FWU Journal of Social Sciences, Spring 2025, Vol.19, No.1, 12-24
DOI: http://doi.org/10.51709/19951272/Spring2025/2

The Hidden Drivers of Social Transfers: Understanding How Risk Perception Influences Social Transfer Decisions in Turkey

Hasan Vergil
Ibn Haldun University, Başak Mah. Ordu Cad. Başakşehir, İstanbul, Türkiye

Asad Ul Islam Khan
Ibn Haldun University, Başak Mah. Ordu Cad. Başakşehir, İstanbul, Türkiye

Targeted transfer programs have gained significant attention as effective tools for poverty alleviation. While the targeting mechanisms in social transfer programs have been successful in identifying individuals in need, their implementation often encounters challenges and failures. This study seeks to examine the differences in risk perception among poor households regarding their participation in social transfer programs. A theoretical model was developed to explore the relationship between risk aversion and financial transfers, and the analysis was further supported by statistical and econometric methods using the Income and Living Conditions Survey of Türkiye. The findings indicate that, under varying levels of risk aversion, while the impact of economy-wide risks on the uptake of social transfers remains consistent, idiosyncratic shocks and changes in utility have differential effects on participation. Specifically, households with higher levels of risk aversion tend to participate more actively in social transfer programs. These results underscore the importance of households' risk perceptions in shaping policies related to social transfers and poverty reduction. Programs should incorporate behavioral factors alongside economic indicators to improve efficiency and fairness. This study's validity is limited by the assumption of a constant risk aversion coefficient for all households, as individual risk preferences were not measurable.
Keywords: human behavior, social environment, social policy, welfare reform, program evaluation, Türkiye

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Social transfer programs are an essential component of many development strategies with governments, as well as non-governmental organizations using them to increase the efficiency of scarce resources in reducing poverty, complementing investments in health, education, and other areas. Social transfer programs can be in the form of unconditional transfers, conditional cash transfers, cash for human development programs, and public works[1]. These different forms have various advantages and disadvantages (Ladhani & Sitter, 2020; Devereux, 2002).

The typical targeted program has components of design and implementation of the policy, determination of directly affected groups, direct spillover and feedback effects of the program, and budgetary costs of the program (Schaffner, 2014). These components determine the costs and the benefits of the program. The program may aim to reduce poverty, or vulnerability, or to affect the behaviors of the targeted individuals or households. Governments choose the proper social transfer instruments based on their policy priorities, the country's poverty profile, administrative capacity, and the resources available to finance the program (Samson et al., 2006).

Policymakers may choose to adopt a targeted or untargeted approach while determining the program design. Compared to untargeted transfers, targeted transfers have a greater potential to reduce poverty and reach a higher number of beneficiaries under a limited budget constraint. Coady et al., (2004a) investigated the programs implemented in the

Correspondence concerning this article should be addressed tosad Ul Islam Kha, Ibn Haldun University, Başak Mah. Ordu Cad. Başakşehir, İstanbul, Türkiye,asad.khan@ihu.edu.tr, asadkhan1983@gmail.com

[1] Among the quite rich literature, see Coady et al., (2004a), Samson et al., (2006), Garcia and Moore (2012), and Abramo et al., (2019) for the details of these programs.

world and found that when compared to an untargeted program, the median targeted program provides 25% more resources in the bottom two quantiles. Despite these advantages, targeted programs come with political risks and require higher administration costs in order to determine who is poor. The success of the program in the targeted approach strictly depends on the accurate targeting of beneficiaries.

Countries employ different targeting methods depending on their social, political, institutional, and economic conditions. We can classify these methods as, (i) individual assessment, which involves retrieving details and information about the poor by using means tests and proxy means tests, which were used in numerous programs such as the Progresa program in Mexico and Familias en Acción program in Colombia, (ii) categorical targeting, where officials specify particular groups concerning geographic location, age, gender, disability or vulnerability, (iii) self-targeting, where the poor can select themselves for the project, and (iv) community–based targeting, such as the Old Age Allowance Scheme in Bangladesh, where community representatives select local beneficiaries. Targeting methods can also be used in combination to increase efficiency like in the Bolsa Familia program in Brazil which combines four different programs (Vadapalli, 2009). Geographic targeting, proxy means tests, and community-based targeting programs are used in combination in Mexico's Oportunidades conditional cash transfer program as well (Samson et al., 2006). Coady et al., (2004b) found that, on average, over two targeting methods are combined in 122 targeted transfer programs in 48 countries.

Targeting mechanisms in social transfer programs were generally successful in identifying who the poor are Researchers, however, have concerns about their effectiveness due to the imprecise identification of truly impoverished households (Ladhani & Sitter, 2020; Coady et al., 2004b; Coady & Parker, 2009; Azevedo & Robles, 2013). In these targeting strategies, especially prevalent in developing countries, the poor may be excluded from the program, or the non-poor may be included in the program. Coady et al., (2004a) examined 122 targeted antipoverty programs and discovered that in one-quarter of these programs, non-poor recipients benefited from a larger share of the program than poor recipients.

The design and implementation of the programs require careful determination of risk perceptions of poor households. Maitre et al., (2020) analyzed social risk groups and their access to social transfers in Ireland, finding that high-risk groups demand more support. They used the 2017 SILC data from Ireland to estimate social risk differences in accessing social transfer programs. The authors defined three different social risk groups, lone parents and their children, individuals in households where at least one working-age member has a disability, and individuals aged over 65. Working-age adults who are not lone parents, and who do not have a disability, along with their children were taken as a reference group. They focused on three specific transfers namely, housing, healthcare, and childcare, and concluded that housing transfers were more common among older respondents, vulnerable social risk groups would get a medical card with a higher probability, and higher social risk groups demanded more childcare. They also discovered that vulnerable groups benefited the most from the transfers and that deprivation of the poor was lower when more than one transfer was used. Sakha (2019) investigated macro and micro-level factors determining changes in risk preference over time in Rural Thailand and concluded that risk preferences were affected by time-varying macro-level and state-dependent micro-level variations. People who were exposed to shocks tended to choose less risky economic activities and the impact continued for a longer period of time after the shock. Similarly, Gollier and Pratt (1996) found that individuals facing higher background risks become more risk-averse, aligning with this study's argument that risk perception affects social transfer participation.

In practice, perfect targeting is not always possible as errors of exclusion and inclusion occur frequently[2]. A reduction in these errors is necessary to increase the efficiency of the program. Studies like Coady et al., (2004a) demonstrate that targeted transfers benefit more recipients under tight budget constraints but also bring political and administrative challenges. Azevedo and Robles (2013) suggested a multidimensional targeting approach to improve the performance of targeting mechanisms. In addition to the monetary income dimension, they also added the education and health-nutrition dimensions. For other dimensions, they included one intermediate indicator while incorporating several risk indicators for the education and health dimensions. They also determined deprivation limit values for each dimension and defined the weight of each indicator in each dimension. They applied their method to the data from the Oportunidades program in Mexico and showed that the multidimensional method reduced traditional targeting errors and raised the efficiency of the program in selecting beneficiaries.

[2] For example, Seleka and Lekobane (2020) assessed the targeting effectiveness of fifteen social programs in Botswana using data from the Botswana Multi-topic Household Survey and found that, except in one case, these programs covered the minimum of the poor. The programs were mostly ineffective and had large leaks to the non-poor. Thus, they suggested reforms in the programs to improve targeting effectiveness and to keep program leakages at minimum.

This study extends the suggestion of Azevedo and Robles (2013) by searching for another room to improve the current targeting models. We argue that households' risk perception along with the idiosyncratic and covariate risks they face is an important dimension in determining the genuine impoverished candidates. Adding the household risk perception dimension is especially important in the self-targeting methods where households decide whether to apply for a program and in the individual assessment targeting methods where program officials select households. This risk perception is contingent on the various stages in the participation process of these programs, namely, identification of households, application for the program, and acceptance into the program.

Establishing a successful social transfer program requires careful analysis of the poor. A person who psychologically thinks that he/she needs to help the most may seek and apply for more social aid even if he/she is not poor. Here, a market failure arises from asymmetric information such that a person is better informed about how much risk he/she is exposed to than other potential poor persons. In these cases, a higher share of the transfers can go to "psychologically desperate" but non-poor recipients instead of the poor but not "psychologically desperate" candidates. As a result, taking into account how households and/or individuals perceive risk when designing a social assistance program will improve targeting decisions and help choose the most effective targeting strategy.

The study by Sadoulet et al., (2004) is related to this article but examines the issue from reverse causality. They inquired about the risk coping role of Conditional Cash Transfer programs in child labor and education in the Mexican Progresa program. Estimations of static and dynamic decision models concluded that Conditional Cash Transfer programs could provide an important safety net role, as they protected child education from several idiosyncratic and common-variable shocks reinforcing the argument that risk exposure should be considered in program design.

This study contributes to the literature by analyzing the effect of risk perceptions when taking up social transfers. The data employed in the analyses is from Türkiye, which has created an integrated social assistance system within the past two decades. This e-government platform streamlines every stage involved in social assistance management. In the past, several social assistance programs had distinct procedures and required separate paperwork to be verified in hard copy forms.

This study comprises five stages. First, we theoretically construct a model showing the relationship between individual risk perception and taking up social transfers; second, determinants of disposable income before the income transfers are estimated; third, the relationship between households' idiosyncratic shocks and frequency of social transfer applications are statistically analyzed; fourth, the targeting performance of Türkiye's social transfer system is evaluated; and, fifth, panel data random effects and panel logit estimations are conducted to investigate how taking up social transfers differs depending on the varying risk perceptions in Turkish households.

To our knowledge, there is an absence of research that examines the risk perceptions of households in the design and determination of social transfers. In addition, the few studies regarding the success of cash transfers in Türkiye are mostly descriptive and/or investigate the impact of social transfers on poverty and/or inequality (Günes, 2012; Abdul-Rahman et al.; 2024, Ceren and Erdem, 2019; Tekguc, 2018; Şeker, 2008; Baylan, 2019).

The results reveal that individuals' perception of shocks is an important factor in accessing social transfer programs in Türkiye. The findings of this research could therefore inspire policymakers to recognize the risk perceptions of households in the program design which in turn would help refine eligibility requirements, strategies for benefit distribution, and governance structure choices.

In the following section, we briefly discuss the social assistance system in Türkiye and move on to construct an empirical model and present the estimation method in section three, with a description of the data in section four. The results and analyses for the impact of risk perceptions on social transfers are stated in section five, followed by the conclusion.

The Integrated Social Assistance Information System of Türkiye

The social benefits model in Türkiye can be studied in four parts. The first of these is the "public central social benefits", which include benefits provided by the central government. In addition, municipalities locally provide "public local social benefits". Enterprises in the private sector provide the "private sector social benefits" and the last type of aid is the "civil social benefits" which is provided by non-governmental organizations and individuals. Each type of benefit has its advantages and disadvantages (Khan et al.; 2024, Incedal, 2018).

Türkiye's current public social transfer system has a history of nearly half a century. The social assistance system prior to this was paper-based, requiring citizens to get documents in hard copy forms from various organizations. Over time, several new social assistance programs were developed and implemented including the provision of coal and food, programs to promote access to education by providing free textbooks and school lunches, cash transfers for widows, and a conditional cash transfer program for education and health. Türkiye's Integrated Social Assistance Information System was developed in 2010 and has been in effect since. It is an e-government system receiving social assistance applications from poor people, creating household files, querying personal data and socio-economic information and wealth positions of individuals from central databases, keeping reports on the households' socio-economic status based on the social investigation carried out on-site, and making decisions regarding eligibility for social transfers. It is an information system that serves the citizens, wherein bank instructions regarding aid payments and automatic accounting for all aid are carried out electronically, and citizens are able to view the results of their social assistance applications through the e-government portal.

The social protection system in Türkiye was assisting only a small section of the society prior to the 2000s. Social transfers became an important social policy tool in Türkiye after the launch of new programs and especially after the development of the Integrated Social Assistance Information System in 2010. Thus far, it has functioned as a supportive mechanism, particularly in eradicating the exclusion of the impoverished from being able to Access healthcare and education and in breaking the cycle of poverty.

Now the social assistance system serves as the most important tool in reducing poverty. Between 2010 to 2017, the Integrated Social Assistance Information System in Türkiye processed 30 million citizens' applications for social assistance and completed 340 million assistance transactions worth a total of US$13 billion (Ministry of Family and Social Policies and World Bank, 2017). The number of people receiving salaries within social protection was reported to be more than 14 million people in 2018 and 2019. The share of social protection assistance in the GDP was 11.8% in 2018 and 12.3% in 2019. In both these years, the three groups that received the largest share of benefits are retired/elderly people, the sick and those in need of medical assistance, and widows/orphans. In addition, while over 90% of the benefits were unconditional, over 67% of the benefits were in cash (TURKSTAT, 2019).

Method

Empirical Model

The empirical model is based on one of the basic models in the uncertainty literature. Suppose that a poor person with a concave utility function has a particular level of certain income, y_c, without any future income prospect, and below a minimum acceptable poverty line, *B*. Let us assume that when an individual engages in his or her regular business activities, the payoffs are uncertain in advance because of an uncertain business environment. We can consider the payoffs as a gamble, whether positive or negative, such that her income will be $y_c + z_s$ where z_s is a payoff with a probability of p_s in states. We assume the payoff z_s to be random and to be a result of the weighted sum of the systematic and idiosyncratic risks faced by individuals. We also suppose that a government decides that a citizen should have a minimum acceptable amount of income, *B*, in cases where their income falls below that level. The government won't take any action if an individual has an income $y_c + z_s \geq B$, however, if the income is $y_c + z_s < B$, the government allows them to apply for social assistance such that the money transfers, *m*, help to pull them out of poverty; $y_c + z_s + m = B$. Therefore, an individual is going to have either an expected income $\sum p_s(y_c + z_s) \geq B$ from her business activities or an income after the money transfer from the government. The money transferred to an individual is like a risk premium for the government to hold their wealth at some constant level and is like insurance for an individual against shocks.

For the poor person, the utility from an income before the government transfer must be equal to the utility from facing a gamble with a certain income. Therefore,

$$V(B-m) = \sum p_s V(y_c + z_s). \quad (1)$$

Applying the Taylor series expansions to the left and right sides of the equation gives:

$$m = \frac{V(B) - V(y_c)}{V'(B)} - \frac{1}{2}\frac{V''(y_c)\sigma_z^2}{V'(B)} \quad (2)$$

The amount of money transferred to an individual depends on (i) how utility rises due to money transfer, $\frac{V(B)-V(y_c)}{V'(B)}$ is normalized by the marginal utility at the basic income level, (ii) how risk-averse that individual is at a certain income, $\frac{V''(y_c)}{V'(B)}$, and (iii) the variance of the payoffs an individual faces, σ_z^2. We can further decompose the variance of the payoffs as shocks specific to that individual and shocks specific to the macro-economic and socio-political environment in which an individual lives (Chaudhuri, 2003). The model deduces that the money transfer will be larger as utility rises more due to the money transfer, an individual is more risk-averse, and an individual is faced with more shocks.

Estimation Methodology

The model in Section 3.1 links the risk perception of an individual with social transfers. Based on equation 2, we can construct the empirical model by adding the poverty level of the household into it:

$$m_{it} = \alpha_{0i} + \alpha_1 (UR)_{it} + \alpha_2 (CWS)_{it} + \alpha_3 (IS)_{it} + \alpha_4 (P)_{it} + u_{it} \tag{3}$$

Where, *UR* is a rise in utility from the money transfer normalized by the marginal utility at the basic income which is the income with social transfers, *CWS* is a country-wide shock, *IS* is an idiosyncratic shock, and *P* is a Foster-Greer-Thorbecke poverty index[3] with α =0, 1, and 2. Theoretically, we expect all coefficients to be positive.

The first step in the analysis is to choose the utility function. Here, we assume that the utility is $U(w)^i = (w_i^{1-\sigma})/(1-\sigma)$ where *w* is a welfare measure of individual *i*, and the parameter σ captures the curvature of the utility function and is interpreted as the household's relative risk aversion coefficient. Individual perception of risk varies depending on the individuals' family background, beliefs, socio-political environment, education, and the type of job they have. Since we cannot estimate the risk aversion coefficient of each individual[4], we assign different values for σ between $[0, 3]$ assuming a common risk aversion coefficient for each individual (Ligon and Schechter, 2003).

To estimate an idiosyncratic shock in a household, we followed the method suggested by Celidoni (2013) who used the model devised by Chaudhuri (2003). In this method, a household's income in any given period depends on the characteristics of the household and the macro-economic and socio-political environment in which they live:

$$y_{h,t} = y(X_{h,t}, \delta_t \gamma_h, u_{h,t}) \tag{4}$$

where $X_{h,t}$ shows the observable household characteristics, δ_t represents a vector of parameters describing the state of the economy at time *t*, γ_h is an unobserved, time-invariant household-level effect, and $u_{h,t}$ is any idiosyncratic shock. We treat $\delta_t \gamma_h$ as fixed effects. Amemiya's (1977) three-step, feasible generalized least squares procedure, is used to get an efficient estimate of the variance of idiosyncratic components of household income.

Data

Data for this study comprises micro and macro variables. The effective exchange rate data was obtained from the database of the Central Bank of Türkiye to calculate country-wide shock, a macro variable. The data for micro variables was taken from the Income and Living Conditions Survey panel data set of the Turkish Statistical Institute, TURKSTAT, with the wave covering the period 2016-2019. 20760 people responded to this wave, with the number of respondents being 5190 each year. The Income and Living Conditions Surveys are carried out regularly every year since 2006 in accordance with the studies compliance with the European Union. To obtain the target variables requested by EUROSTAT, TURKSTAT created the Income and Living Conditions Survey questionnaire to calculate indicators such as income, poverty, and other living conditions.

Based on this survey, the amount of social transfers is calculated as the sum of unemployment benefits, survivors' benefits (including death grants), sickness benefits, disability benefits (including ghazi and honor pensions), the value of child-related allowances in kind, child-related allowances in cash, housing allowances received, other social allowances

[3] The Foster-Greer-Thorbecke indices are proposed by Foster et. al. (1984). Its general formula is $P_\alpha = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{z-y_i}{z}\right)^\alpha$. When α = 0, it measures the share of poor people in the population. α = 1 measures the normalized average poverty gap corresponding to the depth of the poverty, and α = 2 measures the severity of poverty by giving greater weight to income deficits further away from the poverty line.

[4] Measuring individual risk aversion coefficients requires specific risk aversion questions in surveys. Unfortunately, TURKSTAT's Income and Living Conditions Survey does not include this kind of question. For studies calculated individual risk aversion coefficients, see, for example, Guiso and Paielle (2008), Kim and Lee (2012) and Jung (2015).

in cash received in during income and value of other social allowances in kind. These transfers are recorded as part of the household's total disposable income. As a result, we deducted them from the household's total disposable income to calculate disposable household income before government aid.

In all estimations, disposable household incomes before and after government aid are measured at the household level and adjusted for household size and composition using the modified equivalence scale of OECD[5], transformed to real terms, and then used in natural logarithmic forms[6]. Therefore, the household is taken as the unit of the analysis, instead of the individual.

CPI (2010=100) is used to make income real. Poor households are defined as households with an income lower than the poverty line which is 60% of the median income before social transfers. We calculated utility rise as the difference between household disposable incomes after and before government aid, divided by the marginal utility of income after government aid. The country-wide shocks variable is measured by taking yearly percentage changes of the real effective exchange rate of Türkiye.

Results

Türkiye's integrated social transfer system has various advantages, such as the consolidation of services under one single structure, improved information communication and sharing of information, and reduced time and costs. It would be beneficial to measure the targeting performance of Türkiye's social transfer system to understand the magnitude of its success in channeling benefits to the target population before moving to other analyses.

A common approach to measuring errors and accuracy in targeting is to calculate the leakage and under coverage rate of the program (Coady et al.; 2004a, Hassan et al.; 2023, Ravallion; 2016). This approach comprises a calculation of the under-coverage rate which is the portion of poor households categorized as non-poor (exclusion error) and leakage rate which is the proportion of non-poor households categorized as poor (inclusion error)[7].

We achieve perfect, accurate targeting when there are no exclusion and inclusion errors.
Table I shows under coverage and leakages rates following the method devised by Coady et al., (2004a). Since the data set is panel data, the same number of beneficiaries over the period was used in the panel. While 65.9% of poor households were included in the program (successful targeting for the poor), 34% of the poor were not included in the program (under coverage rate, exclusion error), and the proportion of non-poor in the program was 46% (leakage rate, inclusion error). Thus, we can conclude that although there are many beneficiaries in Türkiye's integrated social transfer system, such high levels of under coverage and leakage rates show that the effectiveness of the targeting is not as successful as it is widely used and the system needs to be developed from this point of view.[8] However, despite this, they are not as high as the targeting ineffectiveness in the study by Seleka and Lekobane (2020) for Botswana, where close to half of the program beneficiaries were non-poor and over one-third of the poor people were not covered by programs.

[5] The modified OECD equivalence scale gives a weight of 1 to the reference person of the household, 0.5 for household members age 14 and over and 0.3 for others in the family.
[6] For a few households with negative or zero disposable incomes after the subtraction of cash transfers, we accepted incomes as 2 to add them into the sample.
[7] The under coverage rate is measured by dividing the number of poor households excluded from the program by the total number of poor, the leakage rate is measured by dividing the number of non-poor households in the program by the total number of households in the program. Two other performance indicators showing the success of the programs are (i) the targeting effectiveness ratio which is measured by dividing the number of poor people in the program by the total number of households in the program, and (ii) the coverage ratio which is measured by dividing the number of poor households in the program by the total number of poor households.
[8] The calculations were made by taking the poverty line as 60% of the median income (before the social transfers) of the households in the panel over the period 2016-2019. This poverty line is not the official poverty line in Türkiye and social transfers are not given based on this poverty line. However, they may be a close representative of them even the performance ratios are not the exact indicators.

Table I

Performance Ratios of the Programs in Türkiye

	Welfare Status of Households		
Number of households	**Poor**	**Non-poor**	**Total**
in the program	3382	2906	6288
out of the program	1746	12726	14472
Total	5128	15632	20760
Targeting effectiveness (%)	Leakage rate (%)	Coverage rate (%)	Under-coverage rate (%)
53.7	46.2	65.9	34.0

Notes: Computed by the author from the Income and Living Conditions Survey (TURKSTAT, 2016-2019).

Having determined the effectiveness of the various Turkish social programs, we will proceed to conduct econometric estimations to examine whether risk perceptions of households have any effect on them taking up social transfers. When this effect is discovered, it may prompt officials to look for ways to improve the effectiveness of the programs.

Based on the theoretical model, equation 3 was constructed for this analysis. The idiosyncratic shocks in equation 3 must be separately estimated since this variable cannot be proxied by any other indicator. We estimated them using the method proposed by Amemiya (1977). To do that, equation 4 in Section 3.2 was specified in the econometric model as:

$$\ln y_{ht} = \lambda_o + \lambda_1 X_{ht} + e_{ht} \quad (5)$$

where X_h shows the observable household characteristics and e_{ht} is a composite error term. The state of the economy at the time t, and an unobserved time-invariant household-level effect is described as:

$$e_{ht} = \delta_t \gamma_h + u_{h,t}$$

In equation 5, e_{ht} captures the household's idiosyncratic factors. Chaudhuri (2003) assumes that the variance of e_{ht} is determined by the same household characteristics:

$$\sigma^2_{e,h} = X_h \theta \quad (6)$$

We used Amemiya's (1977) three-step Feasible Generalized Least Squares (FGLS) method to get consistent and asymptotically efficient estimates. The steps in this method are as follows:

i. Model 5 is estimated using the OLS procedure.
ii. The residuals from the first step are used to estimate-

$$\widehat{e}^2_{OLS,h} = X_h \theta + \upsilon_h$$

iii. The predictions from the second step are used again to transform the equation-

$$\frac{\widehat{e}^2_{OLS,h}}{X_h \widehat{\theta}_{OLS}} = \left(\frac{X_h}{X_h \widehat{\theta}_{OLS}} \right) \theta + \left(\frac{v_h}{X_h \widehat{\theta}_{OLS}} \right) \quad (7)$$

The OLS procedure is applied to estimate this transformed equation. Then, $X_h \hat{\theta}_{FGLS}$ provides a consistent estimation of the variance of the idiosyncratic component of household income, $\sigma^2_{e,h}$.

The OLS estimation of equation 5 can ascertain determinants of household income. We used the panel data random-effects method to estimate that model. Besides the suggestion of the Hausman test, it is because the random-effects method allows heterogeneity across units, which is more suitable in our case and the fixed effects model could not estimate the time-invariant variables.

The estimation results are shown in Table II in which the coefficients fit well with theoretical expectations. All coefficients are statistically significant, and income is positively related to education level, age, marriage, and health condition of the household head. In contrast to these results, an individual's income is observed to be lower if the household head is a woman, the household size is larger, and the dependency rate is higher.

Having ascertained the idiosyncratic shocks, the next exercise was to determine the relationship between the idiosyncratic shock households face and the number of beneficiaries in the program. Idiosyncratic shocks induce strong precautionary motives for households to stabilize their incomes. Increasingly diversified and frequent shocks make households more risk averse. One way to reduce the exposure of households to any kind of shock ex-ante is to participate in the country's social assistance program which will help them be more resilient to idiosyncratic and/or common shocks.

Table 2

The Determinants of Household Income

Dependent Variable: ln (disposable per-household income excluding social transfers)	2016-2019
Gender of head	-0.252
	(-5.82)*
Age of head	0.007
	(9.54)*
Household size	-0.035
	(-19.90)*
Education of head	0.229
	(38.30)*
Marital status	0.130
	(7.20)*
Health status	0.042
	(5.93)*
Employment status	0.108
	(13.20)*
Dependency rate	-0.0005
	(-3.77)*
Constant	7.299
	(63.13)*
Number of observations	20760
R-square (overall)	0.29
Wald Chi-square	3066.88
	(0.00) *

Notes: *t*-statistics (derived from heteroscedasticity robust standard errors) are in parentheses, * shows that the coefficient is significant at 1%. Numbers in parentheses for Wald Chi-square are *p*-values.

Table III summarizes the mean values of idiosyncratic shocks and social transfer application frequencies across different categories of society. The first column gives results in line with expectations: mean values of idiosyncratic shocks decrease as the level of health and education of household heads increases. In contrast, they are higher for female-headed households. The mean value of idiosyncratic shocks is lower for married households and increases in households where the household heads are single or have ended their marriage. The last column indicates a pattern between the mean value of idiosyncratic shocks and the number of households in the program. It shows that the category with higher idiosyncratic shocks is also a category with a higher number of households participating in the program. Therefore, it can be concluded that a household faced with larger idiosyncratic shocks participated more in a social transfer program and could thus balance the adverse effects of idiosyncratic shocks.

Table 3

Idiosyncratic Shocks and Applications for Social Transfers Across Categories

Education	Mean value of idiosyncratic shocks	1	2	(2/1)(%)
Illiterate	0.231	1631	1132	69.41
Literate but not a graduate	0.142	1151	635	55.17
Primary school	0.086	8742	2698	30.86
Secondary, v. secondary or primary education	0.062	2518	674	26.77
High school	0.059	1764	355	20.12
Vocational or technical high school	0.047	1544	308	19.95
Faculty/university, college, or higher education	0.048	3410	486	14.25
Gender				
Female	0.258	3608	2354	65.24
Male	0.05	17152	3934	22.94

Marital status				
others (widowed/divorced/separated)	0.261	3351	2265	67.59
never married	0.137	683	219	32.06
married	0.049	16726	3804	22.74
General health status				
very bad	0.161	233	127	54.51
bad	0.142	2310	1110	48.05
so, so	0.106	5910	2037	34.47
good	0.066	11238	2766	24.61
very good	0.057	1069	248	23.20

Notes: 1: total frequency, 2: frequency of households participating in social transfers.

Table IV presents the estimation results of equation 3 with incrementally increased risk aversion coefficients in utility functions. In addition, the model was separately estimated with different poverty indices. As theoretically expected, the coefficients of being poor and facing idiosyncratic and country-wide shocks are statistically significant and positive in all regressions. The effects of poverty and idiosyncratic shocks are higher as common risk aversion coefficients become larger, while the impact of country-wide shocks is constant across different risk aversion coefficients in each regression. If we assume the common contention that poorer people are willing to be more risk-averse than the wealthier, the effects of poverty and idiosyncratic shocks on taking up social transfers become larger as risk aversion is higher.

Table 4

Estimation of Social Transfers: 2016-2019

Dependent Variable: ln (per-household social transfers from the government)

		σ=0	σ=0.5	σ=1	σ=1.5	σ=2	σ=2.5	σ=3
Poverty index with α=0	Constant	0.474 (11.51)*	0.412 (10.09)*	0.372 (9.14)*	0.352 (8.64)*	0.343 (8.42)*	0.339 (8.33)*	0.338 (8.29)*
	Poverty	0.942 (17.89)*	1.054 (20.17)*	1.126 (21.47)*	1.161 (22.01)*	1.177 (22.23)*	1.183 (22.31)*	1.186 (22.35)*
	Idiosyncratic shocks	12.13 (25.51)*	13.39 (29.92)*	14.2 (32.76)*	14.6 (34.07)*	14.77 (34.60)*	14.84 (34.82)*	14.86 (34.90)*
	Country-wide shocks	0.008 (3.48)*	0.007 (3.39)*	0.007 (3.33)*	0.007 (3.29)*	0.007 (3.27)*	0.007 (3.27)*	0.007 (3.26)*
	Utility rise	1.1 (10.58)*	0.526 (9.40)*	0.204 (8.80)*	0.068 (8.18)*	0.021 (7.15)*	0.006 (6.16)*	0.002 (5.55)*
	R^2	0.39	0.36	0.35	0.34	0.33	0.33	0.33
		σ=0	σ=0.5	σ=1	σ=1.5	σ=2	σ=2.5	σ=3
Poverty index with α= 1	Constant	0.552 (13.12)*	0.489 (11.82)*	0.452 (11.03)*	0.434 (10.66)*	0.427 (10.51)*	0.425 (10.46)*	0.424 (10.44)*
	Poverty	1.733 (12.30)*	2.328 (17.93)*	2.704 (21.71)*	2.895 (23.53)*	2.979 (24.33)*	3.013 (24.67)*	3.026 (24.83)*
	Idiosyncratic shocks	12.32 (25.87)*	13.32 (29.67)*	13.85 (31.66)*	14.06 (32.43)*	14.12 (32.70)*	14.14 (32.79)*	14.14 (32.83)*
	Country-wide shocks	0.008 (3.48)*	0.008 (3.53)*	0.008 (3.56)*	0.008 (3.57)*	0.008 (3.58)*	0.008 (3.59)*	0.008 (3.59)*
	Utility rise	0.955 (8.64)*	0.391 (7.10)*	0.122 (5.67)*	0.029 (3.81)*	0.005 (1.90)***	0.0007 (0.68)	0.000 (0.10)
	R^2	0.38	0.36	0.35	0.35	0.35	0.35	0.35
		σ=0	σ=0.5	σ=1	σ=1.5	σ=2	σ=2.5	σ=3
Poverty index with α= 2	Constant	0.613 (14.16)*	0.548 (12.83)*	0.513 (12.11)*	0.498 (11.81)*	0.492 (11.71)*	0.49 (11.68)*	0.49 (11.67)*
	Poverty	0.751 (3.62)*	2.021 (11.10)*	2.822 (16.75)*	3.224 (19.60)*	3.398 (20.84)*	3.466 (21.37)*	3.49 (21.60)*
	Idiosyncratic shocks	12.7 (25.95)*	13.86 (30.44)*	14.39 (32.57)*	14.55 (33.25)*	14.58 (33.45)*	14.58 (33.51)*	14.58 (33.53)*
	Country-wide shocks	0.007 (3.12)*	0.007 (3.20)*	0.007 (3.27)*	0.007 (3.30)*	0.007 (3.32)*	0.007 (3.33)*	0.007 (3.34)*

Utility rise	1.106 (8.76)*	0.41 (6.63)*	0.105 (4.51)*	0.014 (1.82)***	-0.001 (-0.62)	-0.002 (-1.99)**	-0.001 (-2.55)*
R^2	0.35	0.33	0.32	0.32	0.32	0.32	0.32

Notes: The random effects model is used in the estimations. The number of observations is 20760 in each estimation. *t*-statistics (derived from the heteroscedastic robust standard errors) are in parentheses. *, **, *** * shows that the coefficient is significant at 1%, 5% and 7%, respectively. The *p*-values for Wald Chi-square (not shown here) are significant at 1% in all regressions.

In addition, the range of poverty coefficients expands in the models where poverty variables become more sensitive to income changes, as risk aversion coefficients become higher. When a household is more risk averse and when the poverty index indicates the depth and severity of poverty, the impact of poverty on taking up social transfers increases, and decreases when the poverty index is just the headcount index losing sensitivity to income distribution among the poor.

We observe an opposite relationship between utility rise and its effect on taking up social transfers. The coefficients of the utility rise variable become lower in the models as the risk aversion coefficient rises. In the first regression, when poverty is measured by headcount ratio, the coefficients are statistically significant and positive but decrease with higher risk aversion parameters. In the second model, while the effect of utility rise is positive and statistically significant for low-risk aversion parameters, it shrinks quickly and turns out positive but insignificant, as the risk aversion parameter rises. The coefficient of utility rise even turns out to be negative and statistically significant in the third model where the poverty indicator demonstrates the severity of poverty. The higher σ corresponds to the more sharply curved utility function and therefore, the less utility rise from the social transfers and, at the extreme, participating in the program provides less utility for very high risk-averse households when the poverty index gives more weight to the extremely poor.

To strengthen the findings, we estimated the logit model by transforming the dependent variable as a binary variable. It takes a value of 1 if the household takes part in the system and 0 otherwise. Table V gives the panel binary logit estimates of the preceding model using different poverty rate indices. We excluded the utility rise variable from the estimations because of its perfect correlation with the dependent variable. In Table V, since the estimated Wald Chi-square values are highly statistically significant, we can reject the null hypothesis that all coefficients are simultaneously equal to zero. Similarly, significant Chibar-square values show that the random effects logit model is chosen over the pooled logit model.

In all regressions, all variables are individually, as well as collectively and statistically significant at the 1% significance level and display the expected signs. The poverty coefficients expand as poverty indices become more sensitive to income distribution. However, the coefficients of the country-wide shocks and idiosyncratic shocks are almost similar in all models.

Table 5

Logit Estimation of Social Transfers: 2016-2019

Dependent Variable: Participating in the social transfer system

Poverty index with	α=0	α=1	α=2
Constant	-4.476 (-36.08)*	-4.26 (-34.64)*	-4.305 (-32.43)*
Poverty	2.691 (23.16)*	7.102 (22.27)*	9.972 (15.81)*
Idiosyncratic shocks	20.00 (25.81)*	18.79 (23.57)*	20.18 (23.95)*
Country-wide shocks	0.021 (3.46)*	0.022 (3.59)*	0.020 (3.36)*
Wald Chi-square	1298.09 (0.00)*	1112.29 (0.00)*	1220.57 (0.00)*
Chibar-square	4837.83 (0.00)*	4728.51 (0.00)*	5116.49 (0.00)*
Average marginal effects			
Poverty index with	α=0	α=1	α=2
Poverty	0.195	0.475	0.604

	(15.72)*	(19.56)*	(13.60)*
Idiosyncratic shocks	1.454	1.257	1.222
	(37.87)	(33.18)*	(34.99)*
Country-wide shocks	0.001	0.001	0.001
	(3.43)*	(3.57)*	(3.33)*

Notes: The random effects logit model is used in the estimations. The number of observations is 20760 in each estimation. *t*-statistics (derived from heteroscedastic robust standard errors) are in parentheses. The numbers in parenthesis below the Wald Chi-square and Chibar-square tests are the *p*-values. * shows significance levels at 1%.

We must present the marginal effect of each variable on the probability of participating in the social transfer system for each model type since the coefficients do not give us the rate of change of probability for a unit change in the regressor. As observed in Table V, the marginal effects of the poverty variable get higher as poverty indices become more sensitive to income distribution. In contrast to this, the marginal effect of the country-wide shocks variable remains the same and is relatively very low in each model. The average marginal effects of poverty and idiosyncratic shocks are quite large in all three models. For example, the coefficient of 1.454 suggests that if the idiosyncratic shocks rise by one unit, on average, the probability of participating in the social system rises by 145%. Similarly, the coefficient of 0.475 suggests that if the poverty index with α=1 increases by a unit, on average, the probability of participating in the social system increases by 47.5 percent. We can thus conclude that the idiosyncratic shocks have the largest effect on the probability of taking up social transfers followed by the poverty level of the households.

The combined results of the panel data random effects model and logit model show that the idiosyncratic shocks and poverty have the largest effect on the probability of taking up social transfers and the impact of these variables is higher for more risk-averse households. Therefore, we can conclude that more risk-averse households take up social transfers at a higher rate and are also more likely to seek social transfers.

Concluding Remarks

Most targeted programs aim to reduce current poverty by providing cash or food to needy people. The costs to determine who is in need and the impact of the program on directly and indirectly affected groups are two key elements in targeting error discussions. Targeting failures occur because of the asymmetric exchange of information between program officials and poor households.

To reduce targeting errors, a study by Azevedo and Robles (2013) suggests a multidimensional methodology in which they consider poverty beyond a monetary phenomenon. This study aims to examine the scope to improve the current targeting methodologies following the approach by Azevedo and Robles (2013). The study extends risk perception theories by linking them to social transfer participation, emphasizing the psychological aspects of economic decision-making. It suggests considering the risk perceptions of the applicants in determining the target population as well as the design and implementation of the program. We assume that participants in the program will be more likely the members of the community who psychologically think that they need help the most. To the best of our knowledge, this is the first study that examines the risk perceptions of the applicants on the effectiveness of the targeted transfer programs.

This study developed a brief theoretical model to construct the link between risk perceptions of individuals and social transfers. The Income and Living Conditions Survey panel data set from Türkiye was used for statistical and econometric analyses. It was discovered that individual characteristics of households are the main determinants of disposable income levels. The calculations for the effectiveness of the targeting program in Türkiye showed that the program was not as successful as much as it is in the majority of the other parts of the world. Therefore, better methods may be needed to improve the effectiveness of the program. We statistically indicated a pattern between the mean value of idiosyncratic shocks households face and the number of households in the program. The results show that exposure to shocks is different for households across different categories of society. When faced with greater idiosyncratic shocks, the likelihood of participation in a transfer program also increases.

We estimated panel data random effects models derived from the theoretical model by assuming common risk aversion coefficients. The results from random effects models showed that while the impact of country-wide shocks is constant across different risk aversions, the effect of poverty and idiosyncratic shocks is higher when the risk aversion coefficients of households are greater. The panel data logit models also concluded that the idiosyncratic shocks and poverty have the largest effect on the probability of taking up social transfers. These results suggest that individuals' perception of shocks is an important factor in taking up social transfers in Türkiye.

These results, at least in the case of Türkiye, present an important role of individual risk perceptions in taking up social transfers. Policymakers can improve targeting mechanisms by integrating psychological screening tools to assess risk perception among applicants. It would be better to identify the poor beyond the monetary dimension in social programs and considering the risk perception of the applicant is one of them. Given the findings, programs should consider behavioral factors alongside economic indicators to enhance efficiency and fairness.

The validity of our approach is limited by the data such that it could not allow us to measure the risk aversion of each individual. Instead, we had to assume that all households had the same constant risk aversion coefficient. Using individual risk aversion coefficients could provide deeper insights. Future research could explore how non-economic factors (such as cultural norms and trust in institutions) impact program participation. Further studies should investigate the long-term effects of risk perception on economic mobility and dependency on social transfers.

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