Ekonomi-tek, Volume 12, Number 3, 2023, 108-122

Received: December 1, 2023 *Accepted: January 7, 2024* *Research Article*

The Link between Disability and Different Sources of Income: Evidence from Turkish Panel Survey of Income and Living Conditions

Burcu DÜZGÜN ÖNCEL[*]

Abstract

In this study I examine the association between disability status and different sources of income. I derive data from the Panel Survey of Income and Living Conditions (SILC) spanning the years 2018 to 2021, which is compiled by the Turkish Statistical Institute (Turkstat). I characterize disability as a limitation in daily activities resulting from either an impairment or a long-term health condition, expected to endure for six months or longer. I use six income types; i) salary and wage, ii) business income, iii) unemployment benefit, iv) retirement pay, v) disability income and vi) other income. In order to overcome potential selection bias resulting from subjective disability, I match disabled individuals with corresponding nondisabled counterparts according to demographic and socio-economic controls. Then I estimate fractional response models with different sources if income as dependent variables. Main findings are as the following: income composition significantly differs among individuals with and without disabilities, income of individuals with disabilities are lower in almost all income types, people with disabilities may offset income losses in specific categories by pursuing alternative sources of income.

JEL Codes: C33, I14, I30

Keywords: disability, income, matching, fractional response model

[*] Marmara Üniversitesi, İktisat Fakültesi, https://orcid.org/0000-0002-6834-7874 (burcu.duzgun@marmara.edu.tr).

Engellilik ile Farklı Gelir Kaynakları Arasındaki Bağlantı: Türkiye Gelir ve Yaşam Koşulları Panel Araştırmasından Kanıtlar

Öz

Bu çalışmada engellilik durumu ile farklı gelir kaynakları arasındaki ilişkiyi incelemekteyim. Veriler Türkiye İstatistik Kurumu (TÜİK) tarafından hazırlanan 2018-2021 yıllarına ait Gelir ve Yaşam Koşulları Panel Araştırması'ndan (SILC) alınmıştır. Engelliliği, altı ay veya daha uzun süre devam eden veya sürmesi beklenen, bireyin günlük aktivitelerini engelleyen bir bozukluk veya uzun süreli bir sağlık durumu olarak tanımlıyorum. Altı gelir türü kullanıyorum; i) maaş ve ücret, ii) iş geliri, iii) işsizlik ödeneği, iv) emekli maaşı, v) engellilik geliri ve vi) diğer gelirler. Öznel engellilikten kaynaklanan potansiyel seçim yanlılığının üstesinden gelmek için engelli bireyleri, demografik ve sosyo-ekonomik kontrollere göre engelli olmayan benzerleriyle eşleştiriyorum. Daha sonra farklı gelir tiplerinin bağımlı değişken olduğu kesirli yanıt modellerini tahmin ediyorum. Temel bulgular şu şekildedir: Gelir kompozisyonunu engelli ve engelli olmayan bireyler arasında önemli ölçüde farklılık göstermektedir, engelli bireylerin geliri hemen hemen tüm gelir türünde daha düşüktür, engelli bireylerin belirli kategorilerdeki gelir kayıplarını alternatif gelir kaynakları arayarak telafi ettikleri görülmektedir.

JEL Kodları: C33, I14, I30

Anahtar kelimeler: engellilik, gelir, eşleştirme, kesirli yanıt modelleri

1. Introduction

The presence of a disability represents distinct aspects for both labor market dynamics and economic welfare (Ali et al.,2011; Duzgun Oncel and Karaoglan, 2020; Gannon, 2009; Mitra et al., 2013; Schuring et al., 2013; Vornholt et al., 2017). Additionally, it exerts an influence on earned income, as those with disabilities may encounter financial disadvantages. People with disabilities face fewer job prospects, often find themselves in lower-paying positions, incur high medical expenses and ultimately experience diminished economic prosperity (Baldwin and Choe,2014; Baldwin and Johnson, 1994; Brucker et al., 2015; Haveman and Wolfe, 1990; Jatner et al.2020; Kidd et al., 2000; Lindeboom et al., 2016; Meyer and Mok, 2019; Mitra et al., 2013; Rice and LaPlante, 1992).

Disability, whether physical, cognitive, sensory, or mental, can significantly influence an individual's ability to engage in economic activities, affecting their earning potential and shaping the composition of their income. Numerous studies have explored how disability status determines labor income. Baldwin and Choe (2014), for instance, investigate wage differentials between individuals with and without physical disabilities in the United States (US). They apply decomposition methods to wage equations with selectivity corrections, aiming to estimate potential effects of discrimination. The decomposition process breaks down observed wage gaps into two components: one explained by differences in characteristics affecting productivity and the decision to work, and another unexplained part that may be linked to potential discrimination. (Baldwin and Choe, 2014).

Meyer and Mok (2019) by using panel data for the period 1968-2015, examine how disability affects income, earnings and consumption in US. They find that, the long-term incomes of approximately one-sixth of families with a head who is chronically and severely disabled fall below the poverty line. (Meyer and Mok, 2019). In a comparable study, Jajtner et al. (2020) examine trends in income inequality based on household work limitations in the United States from 1981 to 2018. According to their results, there is a higher level of income inequality among households with work limitations compared to those without such limitations. However, literature frequently neglects different income sources for disabled individuals. Due to its significant role in income inequality, it is important to focus on how disability status affects income composition. In a recent study, Pu and Syu (2023) analyze the impact of disability on income and income composition in Taiwan. They use longitudinal data for the period 1999-2015. According to their findings, wage income constitutes the predominant share of income for both individuals with and without disabilities. The impact of disability on income exhibited variations across distinct income sources. The income composition of individuals with disabilities experienced notable changes at various stages of their lives (Pu and Syu,2023).

Along with the discussions above, my main aim in this study is to examine the relationship between disability status and different sources of individual income. I use panel SILC for the years 2018-2021 prepared by Turkstat. The sample contains indivudlas who are aged between 25 and 64 in 2018. In order to overcome sample selection bias that subjective disability status may possess, I matched disabled individuals with a corresponding nondisabled individual according to demographic and socio-economic controls. Then I estimate fractional response model to assess how disability status is associated with different sources of income.

The structure of the study is outlined as follows: the second section delineates the data and methodology, the third section presents the results, and the fourth section provides the conclusion.

2. Data and Methodology

I use data from panel survey of income and living conditions (SILC) for the years 2018 and 2021 by Turkish Statistical Institute (TUIK). Within the scope of its harmonization with the European Union (EU), TUIK has implemented the “Survey of Income and Living Conditions” in order to reveal the distribution of income among households and individuals in Türkiye. Main aim of the survey is to measure individuals’ living conditions, social exclusion and poverty with the income dimension. The scope encompasses all members of households residing within the borders of the Republic of Türkiye. However, certain populations, such as those in nursing homes, prisons, military barracks, private hospitals, hotels, childcare homes, and the immigrant population, are excluded. The income reference period corresponds to the previous calendar year, the labor reference period is the week preceding the survey and the current date, while the reference period for indicators related to living conditions is the current situation. The sampling method is two-stage cluster sampling. The first sample selection stage was clusters consisting of an average of 100 addresses and was determined by selection proportional to size, taking into account the number of addresses in the cluster. In the second stage, the sample selection was determined as 10 clusters from rural settlements and 10 from urban settlements. The weight coefficients are calculated with the population projections of the relevant year revised according to the Address-Based Population Registration System.

I define disability status in accordance with the World Health Organization's (WHO) definition, which categorizes it as a deficiency or a long-term health condition lasting or expected to last for six months or more, obstructing the individual in their daily activities. Identification of individuals with disabilities in the survey is accomplished through two questions (Gannon, 2009; Kidd et al., 2000; Pagan, 2013). The initial inquiry is, "Do you suffer from any chronic, physical, or mental illness lasting more than 6 months?" If the respondent affirms the first question, they are further asked, "Does this chronic problem limit your daily activities?" The response to this query encompasses three categories: no limitations, limitations to some extent, and severe limitations. Table 1 shows disability definitions. Further, in the matching and fractional outcome response estimation I use disability as a binary variable.

The binary disability indicator takes the value of 1 if an individual is nondisabled and disabled with no limitations in daily activities. Conversely, it is set to 0 if the individual is disabled with some or severe limitations.

Table 1. Disability types and definitions

Disability Types	Definition
Non-disabled	Individuals who does not report any chronic, physical, or mental illness lasting more than 6 months.
Disabled with no limitations	Individuals reports any chronic, physical, or mental illness lasting more than 6 months and also report that they have no limitations in daily activities.
Disabled with some limitations	Individuals reports any chronic, physical, or mental illness lasting more than 6 months and also report that they have limitations to some extent in daily activities.
Disabled with severe limitations	Individuals reports any chronic, physical, or mental illness lasting more than 6 months and also report that they have severe limitations in daily activities.

Income is a continuous variable in the dataset and the reference period is the previous calendar year. I adjust income indicators by consumer price index (CPI) throughout the analyzed period. I categorize individual income into the following categories: i) salary and wage, ii) business income, iii) unemployment benefit, iv) retirement pay, v) disability income and vi) other income. Table 2 shows the definitions of income sources in detail.

Table 2. Income types and definitions

Income Types	Definition
Salary and wage	The annual total net wage, salary and per diem wage earned by the individual within the income reference period.
Business income	The annual total net entrepreneur income earned by the individual within the income reference period.
Unemployment benefit	The annual total unemployment benefits and severance pay received by the individual during the income reference period.
Retirement pays	Total annual retirement income, pension and retirement bonus earned by the individual within the income reference period.
Disability income	Total annual disability, veteran, disability retirement income earned by the individual within the income reference period.
Other income	Total annual scholarship, donation, social aid, widow and orphan pension earned by the individual within the income reference period.

In this study I use age, marital status, educational attainment, and labor force status as demographic and socio-economic controls. Age is a continuous variable in the dataset. Educational attainment is a categorical variable with the following categories: i) illiterate, ii) primary school, iii) secondary school, iv) high school and v) university or higher. Marital status has three categories; i) single, ii) married, iii) separated (includes widowed and divorced). Labor force status is a binary variable which is equal to 1 if the individual is in the labor force and is equal to 0 if he/she is out of the labor force. I use individuals who are aged between 25-64 in 2018 and continue to use the same sample in each year. In this sense, I have same 10565 individuals in each year: 5074 males and 5491 females.

Since objective disability indicators are not available in the data set, disability variable I use in the study may possess selection bias. I consider individuals as the unit of analysis by following (Pu and Syu, 2023). Each disabled individual is matched with a corresponding nondisabled individual according to demographic and socio-economic controls (age, marital status, educational attainment, and labor force status). Thus, I match individuals by ensuring a balanced demographic and socio-economic indicators distribution across all time periods. I match 10642 disabled individuals with 31607 nondisabled counterparts.

I implement propensity weighting with multiple treatments to account for time-varying treatment effects in certain observations. Since each observation in the panel data may receive treatment at different points in time, I identify the treatment and control groups based on the time periods when the treatment is applied. The goal is to have a dataset with one observation per individual. To address this, I introduce indicator variables for both treated individuals and treated periods using the entire panel dataset. The original data set is in long form meaning that every observation has data in multiple rows, with each row representing a distinct time period. Any variables that don't change across time will have the same value in all the rows. Thus, I transform the data into a wide format. Since in the wide form, an observation's responses are in a single row and each response in a separate column, the response values do not repeat in the multiple columns. Then, I format pre-treatment before applying a matching procedure. Subsequently, I merge the details of the matched cases back into the original dataset and drop the cases that are not matched.

After matching the dataset, I consider the link between disability status and individual income composition. Income is the sum of six types of income, and I measure the ratio of each income type in total income. I use fractional response model for panel data suggested by Papke and Wooldridge (2008).

By following Papke and Wooldridge (2008), I presume the availability of a random sample in the cross-section, with T observations denoted as t=1,…..,T, for each random draw i. For cross-sectional observation i and time t, the fractional response variable is y_{it}, $0 < y_{it} < 1$, where zero and one outcomses at the endpoints are allowed. The model is as the following:

$$E(y_{it}|\boldsymbol{x}_{it}, e_{it}) = \Theta(\boldsymbol{x}_{it}\boldsymbol{\beta} + e_{it}), \qquad t = 1 \ldots \ldots, T \tag{1}$$

where $\boldsymbol{x}_{it}$ is the matrix of explanatory variables, e_{it} is the unobserved effect and Θ is the logistic function. Because Θ is strictly monotonic, the elements of $\boldsymbol{\beta}$ give directions of the partial effects (Papke and Wooldridge, 2008).

$$\frac{\partial E(y_{it}|x_{it}, e_i)}{\partial x_{it,j}} = \beta_j\, \Theta(\boldsymbol{x}_{it}\boldsymbol{\beta} + e_i) \tag{2}$$

In the case of discrete changes in one or more of the explanatory variables, the model transforms as follows:

$$\Theta\left(\boldsymbol{x}_{it}^{(1)}\boldsymbol{\beta} + \boldsymbol{e}_i\right) - \Theta\left(\boldsymbol{x}_{it}^{(0)}\boldsymbol{\beta} + \boldsymbol{e}_i\right) \quad [3]$$

where $\boldsymbol{x}_{it}^{(1)}$ and $\boldsymbol{x}_{it}^{(0)}$ are two different values of covariates.

After matching the individuals according to demographic and socio-economic status (age, marital status, education and labor force status), the model becomes:

$$E(y_{it}|\boldsymbol{d}_{it}, \boldsymbol{\varepsilon}_{it}) = \Theta\left(\boldsymbol{d}_{it}^{(1)}\boldsymbol{\beta} + \boldsymbol{\varepsilon}_i\right) - \Theta\left(\boldsymbol{d}_{it}^{(0)}\boldsymbol{\beta} + \boldsymbol{\varepsilon}_i\right) \quad [4]$$

where y_{it} is the proportion of each income type to total income, $\boldsymbol{d}_{it}$ represents the disability status (=1 if disabled, 0 otherwise) which is the treatment and $\boldsymbol{\varepsilon}_i$ is the error term. $\boldsymbol{\beta}$ gives average treatment effect on the treated.

3. Results

Table 3 shows the proportions of different disability types in each time period. Proportion of disabled individuals with some and severe limitations in daily activities is about 25 percent in 2018, 2019 and 2021. However, this ratio falls to 23 percent in 2020. Table 4 lists the sample characteristics with respect to demographic and socio-economic indicators before matching. According to Table 4, the proportion of disabled females is higher than disabled males. The mean value of age for individuals without disabilities is 43.06, whereas it is 50.18 for individuals with disabilities. Another important observation is that disabled individuals have lower educational attainment and lower labor force participation on average when compared to nondisabled counterparts.

Table 3. Disability proportions

	2018	2019	2020	2021
Nondisabled	62.84	61.95	65.41	62.40
Disabled with No Limitations	10.73	11.88	11.24	12.78
Disabled with Some Limitations	20.47	18.91	17.47	18.54
Disabled with Severe Limitations	5.96	7.26	5.88	6.29
Observations	10575	10575	10575	10575

Source: Turkstat Panel SILC, 2018-2021.

Table 4. Sample characteristics

	Nondisabled		Disabled	
	Mean	Standard Deviation	Mean	Standard Deviation
Female	0.48	0.49	0.60	0.48
Age	43.06	10.77	50.18	10.67
Marital Status	0.96	0.39	1.06	0.43
Education	2.03	1.34	1.27	1.16
Labor Force Status	0.62	0.48	0.39	0.48

Source: Turkstat Panel SILC, 2018-2021.

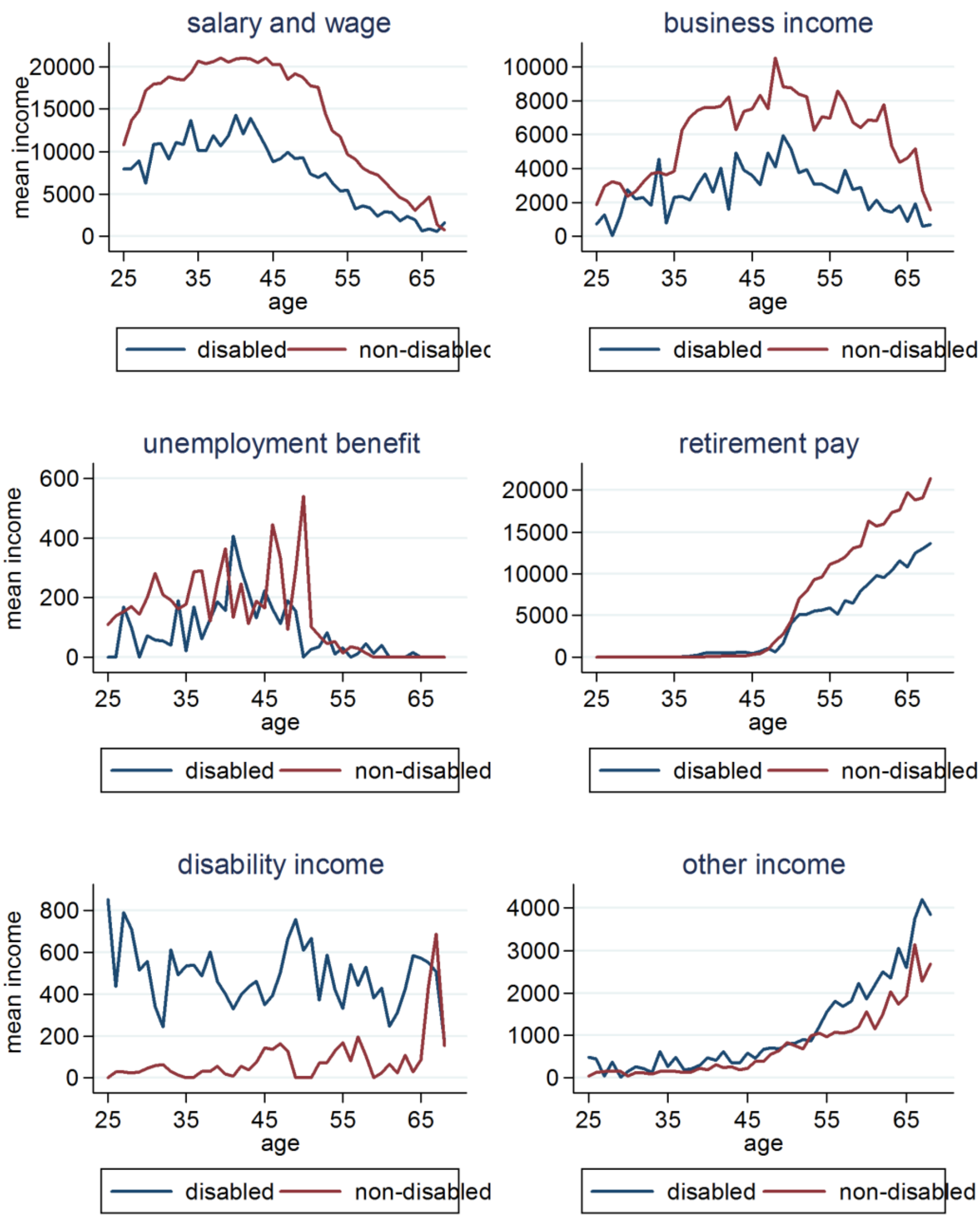
Table 5 presents the unmatched proportions of each income type in total income for nondisabled (non-disabled and disabled with no limitations) and disabled (disabled with some limitations and disabled with severe limitations) individuals respectively. Wage and salary income make up the predominant share of total income for both groups. Nevertheless, the proportion of wage and salary income in relation to total income was notably higher for nondisabled individuals compared to their disabled counterparts. Similarly, the proportions of business income and unemployment benefit are higher for individuals without disabilities. On the other hand, the proportions of retirement pay, disability income and other income to total income for disabled individuals are higher than nondisabled individuals. Figure 1 displays income types according to disability and age. Similar to the results in Table 5, salary and wage and business income are lower on average for individuals with disabilities in every age. On the other hand, according to Figure 1 disability income are higher for individuals for disabilities.

Table 5. Proportion of each income in total income

	Nondisabled		Disabled	
	Mean	Standard Deviation	Mean	Standard Deviation
Salary And Wage	0.64	0.45	0.40	0.46
Business Income	0.17	0.35	0.14	0.33
Unemployment Benefit	0.01	0.08	0.007	0.06
Retirement Pay	0.14	0.35	0.24	0.40
Disability Income	0.002	0.04	0.07	0.26
Other Income	0.036	0.17	0.11	0.30

Source: Turkstat Panel SILC, 2018-2021. Income types are adjusted by CPI.

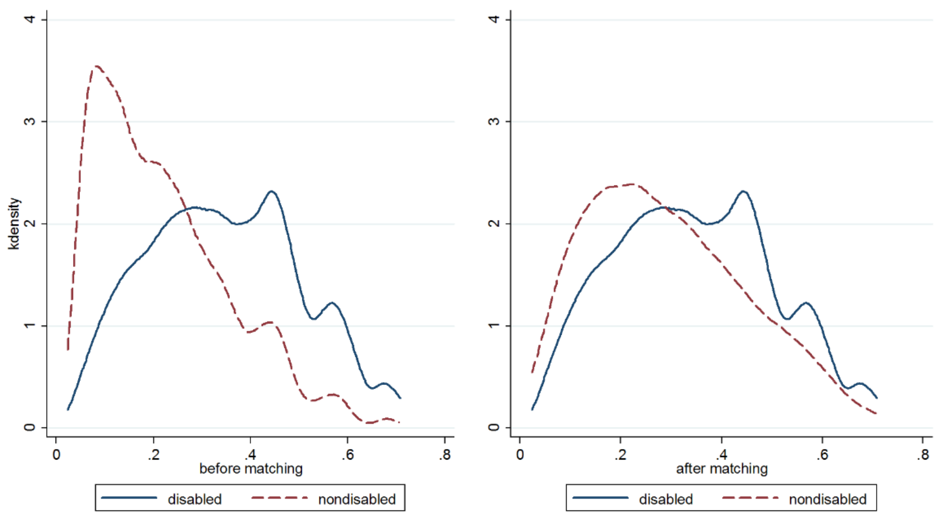
Figure 1. Income types according to disability status and age



Source: Turkstat Panel SILC, 2018-2021.

Next, in order to control sample selection bias of disability status, I apply the matching procedure. My aim here is groups having the same observable and unobservable features for control variables. Figure 2 shows differences between means of control variables (age, marital status, education, labor force status) in the unmatched and matched samples. The left panel of Figure 2 illustrates the distribution of covariates before the matching process, while the right panel depicts the distribution of covariates after the matching. The convergence of propensity scores in Figure 2 following the matching process indicates the effective functioning of the matching procedure. Moreover, Table 6 shows mean values of the control variables after the matching. Insignificant P-values in Table 6 indicates that there are no significant differences between control and treatment groups. The results evidently illustrate notable differences among the control variables before the matching process, and the matching procedure successfully eliminates these significant differences.

Figure 2. Matching graphs



Source: Turkstat Panel SILC, 2018-2021.

Table 6. Mean values of control variables after matching

	Mean		T-Test	
	Treated	Control	T-Stat	P-Value
Age	50.281	50.177	0.02	0.981
Age Square	2632	2631.4	0.04	0.964
Primary School	0.463	0.455	-0.23	0.815
Secondary School	0.104	0.102	0.11	0.910
High School	0.107	0.104	0.02	0.982
University	0.712	0.698	0.24	0.809

Married	0.806	0.811	-0.38	0.702
Separated	0.124	0.129	-0.20	0.838
Labor Force Status	0.390	0.388	0.11	0.911

Source: Turkstat Panel SILC, 2018-2021.

Then, I estimate fractional logit models to reveal the association between disability and the proportion of each income type in total income. Table 7 lists average treatment effect on the treated for the matched sample. In column 1 the dependent variable is proportion of salary and wage income to total income, in column 2 the dependent variable is the proportion of business income to total income and so forth. According to Table 7, treatment effect is significant and negative for individuals with disabilities when the dependent variables are proportion of salary and wage and retirement pay. Proportion of salary and wage and retirement pay decreases by 0.017 and 0.004 respectively when an individual is disabled. Conversely, proportion of disability income increases by 0.004 when an individual is disabled. However, the coefficients are insignificant when the dependent variables are the proportions of business income, unemployment effect and other income. These findings may imply that people with disabilities might offset income loss in specific categories by pursuing alternative sources of income. The income composition for individuals with disabilities undergoes worthy changes as a result.

Table 7. Fractional outcome response model results of the matched model

	(1) Salary and wage	(2) Business income	(3) Unemployment benefit	(4) Retirement pay	(5) Disability income	(6) Other income
ATT of disabled	-0.017***	-0.004	-0.001	-0.004***	0.004***	0.0001
	(0.007)	(0.05)	(0.001)	(0.0009)	(0.0005)	(0.007)

Source: Turkstat Panel SILC,2018-2021. Sample weights applied. *Significant at 10% level. **Significant at 5% level. Heteroscedasticity consistent standard errors are in parenthesis.

4. Conclusion

Individuals with disabilities encounter limited job opportunities, frequently ending in lower-paying jobs, facing elevated medical costs, and ultimately enduring reduced economic well-being. Although literature analyzes the effect of disability on total or wage income, studies examining the relationship between disability and income composition is limited. In this sense, my main aim in this study is to present how income composition differs for individuals with and without disabilities. I use panel of SILC by Turkstat for the years 2018 and 2021. In order to solve the potential selection bias in subjective disability status, I match disabled individuals with nondisabled counterparts according to demographic and socio-economic controls. After matching the sample successfully, findings show that income composition significantly differs among individuals with and without disabilities. Results also imply that people with disabilities may offset income losses in specific categories by pursuing alternative sources of income which is in line with (Pu and Syu, 2023). As a result, public policies should be developed with the objective of ensuring the sustainability of income sources for individuals with disabilities.

This study has some limitations. First, the time span is short. If longer years were available in the dataset, it would be possible to observe the same individuals for longer time periods and how income composition changes through time after an individual becomes disabled. In this sense, results would have implied sustainable policy designs for disabled individuals for the medium and long run. Second, disability and income indicators are self-reported which means that measurement errors are possible. For instance, individuals who are out of labor force may have a tendency to over report their disability status. Third, the study's findings can only be interpreted as associations rather than causations, given the potential endogeneity between disability status and income. Due to data limitations, correcting for potential endogeneity is not possible for this study.

References

Ali, M., Schur, L., & Blanck, P. (2011). What types of jobs do people with disabilities want?. Journal of occupational rehabilitation, 21, 199-210.

Baldwin, M. L., & Choe, C. (2014). Re-examining the models used to estimate disability-related wage discrimination. Applied Economics, 46(12), 1393-1408.

Baldwin, M., & Johnson, W. G. (1994). Labor market discrimination against men with disabilities. Journal of Human Resources, 1-19.

Brucker, D. L., Mitra, S., Chaitoo, N., & Mauro, J. (2015). More likely to be poor whatever the measure: Working-age persons with disabilities in the United States. Social Science Quarterly, 96(1), 273-296.

Duzgun Oncel, B., & Karaoglan, D. (2020). Disability and labour force participation in a developing country: evidence from Turkish males. Global Business and Economics Review, 22(3), 270-288.

Gannon, B. (2009). The influence of economic incentives on reported disability status. Health Economics, 18(7), 743-759.

Haveman, R., & Wolfe, B. (1990). The economic well-being of the disabled: 1962-84. Journal of Human Resources, 32-54.

Jajtner, K. M., Mitra, S., Fountain, C., & Nichols, A. (2020). Rising income inequality through a disability lens: trends in the United States 1981–2018. Social indicators research, 151, 81-114.

Kidd, M. P., Sloane, P. J., & Ferko, I. (2000). Disability and the labour market: an analysis of British males. Journal of health economics, 19(6), 961-981.

Lindeboom, M., Llena-Nozal, A., & van der Klaauw, B. (2016). Health shocks, disability and work. Labour Economics, 43, 186-200.

Meyer, B. D., & Mok, W. K. (2019). Disability, earnings, income and consumption. Journal of Public Economics, 171, 51-69.

Mitra, S., Posarac, A., & Vick, B. (2013). Disability and poverty in developing countries: a multidimensional study. World Development, 41, 1-18.

Pagán, R. (2013). Time allocation of disabled individuals. Social Science & Medicine, 84, 80-93.

Papke, L. E., & Wooldridge, J. M. (2008). Panel data methods for fractional response variables with an application to test pass rates. Journal of econometrics, 145(1-2), 121-133.

Pu, C., & Syu, H. F. (2023). Effects of disability on income and income composition. *Plos one*, *18*(5), e0286462.

Rice, D. P., & LaPlante, M. P. (1992). Medical expenditures for disability and disabling comorbidity. *American journal of public health*, *82*(5), 739-741.

SILC (2021), Survey of Income and Living Condition, 2018-2021, Turkish Statistical Institute (TURKSTAT).

Schuring, M., Robroek, S. J., Otten, F. W., Arts, C. H., & Burdorf, A. (2013). The effect of ill health and socioeconomic status on labor force exit and re-employment: a prospective study with ten years follow-up in the Netherlands. *Scandinavian journal of work, environment & health*, 134-143.

Vornholt, K., Villotti, P., Muschalla, B., Bauer, J., Colella, A., Zijlstra, F., ... & Corbière, M. (2018). Disability and employment–overview and highlights. *European journal of work and organizational psychology*, *27*(1), 40-55.

DISCLOSURE STATEMENTS:
Research and Publication Ethics Statement: This study has been prepared in accordance with the rules of scientific research and publication ethics.
Contribution rates of the authors: First author (100%).
Conflicts of Interest: Author states that there is no conflict of interest.
Ethics Committee Approval: Ethics committee approval was not obtained because human subjects were not used in the research described in the paper.