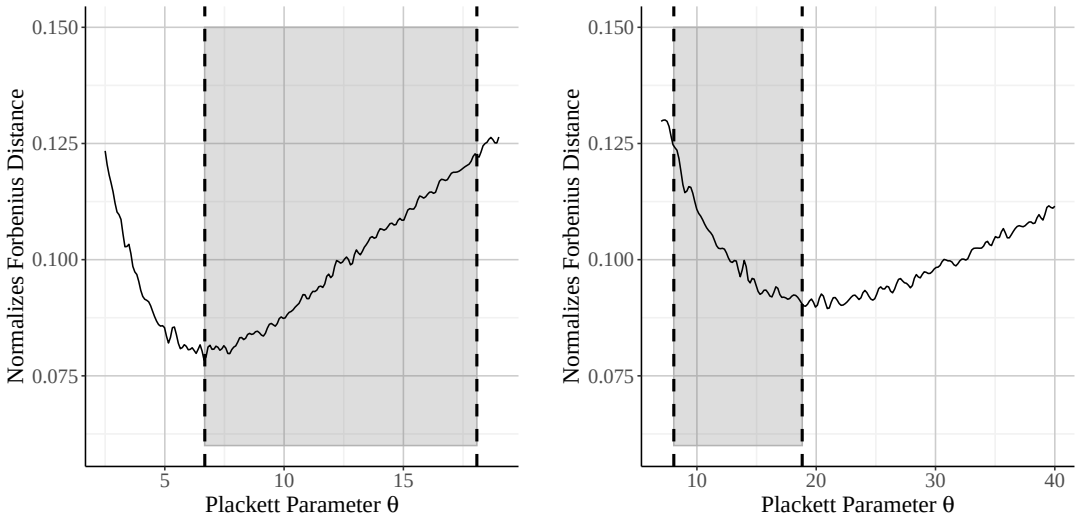
Figure 8: 1993-94 Transition Matrices



(a) Rural (b) Urban (c) Tehran

Note: Calculated by Salehi-Isfahani and Majbouri (2013) ignoring movements more than 20%.

Figure 9: Dependence parameter estimation of 1993-94 transition matrix

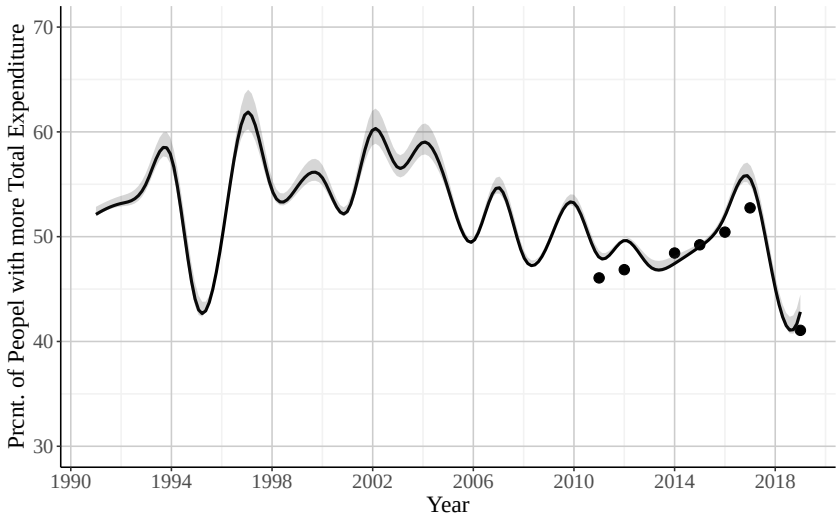


(a) Rural (b) Urban

Note: Normalized Forbenius distance between transition matrices calculated by Salehi-Isfahani and Majbouri (2013) and Plackett copulas with different dependence parameter. Highlighted intervals are corresponding to parameter intervals used to estimate absolute intragenerational mobility. Best parameter's for this matrices are approximately in selected intervals.

Having estimated the dependence parameter, we can simulate pair of uniform random variables witch represent the position of an individual or family in each year and transform them into expenditure per capita values using marginal expenditure distribution calculated from HEIS. We then can estimate the absolute intragenerational mobility as the percent of families or individuals who have expend more in the next year. The results are available in Figure 10. According to this figure, the mobility estimated by copula modeling well approximates the mobility estimated from panel data (red dots). The mobility estimated by Placket parameter which is the best for Salehi-Isfahani and Majbouri (2013)'s matrices will be inside the shadow lines. Absolute intragenerational income mobility in Iran for urban households has been moving between around 43 to 62%. Most of the years before 2007, the breakpoint year of real income per capita level in Iran (Figure 1), the mobility is more than 50% but most of the years after that the mobility is less than 50%.

Figure 10: Estimated Absolute Intragenerational Mobility



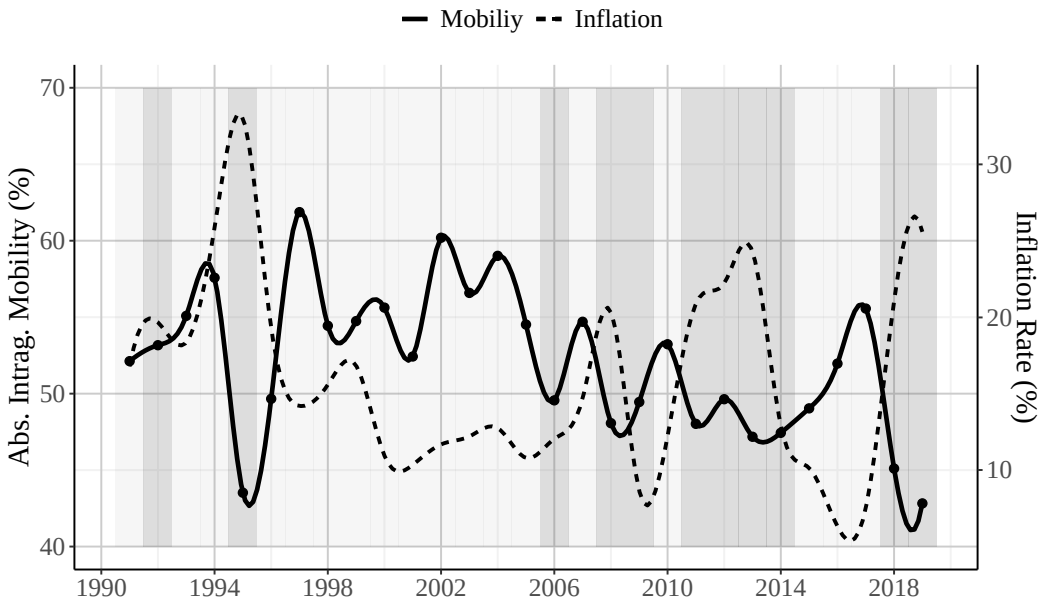
Note: Estimated absolute intragenerational mobility using Plackett copula and cross-sectional income distribution from HEIS for urban families in last three decades. Shadowed interval is representing boundaries of dependence parameter estimated in figure 6, and points are representing the real value of absolute intragenerational mobility as calculated in section 3 using panel data from HEIS. For rural families check figure 22 in appendix B.

5 Mobility decomposition

We defined mobility as the probability of getting more (real) income in the following period; therefore, we can assume that mobility depends on the difference of marginal distribution of income on each year, and these marginal distribution changes can be interpreted as the changes in growth and inequality indexes such as Gini index.

Another essential economic index that has had lots of variation in the last couple of decades in Iran is inflation. Inflation can be interpreted as redistribution of wealth and income so that individuals who have more assets benefit from the rising price levels and others suffer from these phenomena. Therefore, we anticipate having lower mobility rates in years in which we have experienced a high inflation rate. Figure 11 shows the evaluation of mobility and inflation (positive and negative income growth by background color) in the last three decades. There is a positive correlation between mobility and each of income growth and Gini index and a negative correlation with inflation. However, because economic growth, inflation and Gini index are correlated with each other we need to estimate the correlations conditional

Figure 11: Mobility vs. Inflation and Growth



Note: Shadowed intervals are corresponding to negative expenditure per capita growth. As we can see, negative growth is correlated with mobility drops. Calculated for urban families. Too see results for rural families, check figure 23 in appendix B.

on other indices.Then we regress mobility at the same time on the three variables. Columns 1 and 4 shows that higher inflation and Gini index are associated with lower mobility rates. Column 2 shows the positive unconditional correlation between mobility and income growth. However, column 5 shows that only economic growth is positively correlated with mobility conditional on the two other variables.

A benefit of modeling mobility as a copula is that it enables us to run different scenarios and observe how mobility changes in each one. As discussed in the previous paragraph, we assume that the primary variable determining mobility is annual per capita growth. To see the effects of income growth, we run a scenario in which the average expenditure per capita in the two following years is the same, and the only difference is the shape of their distribution. Another important scenario is when we eliminate the effect of changes in distribution; therefore, we run a scenario in which the form of the distribution in two following years is constant, and their average is the same as actual distributions. Figure 12 shows the result for each scenario.

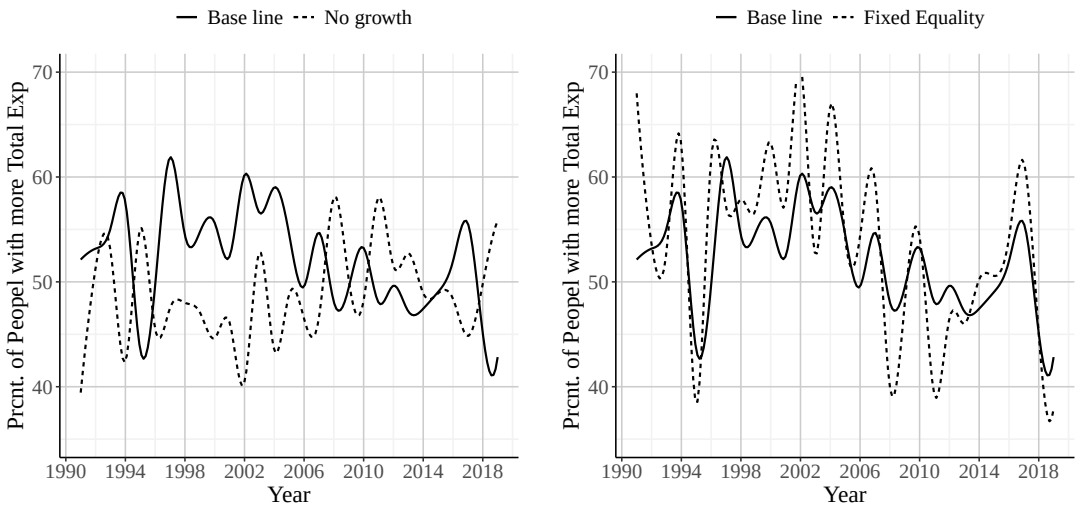
Table 2: Coefficients of different regression models for mobility.

	Dependent variable:				
	mobility				
	(1)	(2)	(3)	(4)	(5)
inflation	−0.363***		−0.089		−0.072
	(0.127)		(0.102)		(0.106)
growth		0.662***	0.614***		0.548***
		(0.104)	(0.111)		(0.129)
rural	1.286	0.889	3.618		3.423
	(3.009)	(0.850)	(2.357)		(2.418)
inflation × rural	−0.096		−0.168		−0.166
	(0.169)		(0.134)		(0.139)
growth × rural		0.024	−0.065		−0.056
		(0.144)	(0.153)		(0.164)
Gini				228.136***	28.273
				(59.974)	(53.112)
Constant	58.005***	51.452***	52.934***	−38.334	41.684*
	(2.197)	(0.599)	(1.792)	(23.863)	(21.212)
Observations	58	58	58	54	54
R^2	0.321	0.621	0.679	0.218	0.618
Adjusted R^2	0.283	0.600	0.649	0.203	0.569

*p<0.1; **p<0.05; ***p<0.01

Note: Each column represents the calculated coefficients of a linear regression model with mobility as its dependent variable. "inflation" is the annual rate of inflation calculated for urban and rural families using consumer price index provided by SCI, "growth" is the annual rate of real expenditure per capita growth calculated for urban and rural families using HEIS, "rural" is a dummy variable which is 1 if a family is rural and 0 otherwise, and finally "Gini" is the Gini index provided by CBI for years before 2017. As shown in the table, there is no significant difference between rural and urban families in each model. The main variable explaining changes in mobility is the annual growth rate, even when we control for other variables.

Figure 12: Simulated Scenarios



(a) No growth

(b) Fixed Equality

Note: Estimated absolute intragenerational mobility for urban families using Plackett copula and simulated cross-sectional income distributions for each scenarios.

6 Conclusion and Discussion

In this paper, we estimated the absolute intragenerational income mobility for Iran over the three decades from 1990 to 2019. We did this in a few steps. First, we estimated the absolute intragenerational income mobility for the years 2010 to 2019 (excluding panels 2012-13 and 2017-18) from the rotating panel data. Next, we showed that Plackett copula well approximates the panel data results for 2010 to 2019. In the third step, we used the Plackett copula and marginal income distributions from 1990 to 2019 to estimate the absolute intragenerational mobility in Iran. Next, as a robustness check we found the Plackett copula parameter that has the least errors in approximating the mobility estimated in Salehi-Isfahani and Majbouri (2013) using the panel data sets from 1992-95 for Iran and showed that our results are not sensitive to replacing this parameter in Plackett copula instead of our original one.

According to our results, absolute intragenerational income mobility in Iran for urban households has been moving between around 43 to 62%. Most of the years before 2007, the breakpoint year of real income per capita level in Iran (Figure 1), the mobility is more than

50% but most of the years after that the mobility is less than 50%.

To the best of our knowledge, there is no evidence on absolute income mobility prior to our work. However, a few papers have studied the *relative* income mobility in Iran. Our results on relative mobility, i.e, the transition matrices, confirm the relative mobility estimated in Salehi-Isfahani and Majbouri (2013). However, we show higher relative mobility in Iran compared to Raghfar and Babapour (2017). They cannot track the households over time and then use a pseudo panel of cohorts and track the average of the cohorts over time. Aggregating on cohort level will dampen the relative mobility systematically because the mobility within a cohort is ignored.

Next, we tried to investigate the correlations of mobility with income growth, inflation and Gini index. Our results showed that there is a positive correlation between mobility and each of income growth and Gini index and a negative correlation with inflation. However, regressing mobility at the same time on the three variables showed that only economic growth is positively correlated with mobility conditional on the two other variables.

Our study has at least two limitations. First, we have the panel data only in years 2010 to 2019 (excluding the 2012-13 and 2017-18 panels) then cannot track the households for the other years. We estimate the Plackett copula parameter from these limited years and also from the Salehi-Isfahani and Majbouri (2013) study for 1992-1995 and assume that it will not change dramatically in the remained years. This assumption cannot hold if the remained years differ systematically and we cannot test for it. In addition, panel data is necessary to study the heterogeneities and the characteristics of the households better or worse off. Second, even in years with panel data, we cannot track the households for more than two (three for a small sample of households) years. Tracking the households for longer periods may help us to estimate the mobility for longer periods instead of two consecutive years like this study.

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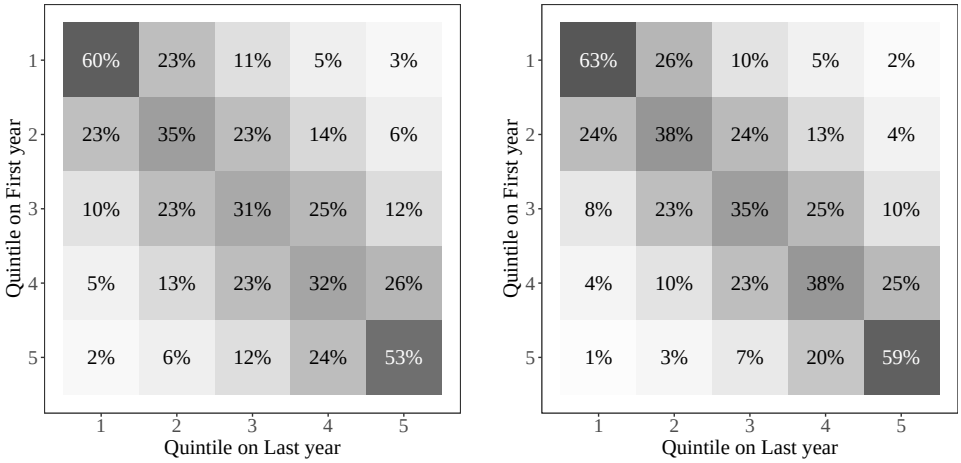
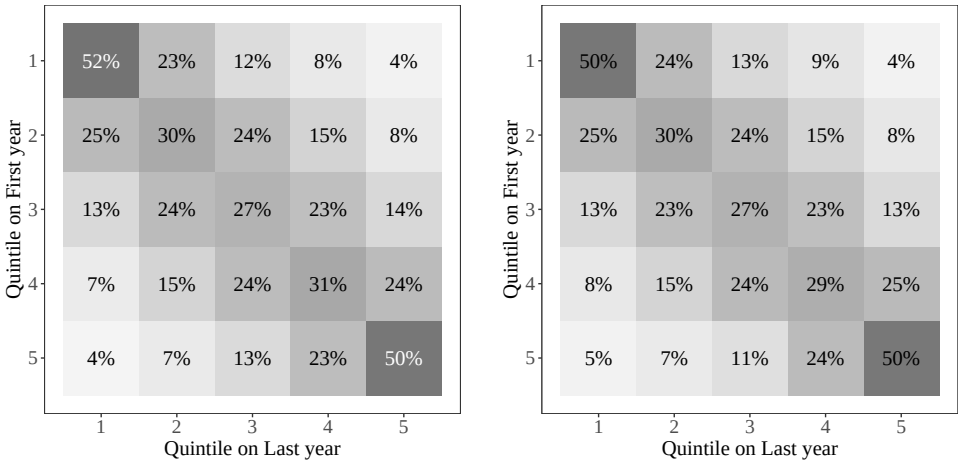
A Transition Matrix

Figure 13: Average Transition Matrix for Total Expenditure Per Capita



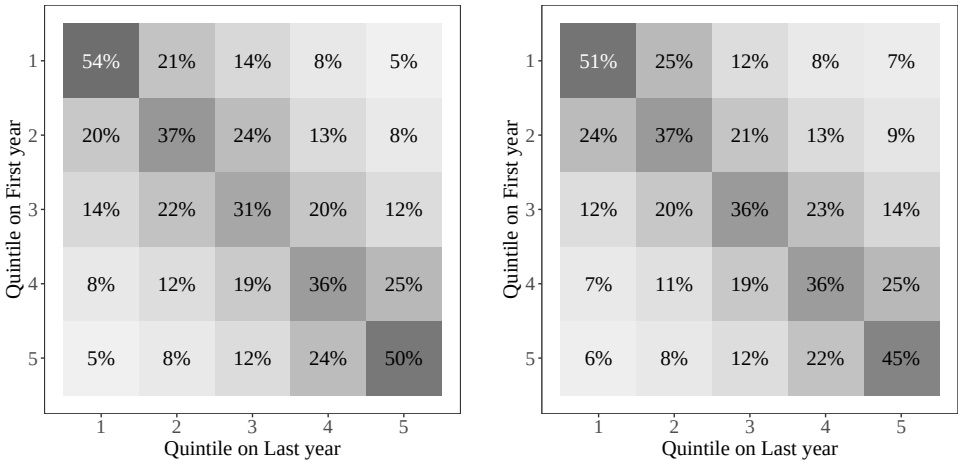
(a) Rural (b) Urban

Figure 14: Average Transition Matrix for Food Expenditure Per Capita



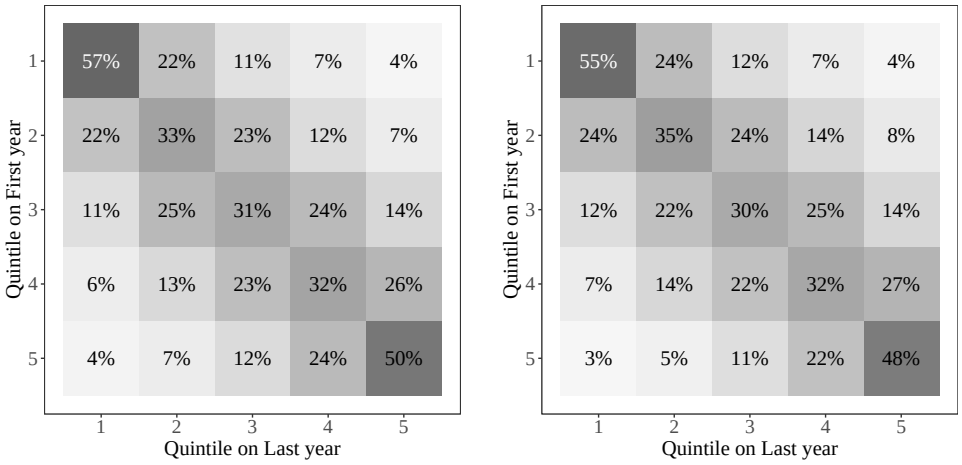
(a) Rural (b) Urban

Figure 15: Average Transition Matrix for Durable Expenditure Per Capita



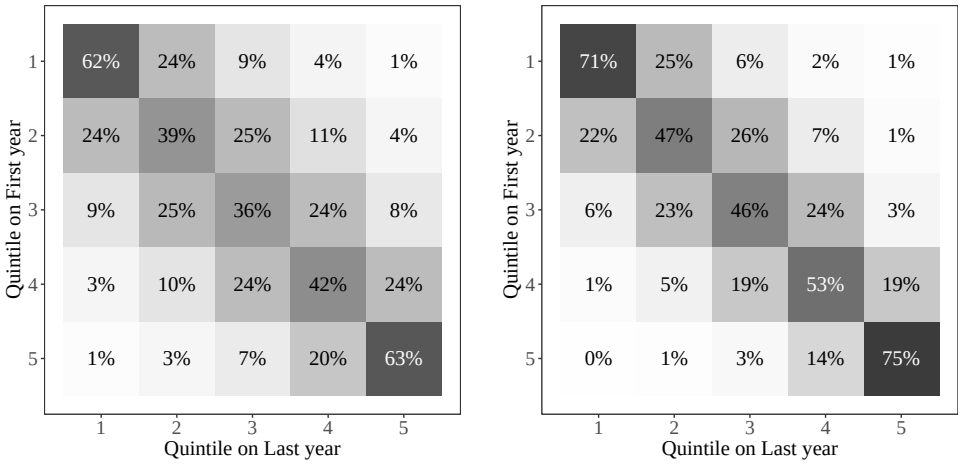
(a) Rural (b) Urban

Figure 16: Average Transition Matrix for Communication Expenditure Per Capita



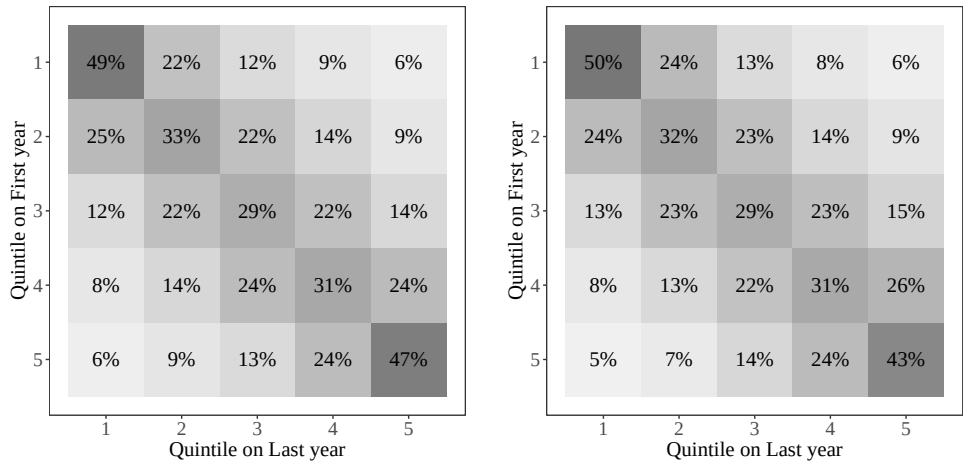
(a) Rural (b) Urban

Figure 17: Average Transition Matrix for Home Expenditure Per Capita



(a) Rural (b) Urban

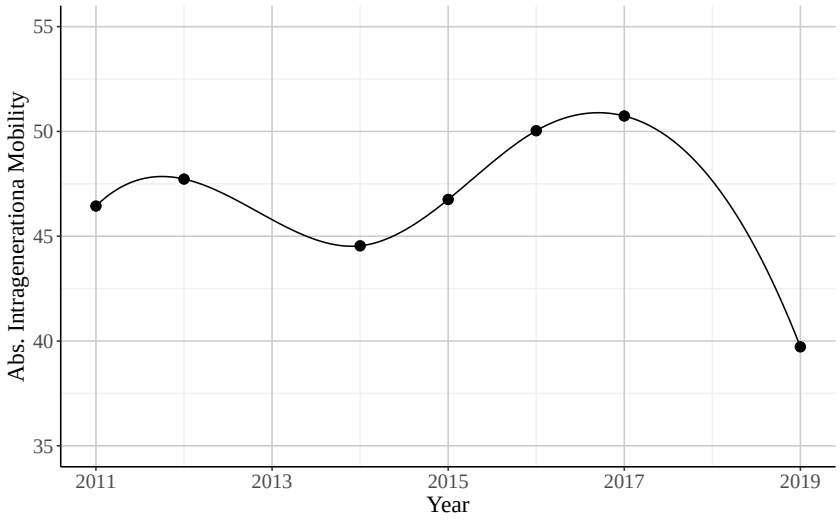
Figure 18: Average Transition Matrix for Transportation Expenditure Per Capita



(a) Rural (b) Urban

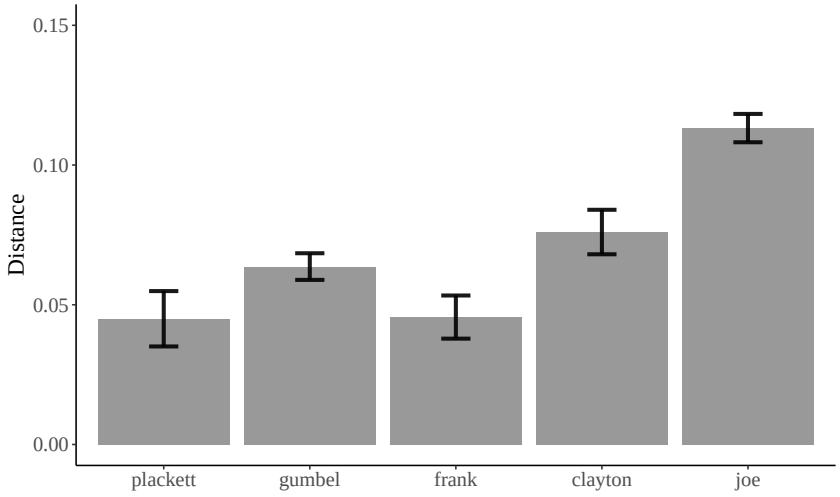
B Result for rural families

Figure 19: Real Absolute intragenerational mobility



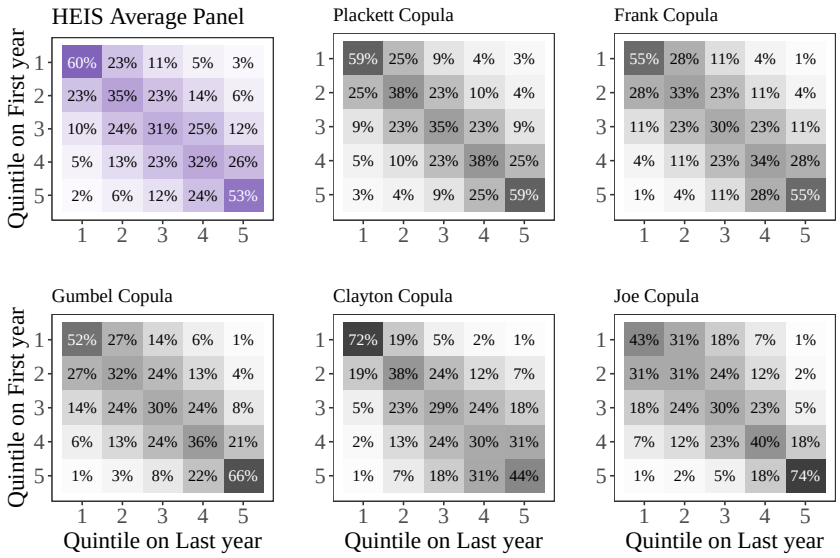
Note: Percent of rural families who had more real income per capita from the previous year. Calculated from panel data of HEIS. For urban families check figure 2.

Figure 20: Normalized Forbenius Distance



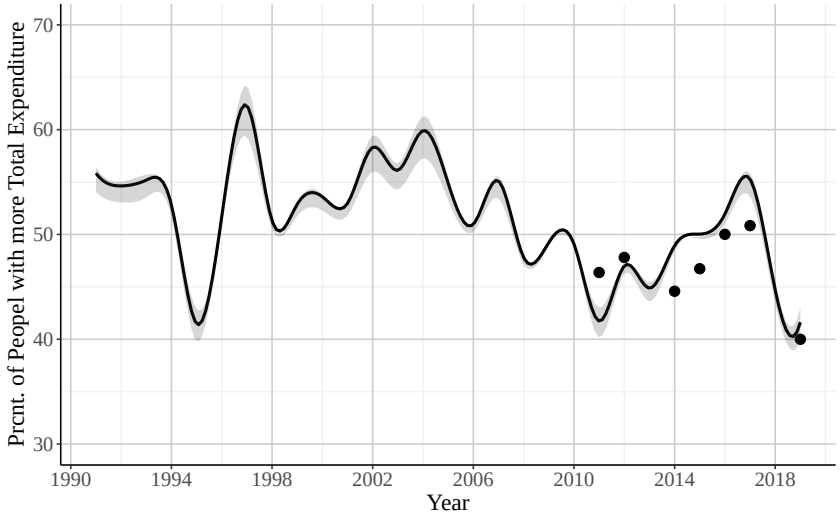
Note: Normalized Forbenius distance between estimated transition matrix for different copulas and real transition matrices calculated from HEIS panel data for urban families. Figure 21 shows the difference between different copula estimations. For urban families check figure 4.

Figure 21: Estimated transition matrices



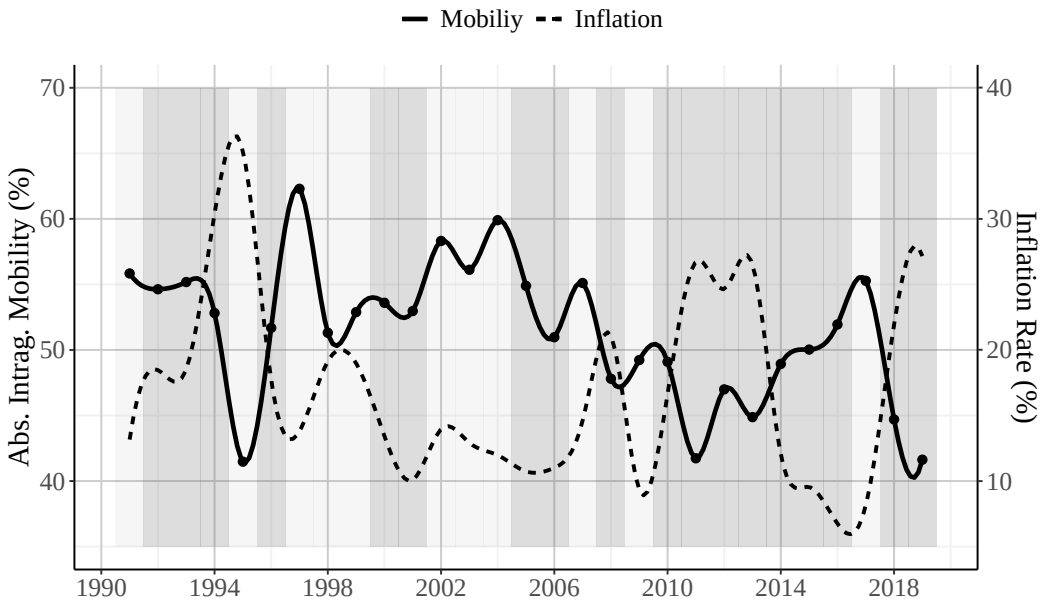
Note: Transition matrices estimated for rural families with different copulas. As we can see Plackett and Fanrk are the better estimation than other copulas. For urban families check figure 5.

Figure 22: Estimated Absolute Intragenerational Mobility



Note: Estimated absolute intragenerational mobility using Plackett copula and cross-sectional income distribution from HEIS for rural families in last three decades. Shadowed interval is representing the boundaries of dependence parameter as estimated in figure 6, and points are representing the real value of absolute intragenerational mobility as calculated in figure 19 using panel data from HEIS. For urban families check figure 10.

Figure 23: Mobility vs. Inflation and Growth



Note: Shadowed intervals are corresponding to negative expenditure per capita growth. As we can see, negative growth is correlated with mobility drops. Calculated for rural families. Too see results for urban families, check figure 11.