Absolute Intragenerational Income Mobility in Iran *

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2023
Quarterly Review of Economics and Finance
Accepted Version

Abstract

Absolute intragenerational income mobility (AIIM), defined as the percentage of households with higher income compared to their previous year, is a complementary index to aggregate measures such as income per capita and the Gini index to show a more detailed picture of an economy. Panel data on household income is necessary to estimate AIIM, but it is not usually available in developing countries and, in the long run, for most developed countries. In this paper, we use copula modeling and cross-sectional income data in a developing country, Iran, and well approximate the mobility estimated by panel data for the years 2011 to 2019 and then use the copula method to extend our estimation backward until 1991. According to our results, absolute intragenerational income mobility in Iran for urban households has been moving between 40% to 62%. AIIM is higher for low-income households.

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

*We are grateful for the insightful comments by Amir Kermani, Hamed Ghoddusi, Gholamreza K. Haddad, Hosein Joshaghani, QREF editor, and three anonymous reviewers. We also thank the seminar participants at the Fourth Iran Economic Forum, Tehran Institute for Advanced Studies (TeIAS), and Sharif University of Technology for their helpful suggestions. The major part of this research was completed while Naser Amanzadeh was affiliated with the Tehran Institute for Advanced Studies (TeIAS), Khatam University. All remaining errors are ours.

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1 Introduction

Aggregate measures such as the income per capita and the Gini index have limitations in showing a comprehensive picture of an economy. They cannot describe *how many individuals and households are better or worse off* following economic booms and busts, recessions, and recoveries (Berman 2022a). For an assumed income growth and distribution, we can consider cases where the significant parts of people are beneficiaries, cases where most of them are losers, and lots of intermediate cases. See Table 1 for a toy conceptual example. In this table, you can see four different scenarios for a one percent income growth rate and exactly the same income distribution between two consecutive years. However, percent of people better (or worse) off is completely different among the cases, from 25 to 100 percent. This difference in the percent of people better (worse) off can lead to crucially different perceived fairness and political acceptability of different scenarios even with exactly the same income growth and inequality (Kraay and Van der Weide (2022)). Absolute intragenerational income mobility (AIIM), defined as the fraction of households with higher real income per capita compared to the previous year, can help us solve this problem and better interpret the aggregate income growth and inequality changes.

Kraay and Van der Weide (2022) highlights the importance of intragenerational income mobility measure for the World Bank Group's goal of "shared prosperity," which includes growth in the bottom 40 percent of a country's income distribution. To effectively evaluate interventions aimed at helping the initially poor members of the bottom 40 percent, it is crucial to determine if membership in this group is stable or if those initially poor beneficiaries of these interventions move up and out of the bottom 40 percent and are replaced by those who were initially richer but have become relatively poorer. Another real-world example is Argentina and Mexico's case in the 1990s. Despite the increasing trends of inequality in these countries in the 1990s and then the initial guess that the higher income individuals may gain more in this period than the lower incomes, Fields et al. (2007) show that those individuals who started at the lower end of the income distribution, gained at least as much as those who started higher in income distribution. They assert that income inequality measures such as the Gini index cannot necessarily show the dynamics of movements of specific households along the income ladder as well.

Mobility can be relative or absolute and inter or intra-generational. In relative measures, the income ranks are compared instead of the absolute income. Also, inter-generational mobility compares the children with their parents at the same age instead of the same individuals during the time in the intra-generational case. Relative mobilities have been studied for a long time in 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 income such as occupational status (Arrow et al. 2018) and educational attainment (Duncan and Murnane 2011). Chetty et al. (2017) for the first time estimated the *absolute* intergenerational income mobility trend for the United States.

Despite the importance of these mobility measures, the scarcity of data is severely constraining their estimation. Basically, tracking the households or individuals' income over time is necessary to estimate the absolute intragenerational income mobility. Panel data surveys such as PSID[1] or administrative data sets such as 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. However, unfortunately, similar datasets are not available for developing or most developed countries for an extended 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 2012-2013 and 2017-2018 panels.

A few recent studies show that it is possible to well estimate mobility using cross-sectional data, too. Initially to estimate the *intergenerational* income mobility, Berman (2022b) 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 of the same age, and well

[1] Panel Study of Income Dynamics

[2] Household Income and Expenditure Survey (HIES) provided by the Statistical Center of Iran

approximate the detailed panel data results of Chetty et al. (2017). Next, in Berman (2022a), he uses the copula modeling and cross-sectional income data for the same generations to estimate the absolute intragenerational mobility in the United States from 1962 to 2014. He shows that the copula modeling results well approximate the mobility estimated from the PSID panel data set.

In this paper, following the method used in Berman (2022a), we estimate the absolute intragenerational income mobility in Iran as a middle-income developing country over three decades from 1991 to 2019 for the first time. We do this in a few steps. First, we estimate the absolute intragenerational mobility for the years 2011 to 2019 (excluding panels 2012-13 and 2017-18) from the HIES rotating panel data. Next, we use the copula method to approximate the mobility for the same years as the first step. Here, we estimate the copula parameters for five different functional forms, using the rotating panel data from 2010 to 2019, and show that among them, the Plackett copula has the minimum error rate (less than 5%) in approximating the panel data results. Then, we select it as our main copula model for the rest of our study. In the third step, we use the Plackett copula and marginal (cross-sectional) income distributions from 1990 to 2010 to extend our mobility estimations backward to 1991.

Our central assumption for extending the mobility backward to 1991, the third step above, is that the structure of movements in the income ladder (transition matrix) is constant over time. Potentially, this assumption can be a strong one, especially for a developing country like Iran with severe economic fluctuations in recent decades (see Figure 1). To address this concern, as explained in the second step above, we check that our copula model well approximates the actual panel results for 2011 to 2019 while Iran had severe recessions and recoveries in that period (Figure 1). However, someone may still have concerns about extending this model back to 1991. To address this concern, we show that our copula model again well approximates the mobility estimated in Salehi-Isfahani and Majbouri (2013), which is estimated from actual panels of 1992-1995. More specifically, here we find the Plackett copula parameter that has the least errors in approximating the mobility estimated in Salehi-Isfahani and Majbouri (2013) for Iran and show that our results are not sensitive to replacing this parameter in Plackett copula instead of our original one.

According to our results, year-by-year AIIM in Iran from 1991 to 2019 is within 40.6% - 62% and 39% - 60.9% for urban and rural households, respectively. Except in 1995, the AIIM of urban households is more than 50% from 1991 to 2005 which means the fraction of people better off is larger than those who are worse off but this pattern changes from 2006, and except in 2007, 2010, and 2017 the AIIM is below 50%. There is a similar pattern but with lower mobilities for rural households, too. In addition, mobility is decreasing with income rank and lower-income households are more likely to move upward and experience higher incomes.

In this paper, we contribute to the literature at least in two ways. First, as we discussed above, despite the importance of intragenerational mobility measures, the panel data scarcity for the majority of countries and years restricts researchers to estimate and use it for most of the countries and years. Berman (2022a) uses the copula method and cross-sectional income distributions for the United States[1] to estimate the intragenerational mobility without panel data. But, this method is more necessary for developing countries since they likely don't have panel income datasets. We use a similar method but for a developing country, Iran, and show that it works in this case, too. This can help future research to investigate the accuracy of this method for other developing countries. Second, we are estimating the intragenerational income mobility in Iran for the first time in three decades. Previously, Salehi-Isfahani and Majbouri (2013) studied the relative income mobility in Iran but only for the years 1992-1995. We are estimating the income mobility in Iran from 1991 to 2019.

The rest of the paper is organized as follows. In the next section, we describe the household income and expenditure survey data and its rotating panel structure as well as the rural and urban CPI data used to adjust for inflation. In section 3, we provide results of year-by-year AIIM using actual panel data set from 2011 to 2019. In section 4, we introduce the copula method, select the best copula functional form, and estimate the year-by-year AIIM from 1991 to 2019 using the copula method. In the final section, we discuss and conclude.

[1] Similarly, Berman (2022b) estimate the intergenerational mobility for the 10 developed countries.

2 Data

The Statistical Center of Iran[1] (SCI) provides an annual survey on the income and expenditure of Iranian urban and rural households known as the household income and expenditure survey (HIES). HIES has been conducted from 1963 and 1968 for rural and urban households, respectively. From 1974, in addition to the expenditure, they collected information on individuals' income data, too. However, the unit record raw data is publicly available since 1984. The main purpose of SCI for this survey is to estimate the income and expenditure of rural and urban households at provincial and national levels. HIES contains detailed information on household expenditure categorized into 12 main groups: food and beverages, housing, clothing, health, transportation, communication, furniture, amusement, education, hotel and restaurant, durable goods, and others[2]. It also contains individual-level income data categorized into wage (public and private), self-employed business (agricultural and non-agricultural), and others (rent, retirement, cash transfers, etc.). Households have some implicit income sources that should be extracted from expenditure tables such as imputed rent and non-monetary compensations for their jobs.

To calculate the annual expenditure of a household, we sum up all the expenditures except for education and durables and multiply it by 12 and then add the education and durables to it. This is because households are asked about their expenditures during the last month for all expenditure categories except for education and durables that are originally asked for the last year. We sum up all income sources of the household to provide the annual income of the household since the questionnaire asks for the income during the last year. We divide total expenditure and income to the adult equivalent household size (OECD-modified scale) to provide the per capita variables[3]. We use "expenditure" per capita instead of income per capita to avoid the potential under-reporting of income by households[4].

[1] https://www.amar.org.ir

[2] HIES also provides a table of information on household investments but, it is not part of household's total expenditure.

[3] This scale, first proposed by Hagenaars et al. (1994), assigns a value of 1 to the household head, of 0.5 to each additional adult member and of 0.3 to each child.

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

Since 2010, SCI has added a rotating panel feature to HIES so that some households are re-sampled for up to three consecutive years. The first round of rotating panel sampling was designed for the years 2010-12, then for 2013-17, and the last round has started in 2018. Then it has no rotating panel structure in the years 2012-13 and 2017-18. Each round of rotating panel samples is based on the information provided in the previous Population and Housing Census of Iran[1].

The Statistical Center of Iran initially tracks the postal addresses (houses) not the households. This can be problematic if the household is replaced with another one between two years of sampling. SCI assigns the same address id to the new household even if it is replaced with the previous one. However, there is a flag in the HIES data which determines the replacement of households living in the address by the term "moved" and "not-moved" for each address. But, unfortunately, we observe that this variable is not completely reliable since there are households labeled as "moved" but have exactly the same characteristics (number of family members, their age, and gender) as previous year and more importantly, households who have been marked as "not-moved" but with totally different characteristics. In addition, obviously, the structure of families can be changed due to events such as birth, death, marriage, or divorce, which may be interpreted as expenditure per capita movements (up or down) but here, we are not interested in these kinds of mobilities and try to focus on the dynamics of income and expenditure in each family and not the movements because of changes in family structures.

To solve these problems and make sure that we track the exact same households as a panel, we only treat households with exactly the same characteristics in two consecutive years. Therefore, we extract the number of family members in the first year who don't match anyone in the second year, and similarly, the number of family members in the second year who don't match anyone in the first year. Then we remove all households that these two numbers are not zero for them. In doing so, besides getting rid of families with completely different characteristics each year, we remove households whose structure had changed due

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

to the reasons such as birth, death, marriage, or divorce. Another concern here is that the time interval between revisiting the panel households is not exactly 12 months. Between 1.7% to 3.5% of the families in different panel years are revisited in less than 10 or more than 14 months. We also remove these households from the panel analyses. More details on the HIES data cleaning process are provided in Appendix A.

To adjust for inflation, we use the monthly Consumer Price Index (CPI) provided by SCI for urban and rural households separately with the base year 2016. We also use the Gini index data provided by the Central Bank of Iran[1] (CBI) for urban households[2]. Figure 1 shows the median real expenditure per capita for urban and rural households from 1990 to 2019 in Iran in panel A and the urban Gini index in panel B. As expected, urban households always expend more than rural ones but the gap between them is going to be larger during the last three decades[3] The expenditure per capita trend changes from 2006-7 for both urban and rural households from a positive to a negative growth rate which lasts until recent years. The Gini index is always around 0.4 in Iran with a slight improvement during 2009-2011 maybe due to the large-scale unconditional cash transfers policy during those years.

3 Panel data estimates of mobility, 2011 - 2019

In this section, we estimate the absolute intragenerational income mobility from 2011 to 2019 in Iran using panel data. Here we track the same households for two consecutive years[4] and then compare a household's real expenditure per capita during these two years to see whether it is better or worse off. The percent of households with higher real income per capita in the second year equals the absolute intragenerational income mobility by definition. Figure 2 shows the year-by-year mobility for rural and urban households from 2011 to 2019. For example, the year 2011 in this figure shows what percentage of households have higher real

[1] https://www.cbi.ir

[2] CBI provides the Gini index for urban households only.

[3] See Figure B1 that is similar to Figure 1 panel A but shows the growth of real expenditure per capita relative to 1990.

[4] all two consecutive years from 2010 to 2019 except 2012-13 and 2017-18 since we don't have rotating panel data for these years

income per capita in 2011 compared to 2010. Excluding 2017 for urban households, the percentage of households better off is always less than 50% which means that looking at every two consecutive years from 2011 to 2019, *more* than half of the households are worse off.

To compare our results with previous studies on relative mobility and also for a methodological need that we explain in the next section, we provide the relative intragenerational income mobilities that are 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, 68.2% of urban households which were in quintile 1 (poorest quintile) in the year 2016, remains there in 2017, too. They move to quintiles 2-5 with the probabilities of 19.7, 8.2, 3.2, and 0.6 percent, respectively[1].

4 Mobility using copula method, 1990 - 2010

As explained in section 3, to estimate AIIM, we need to track and compare the same households for at least two consecutive years, or in another word, we need panel data. However, expenditure and income panel data is not available in many developing countries and in long run for most developed countries. For example, the rotating panel feature of Iran HIES is only available since 2010. Nevertheless, Berman (2022a) shows that as long as the dynamics of movements in the income ladder are constant (constant transition matrix), we can use cross-sectional data and copula modeling to estimate absolute intragenerational mobility with good precision without the need for panel data sets.

Copula was first introduced by Sklar (1959) to estimate the joint distribution of random variables using their marginal distributions (Trivedi and Zimmer (2007)). A Copula estimates the cumulative joint distribution of two or more variables using the marginal cumulative distributions and some dependence parameters. According to Trivedi and Zimmer (2007), for an m-variate function F, the copula associated with F is a distribution function $C : [0, 1]^m \rightarrow$

[1]See Figure B2 for the median expenditure per capita in 2016 by percentile as well as the borders of the quintiles. Note that the differences between income levels of different quintiles, especially for neighborhood quintiles and particularly for middle incomes, are not that high, and sometimes a small change in a household's income (expenditure) may lead to a transition to the upper (lower) quintiles.

$[0,1]$ that satisfies:

$$F(y_1, \ldots, y_m) = C(F_1(y_1), \ldots, F_m(y_m); \theta) \tag{1}$$

where θ is the *dependence parameter*, which measures the dependence between the marginal distributions. In other words, the joint distribution of m random variables is expressed in terms of its respective marginal distributions and a function C (or Copula) that binds them together. We can represent each copula with its transition matrix and then estimate the dependence intervals with copulas (Trivedi and Zimmer (2007))[1].

Because copulas separate marginal distributions from dependence structures, the appropriate copula for a particular application is one that best captures the dependence features of the data. A variety of functional forms are proposed in the literature, and each of these imposes a different dependence structure on the data (Trivedi and Zimmer 2007). Table 2 summarizes some of the most common bivariate copulas. In addition to these copulas, we use the Plackett copula as well. According to Berman (2022a), Plackett copula, $C_\theta(u_1, u_2)$, is defined as:

$$C(u_1, u_2) = \frac{1}{2}\theta^{-1}\left(1 + \theta(u_1 + u_2) - \left[(1 + \theta(u_1 + u_2))^2 - 4\theta(\theta + 1)u_1 u_2\right]^{\frac{1}{2}}\right) \tag{2}$$

where θ is the dependence parameter and u_1 and u_2 are two marginal distributions. Berman (2022a) 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 show similar results for France.

To find the best copula for modeling the transition matrix in Iran, we use different copula models from Table 2 and also Plackett copula and calculate the average transition matrix for each of them. Figure 4 shows the transition matrices estimated by each of the copulas as well as the average matrix that is calculated from the panel data (original matrix) for comparison. The Plackett matrix is the nearest one to the original one. However, to compare

[1] For more information on copula modeling see Trivedi and Zimmer (2007)

them more clearly, we use Normalized Forbenius Distance (NFD)[1] between estimated and original transition matrices as a measure of fitness and show that, as Berman (2022a) and Bonhomme and Robin (2009) conclude, the Plackett copula is the best fit for our transition matrices, too (Figure 5).

After choosing the Plackett as our preferred copula model, we estimate the dependence parameter for each round of panel data available from 2010 to 2019 separately for rural and urban households (Figure 6). We use the average of these estimated parameters as a fixed dependence parameter to estimate absolute intragenerational income mobility during 1991 - 2019. To do so, using a Plackett copula and the average dependence parameter, we simulate pairs of uniform random variables which represent the positions of a household in two consecutive years. Then, transform these ranks into expenditure per capita values using marginal expenditure distributions or cross-sectional HIES data. We then estimate the AIIM as the percentage of households that have higher expenditure per capita in the second year. We do this for three decades from 1990 to 2019 when consistent cross-sectional HIES data is available.

Figure 7 shows the absolute intragenerational income mobility in Iran for urban households over three decades from 1991 to 2019[2]. According to this figure, the mobility estimated by copula well approximates the mobility estimated from the panel data from 2011 to 2019 that panel data is available. The copula is not necessary when we have panel data but we use copula for these years to show our copula model results are similar to panel data results and then we extend it back to 1991. AIIM in Iran for urban households has been moving between around 40.6 to 62%. For most of the years before 2007, the breakpoint year of real expenditure per capita level in Iran (Figure 1), the mobility is more than 50% but for most of the next years, it is less than 50%.

Next, we try to analyze the sensitivity of our results to variations in the model and parameters that we use. First, we analyze the sensitivity of the Plackett copula to the variations

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

[2] Find the similar figure for the rural households in Figure B5 and also a complete set of results in Table B1

of the dependence parameter (θ). In this regard, we calculate the standard deviation of dependence parameters estimated by every two consecutive years of panel data that are shown as solid circles in Figure 6 and show the intervals of the average plus/minus five[1] standard deviations as a shadow area in Figure 6. Figure 8 shows the transition matrices corresponding to the minimum of shadow area (average minus five standard deviations or lower bound), average, and maximum of shadow area (average plus five standard deviations or upper bound) dependence parameters. The transition matrices generated from the Plackett copula will be symmetric and as you increase the parameter θ, the distribution will be more intense on the main diagonal. We use these boundaries (upper and lower bound) instead of our main Placket parameter and re-estimate the mobility. The shadow around the absolute intragenerational mobility line in Figure 7 corresponds to this. Clearly, the pattern of the main result is not changing and the shadowed area is small enough.

Second, by using a fixed dependence copula parameter to extend the analyses backward to 1991, we assume that the structure of movements in the income ladder (transition matrix) in these years is similar to the recent decade (2010 to 2019). This assumption can potentially be violated, especially in a developing country like Iran with severe economic fluctuations in recent decades (see Figure 1). To address this concern, we use transition matrices calculated by Salehi-Isfahani and Majbouri (2013) in Figure 9 to estimate the Plackett dependence parameter for 1993-94. Salehi-Isfahani and Majbouri (2013) use panel data to generate these transition matrices. Then, if our copula model which is estimated from 2010 to 2019 data, well approximates the transition matrices of 1993-94, we can conclude that our assumption is not too strong. To investigate this, we use the Normalized Forbenius Distance to find the best dependence parameter that provides a transition matrix with the minimum Forbenius distance compared to original matrices in Salehi-Isfahani and Majbouri (2013). The best dependence parameters are the minimums of curves in Figure 10. Shadowed areas in this figure are the same as shadow areas of Figure 6. Now it is clear why we selected *five* standard deviations to define the upper and lower bounds in Figure 6. Five standard deviations generate the

[1] In the next paragraph, we will explain why we use *five* standard deviations and not a smaller or larger one.

smallest interval around the average dependence parameter which includes this best parameter for approximating the transition matrices in Salehi-Isfahani and Majbouri (2013). Then the shadows around the main results in Figure 7, also include the result of Salehi-Isfahani and Majbouri (2013), too.

Finally, we try to investigate the heterogeneities of mobility for different levels of income. We define low-income, middle-income, and high-income households of a year as deciles 1-3, 4-7, and 8-10, respectively. Then, estimate the AIIM for each of them separately. Figure 11 shows the AIIM for each of the three income levels and for the average of all years in panel data as well as separately for panels of 2010-2011 and 2018-2019. We can see two patterns in this figure. First, a decline in average mobility from low to high-income families which may be due to the regression toward the mean[1]. Second, a difference between the mobilities of low-incomes (and partially middle-incomes) in panels 2010-2011 and 2018-19. The sanctions against Iran are at the highest intensity in both 2011 and 2018 (Laudati and Pesaran 2021). 2011 is the first year of oil and financial system sanctions and 2018 is the year of President Trump's unilateral withdrawal from the JCPOA agreement (Laudati and Pesaran 2021). However, there is at least an important difference between these two years which is the large-scale unconditional cash transfers program in Iran in 2011. In this program, the government made monthly payments for which all citizens were eligible as compensation for the removal of energy subsidies[2]. Although the absolute amount of cash was constant among all individuals but the relative amount was higher for poor incomes[3]. Although the high intensity of sanctions in both 2011 and 2018, the cash transfer program in 2011 maybe help the low-income (and partially middle-income) households not suffer as large as they suffered in 2018[4].

[1]When a sample of a random variable is extreme the next sample of the same random variable is likely to be closer to its mean

[2]Mostafavi-Dehzooei et al. (2020) show a positive effect of this program on the nutrition of poor households in Iran

[3]The ratio of the transfers to expenditures (in the year prior to transfers) ranges from 63 percent for the lowest decile to 4 percent for the highest decile (Mostafavi-Dehzooei et al. 2020)

[4]Note that this is just our initial guess and we think that this may be an interesting research question for the future.

5 Discussion and conclusion

In this paper, we estimated the absolute intragenerational income mobility in a developing country, Iran, over the three decades from 1991 to 2019. We did this in four steps. First, we estimated the absolute intragenerational income mobility (AIIM) for the years 2011 to 2019 (excluding panels 2012-13 and 2017-18) using panel data. Next, we showed that the Plackett copula well approximates the panel data results, estimated in the first step, for 2011 to 2019. In the third step, we used the Plackett copula and marginal income distributions from 1990 to 2010 to extend the AIIM estimates backward until 1991. Next, as a robustness check, we found the Plackett copula parameter that has the minimum 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. Finally, we showed that the intragenerational income is decreasing in the income level of the households.

According to our results, AIIM in Iran for urban households has been moving between 40 to 62%. Overall, the pattern of mobility across the years makes sense and is consistent with what we expected. In most of the years before 2006-7, the breakpoint year of real income per capita in Iran (Figure 1), the mobility is higher than 50% but for most of the next years, it is less than 50%. Mobility higher than 50% means that the share of people earning higher than their previous year (better off) is larger than those who earn lower (worse off). We see a dramatic mobility drop in 1995, a year with high inflation of around 50% and negative growth. After 1995, mobility remains higher than 50% until 2005. During this period, Iran experiences stable positive growth and a relatively low inflation rate. Since 2006, negative income growth is a prevailing pattern in Iran's economy.

Since 2006, Iran experiences a high-intense level of sanctions with a maximum level in 2011, a period of relatively low-intense sanctions from 2014 to 2017, and again a sharp increase in sanction intensity in 2018 (Laudati and Pesaran 2021)[1]. Sanctions have significant effects

[1]Sanction intensity level increases dramatically in 2006 with US Nuclear-related bans and assets freeze. They are at the highest level of intensity in 2011 by oil and financial system sanctions. The years 2014 to 2017 are relatively low-intense sanction years after the partial lifting of U.N. sanctions under the Joint

on inflation and economic growth (Laudati and Pesaran (2021)) and the mobility trend is consistent with the patterns of economic growth and inflation.

To the best of our knowledge, there is no evidence of absolute income mobility in Iran before this paper. Two 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). Maybe because of the fact that 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 at the cohort level will dampen the relative mobility systematically because the mobility within a cohort is ignored[1].

Our study has at least two limitations. First, we have the panel data only for the years 2010 to 2019 (excluding the 2012-13 and 2017-18 panels) and then cannot track the households for the previous 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 to estimate the mobility for longer periods instead of two consecutive years and may be economically more informative.

Comprehensive Plan of Action (JCPOA) and again another high-intense sanction level started in 2018 after President Trump's unilateral withdrawal from the JCPOA agreement (Laudati and Pesaran 2021).

[1]A comparison with the AIIM estimated with other countries especially developing countries similar to Iran will be informative as well. However, the absolute intergenerational mobility measure is relatively new in the literature and to the best of our knowledge there is no such evidence from other countries, yet.

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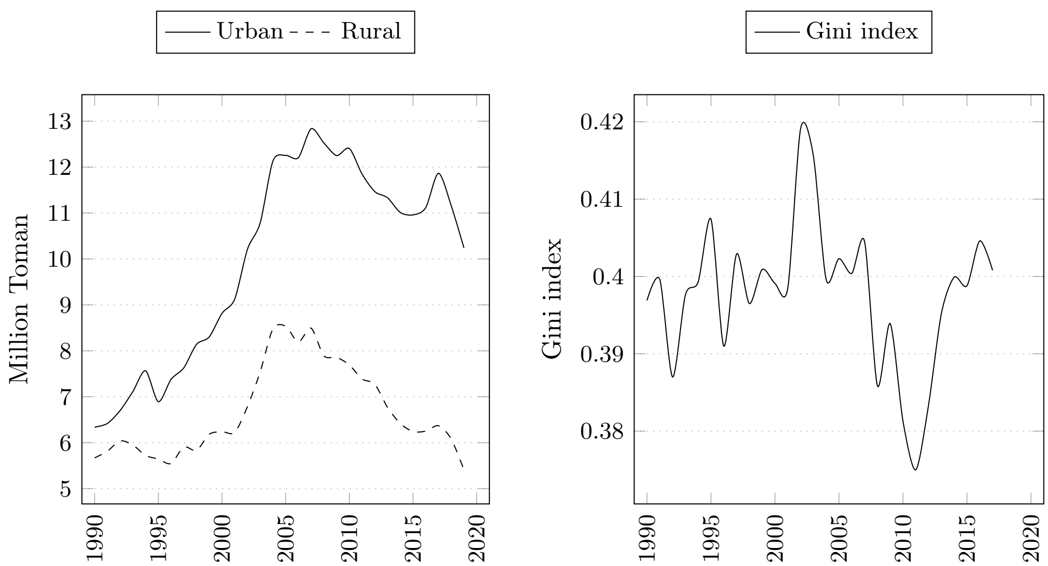
Figure 1: Expenditure per capita and Gini index from 1990 to 2019 in Iran

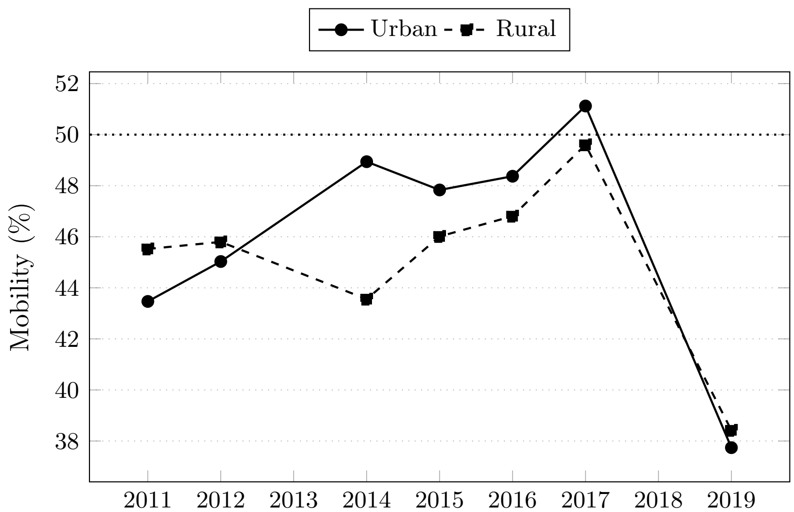


(a) Median real expenditure per capita in 2016 prices

(b) Gini index of urban households

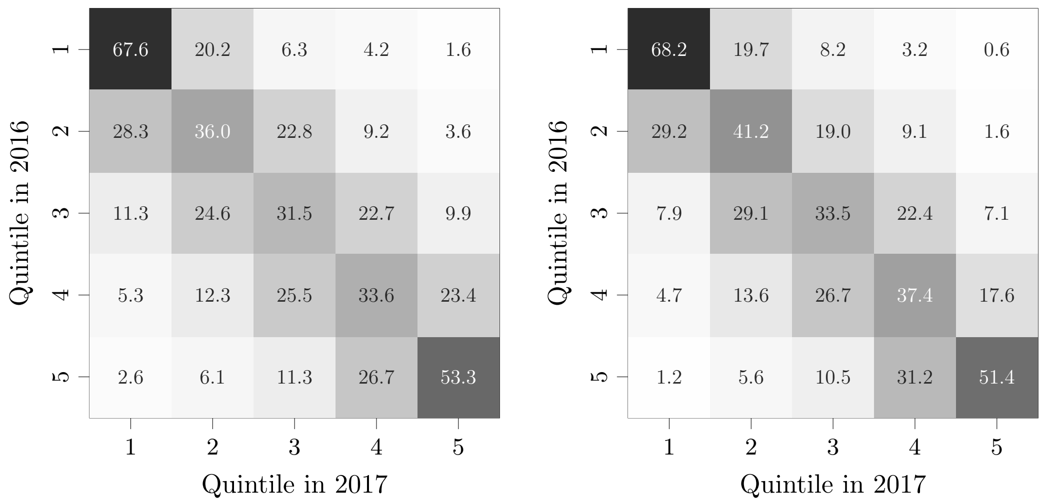
Note: Figure shows real expenditure per capita and Gini index in panels (a) and (b), respectively. The expenditure per capita is calculated by the authors using the HIES. The Gini index is provided by the Central Bank of Iran for urban households.

Figure 2: Absolute intragenerational mobility from 2011 to 2021 using panel data



Note: Percent of rural and urban households with higher real expenditure per capita compared to the previous year. Calculated from panel data of HIES. Each point in the figure shows the year-by-year mobility for two consecutive years

Figure 3: Transition matrix for HIES panel 2016-17

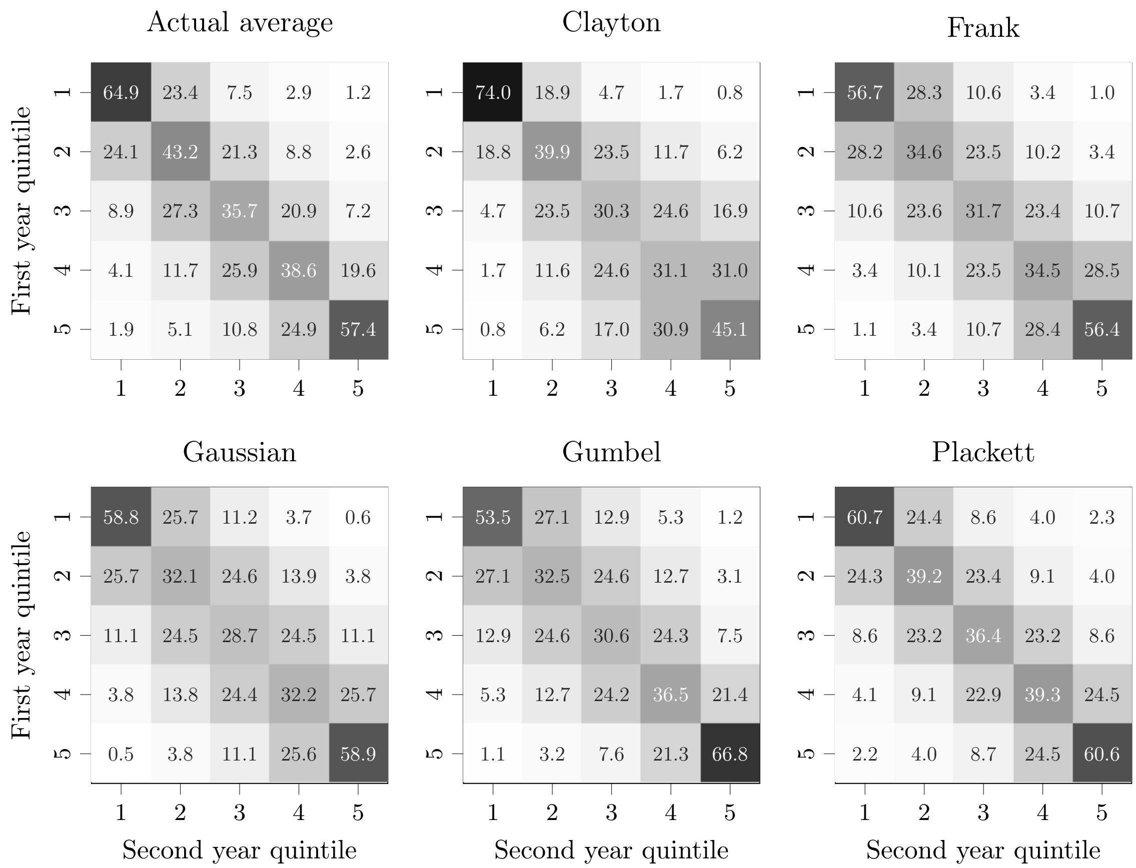


(a) Rural

(b) Urban

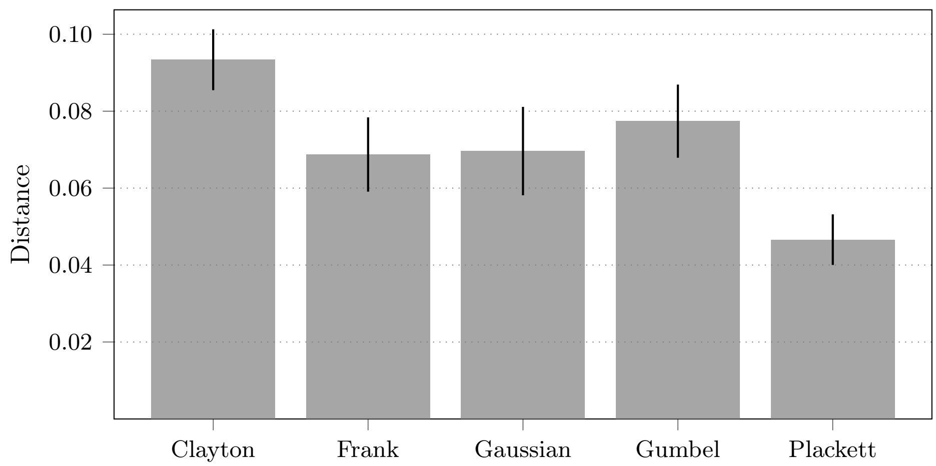
Note: Matrix of probabilities to move between total expenditure per capita quintiles. The element ij of each matrix shows the percent of households from ith quintile who end up in the jth quintile in the following year.

Figure 4: Estimated transition matrices for different copulas



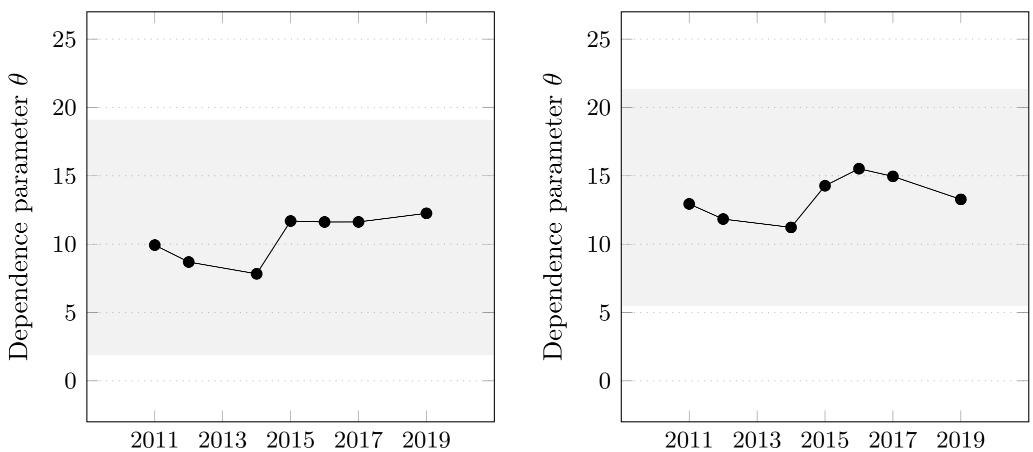
Note: Transition matrices estimated for urban households with different copulas. For rural households check figure B4 in appendix B.

Figure 5: Normalized Forbenius Distance (NFD)



Note: Normalized Forbenius Distance between estimated transition matrices for different copulas and the original transition matrix calculated from HIES panel data for urban households. Figure 4 shows the transition matrices used to calculate NFD here. For rural households check figure B3 in appendix B.

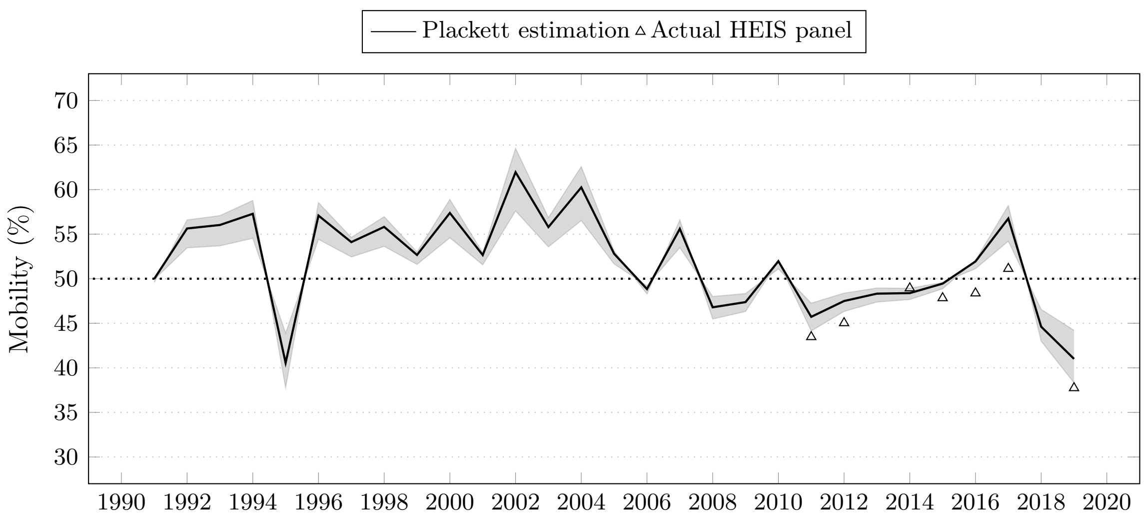
Figure 6: Dependence parameter for HIES panels



(a) Rural (b) Urban

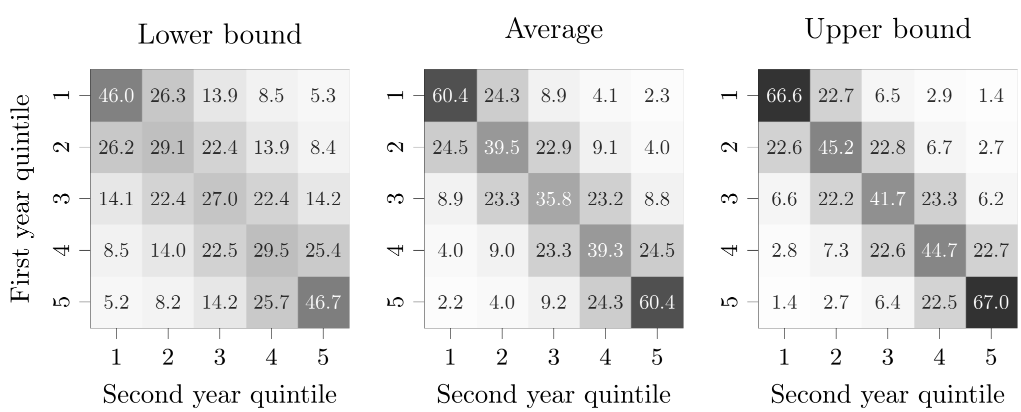
Note: Estimated Plackett dependence parameter for each year in HIES panel. Shadowed intervals are representing estimation boundaries (average plus/minus five standard deviations). Figure 8 shows the corresponding transition matrices for each boundary.

Figure 7: Absolute intragenerational income mobility in Iran, 1991 - 2019



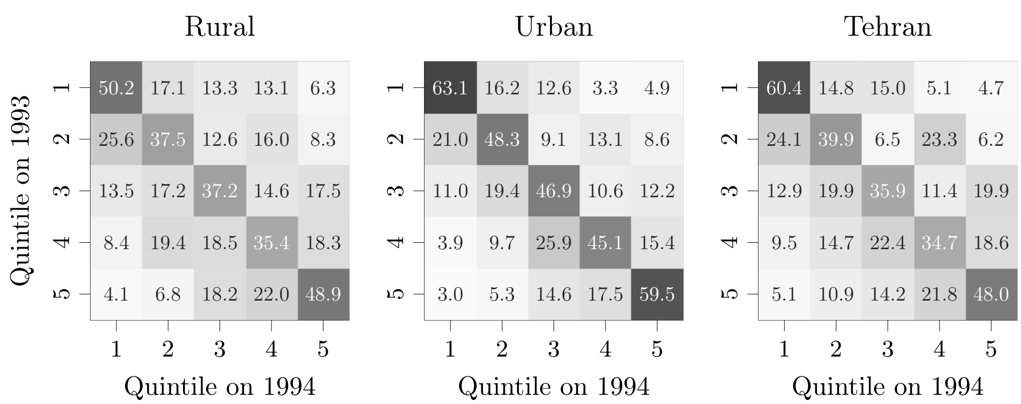
Note: Estimated absolute intragenerational mobility using Plackett copula and cross-sectional income distribution from HIES for urban households in last three decades. The shadowed interval is representing boundaries of the dependence parameter estimated in figure 6, and points are representing the real value of absolute intragenerational mobility as calculated in section 3 using panel data from HIES. For rural households check figure B5 in appendix B.

Figure 8: Transition matrices corresponding to Plackett boundaries



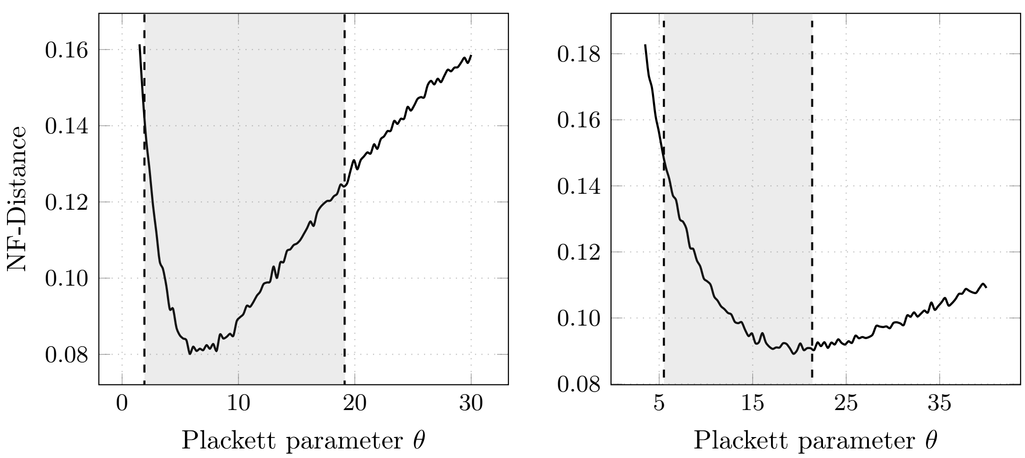
Note: Corresponding matrices of Plackett dependence parameter as plotted in figure 6.

Figure 9: 1993-94 transition matrices



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

Figure 10: Dependence parameter estimation of 1993-94 transition matrix

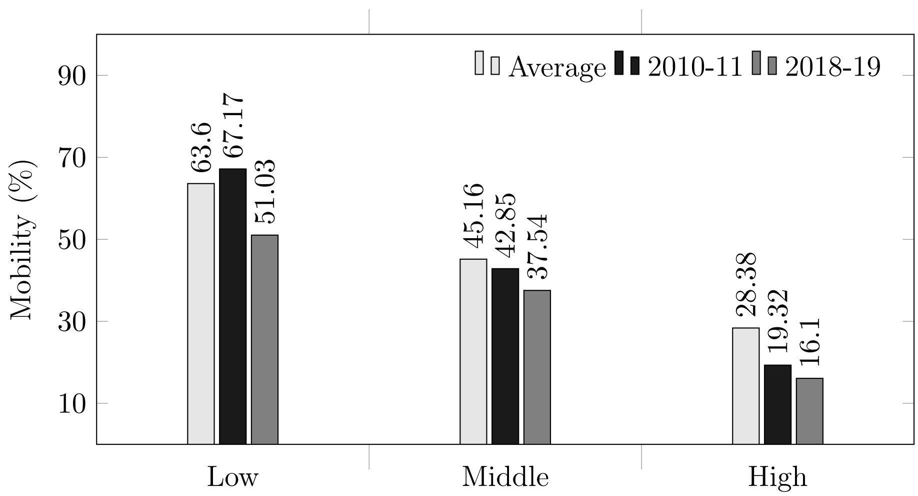


(a) Rural

(b) Urban

Note: Normalized Forbenius Distance between transition matrices calculated by Salehi-Isfahani and Majbouri (2013) and Plackett copulas with different dependence parameters. Dashed intervals are corresponding to parameter intervals used in Figure 6. The best parameters (minimum distance) for these matrices are inside the dashed intervals.

Figure 11: Heterogeneities of mobility across income levels



Note: Figure shows the mobilities for the different levels of income defined as low-income (deciles 1-3), middle-income (deciles 4-7), and high-income (deciles 8-10). For each income level, this figure provides the average mobilities estimated from all two consecutive years of 2010 to 2019 and separately for panels of 2010-11 and 2018-19.

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

Note: Each color shows 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.

Table 2: Some standard bivariate copula functions

Copula type	Function $C(u_1, u_2)$	θ-domain
Product	$u_1 u_2$	N.A.
FGM	$u_1 u_2(1 + \theta(1 - u_1)(1 - u_2))$	$-1 \leq \theta \leq +1$
Gaussian	$\Phi_G[\Phi^{-1}(u_1), \Phi^{-1}(u_2); \theta]$	$-1 < \theta < +1$
Clayton	$(u_1^{-\theta} + u_2^{-\theta} - 1)^{-\frac{1}{\theta}}$	$\theta \in (0, +\infty)$
Frank	$-\frac{1}{\theta} log \left(1 + \frac{(e^{-\theta u_1} - 1)(e^{-\theta u_2} - 1)}{e^{-\theta} - 1}\right)$	$\theta \in (-\infty, +\infty)$

Note: FGM is the Farlie–Gumbel–Morgenstern copula. *Reference:* Trivedi and Zimmer (2007)

A Data Cleaning Appendix

As mentioned in the section 2, the panel data provided by the Statistical Center of Iran (SCI) is based on postal addresses of households with an additional flag that states whether the household in question has moved since the previous survey or not. But as can be seen from the table A1, there are many families that were labeled as "not moved" and have a significant size difference from the last year. Furthermore, changes in family characteristics could be a significant contributor to their movement inside the income ladder which is the subject of this study.

In order to tackle these two problems, we developed a method in which we can assess two families and check whether they are the same or not. In this method, we use the age, gender, marital status, and relation to the household head for each individual and calculate the difference between two families as two numbers. First, the number of individuals that are present in the second year but not in the first, and second, the number of individuals who are present in the first year and are absent in the second year. Then we remove all households that have at least one difference regardless of their flag.

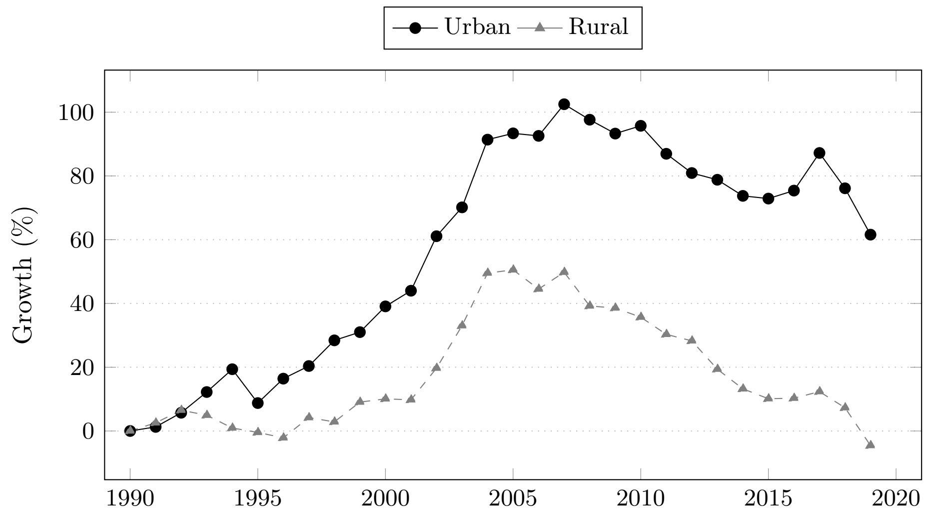
Table A1: Number of removed households

Panel	"moved"			"not moved"			Overall		
	Total	Removed	Ratio (%)	Total	Removed	Ratio (%)	Total	Removed	Ratio (%)
2010-11	2426	2383	98.23	23196	14999	64.66	25622	17382	67.84
2011-12	1963	1931	98.37	23982	14802	61.72	25945	16733	64.49
2013-14	2946	2899	98.40	17411	10786	61.95	20357	13685	67.23
2014-15	2666	2628	98.57	17466	10051	57.55	20132	12679	62.98
2015-16	2386	2358	98.83	17322	9762	56.36	19708	12120	61.50
2016-17	3179	3070	96.57	16957	9744	57.46	20136	12814	63.64
2018-19	2850	2820	98.95	15264	8174	53.55	18114	10994	60.69

Note: Table shows the number of households that are removed from each panel. Between 96 to 98 percent of families who were identified as moved households were removed in our cleaning process. The ratio for "not moved" families varies between 53 to 65 percent.

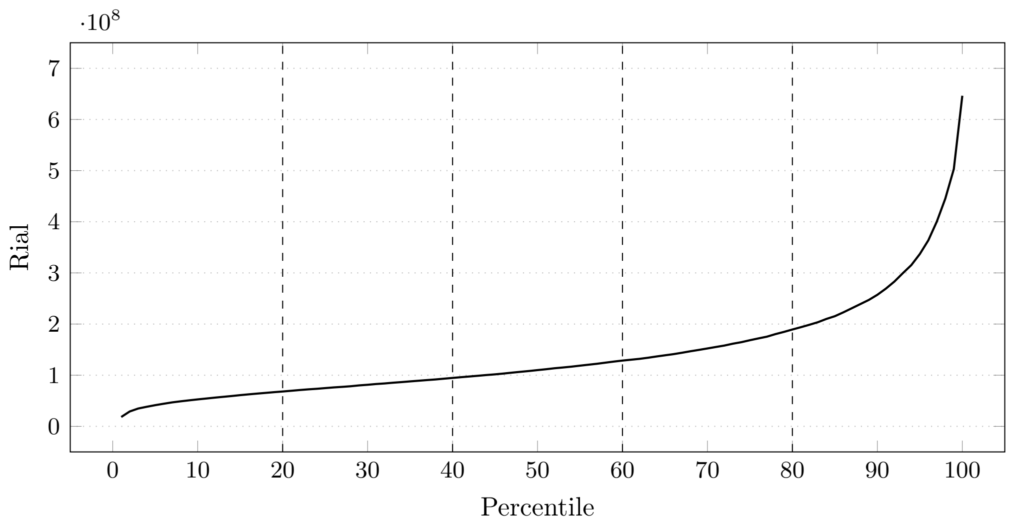
B Further results

Figure B1: Percent growth in median real expenditure per capita relative to 1990



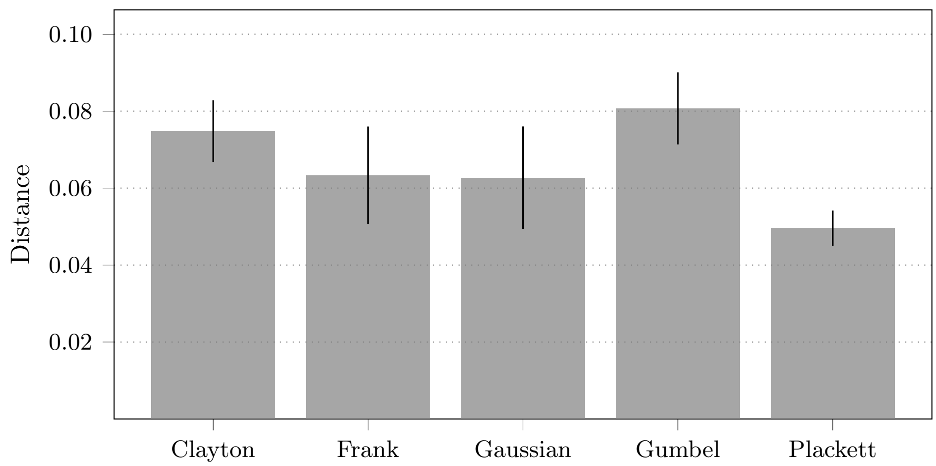
Note: Growth of median expenditure per capita for urban and rural households in Iran relative to 1990.

Figure B2: Median expenditure per capita of each percentile - 2016



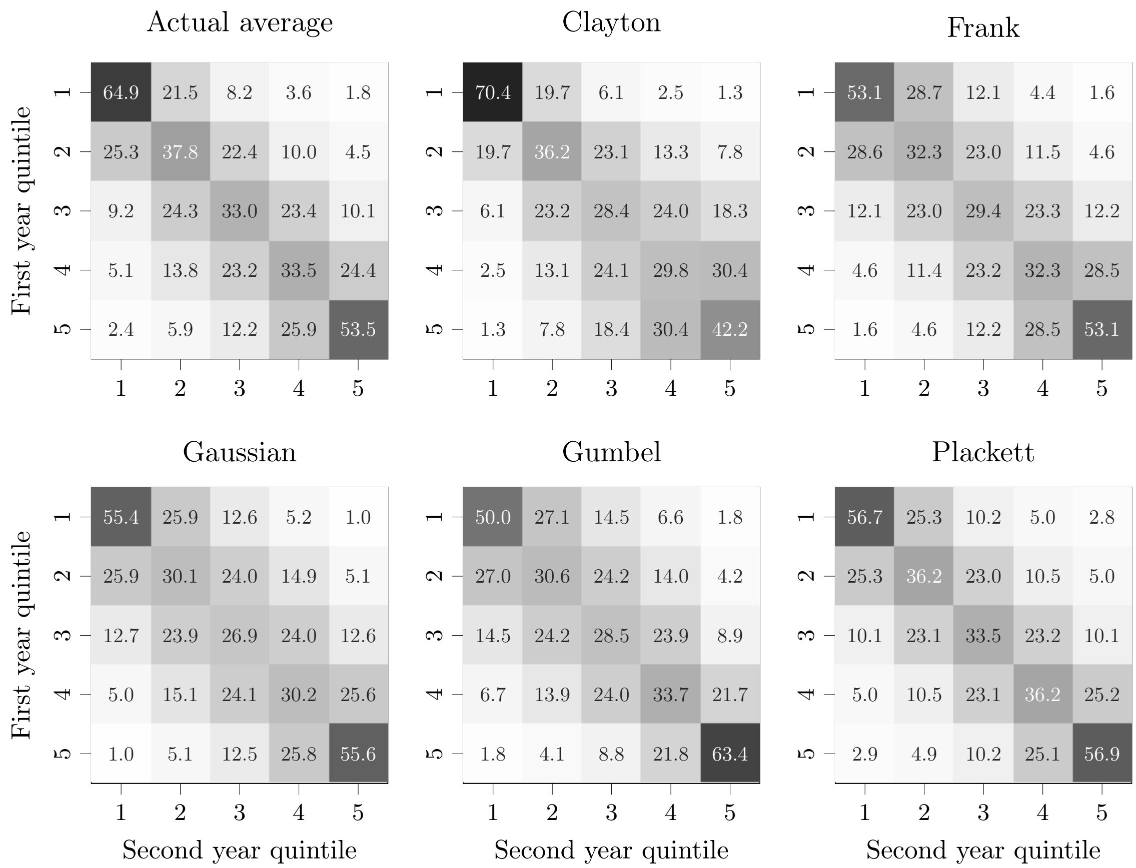
Note: Vertical dashed lines show the borders of each quintile.

Figure B3: Normalized Forbenius Distance - Rural



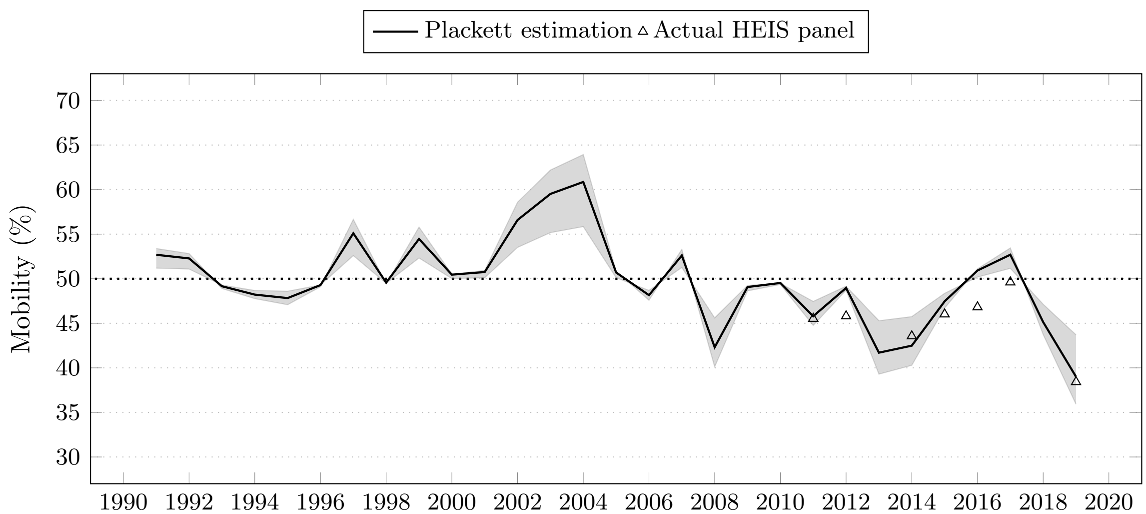
Note: Normalized Forbenius distance between estimated transition matrix for different copulas and real transition matrices calculated from HIES panel data for urban households. Figure B4 shows the difference between different copula estimations. For urban households check figure 5.

Figure B4: Estimated transition matrices - Rural



Note: Transition matrices estimated for rural households with different copulas. As we can see Plackett and Frank are better estimations than other copulas. For urban households check Figure 4.

Figure B5: Absolute intragenerational income mobility in Iran from 1991 to 2019 - Rural



Note: Estimated absolute intragenerational mobility using Plackett copula and cross-sectional income distribution from HIES for rural households in last three decades. Shadowed interval is representing the boundaries of the dependence parameter as estimated in figure 6, and points are representing the real value of absolute intragenerational mobility as calculated in panel A of figure 2 using panel data from HIES. For urban households check figure 7.

Table B1: AIIM estimated from panel and copula, 1991 - 2019

year	Urban		Rural	
	Panel	Plackett	Panel	Plackett
1991		50.0		52.7
1992		55.6		52.3
1993		56.0		49.2
1994		57.3		48.2
1995		40.6		47.8
1996		57.1		49.3
1997		54.1		55.1
1998		55.8		49.6
1999		52.7		54.5
2000		57.4		50.5
2001		52.7		50.8
2002		62.0		56.6
2003		55.8		59.5
2004		60.2		60.9
2005		52.8		50.7
2006		48.8		48.2
2007		55.6		52.6
2008		46.8		42.3
2009		47.4		49.1
2010		52.0		49.5
2011	43.5	45.7	45.5	45.8
2012	45.0	47.5	45.8	49.0
2013		48.3		41.7
2014	48.9	48.4	43.6	42.5
2015	47.8	49.5	46.0	47.5
2016	48.4	51.9	46.8	50.9
2017	51.1	56.8	49.6	52.7
2018		44.6		45.1
2019	37.7	41.0	38.4	39.0

Note: Table provides the main results of the paper estimated from the panel data as well as Plackett copula for urban and rural households.