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Abstract

This paper studies the impact on personal income resulting from the onset of disability. Using the longitudinal *Survey of Health Ageing and Retirement in Europe*, we compare the income trajectories of individuals who become disabled and of those remaining in healthy conditions during the same period. Assuming that a disability shock may result in a loss of global income due to the negative effect on wages being much higher than the positive effect on compensation incomes, we strive to identify a causal impact by combining a difference-in-differences approach with kernel propensity score matching, thus allowing us to take into account observable and time-invariant unobservable individual characteristics. We find a clear heterogeneity of effect according to the level of disability. Although the Global Activity Limitation Indicator shows no effect on personal income, our findings suggest a negative impact on personal income when the shock of disability appears to be strong, as in the case of a more severe disability.

Keywords

Disability, older workers, personal income, compensation incomes, wages, difference-in-differences, propensity score matching, panel data model

JEL classifications

C31, C33, D31, J14, J31, J33

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1. Introduction

The interaction between health and labour market outcomes is currently an important issue in Europe. Indeed, population ageing and working conditions have influenced European policy reforms such as increasing full retirement ages, quotas for disabled workers, and preretirement for unhealthy people.

According to Eurostat, precisely 25% of the EU population has reported long-standing limitations in 2018 (see Figure A1-A in Appendix 1), which pose several disadvantages to this population not only in real life but also regarding labour market outcomes. This amount is increasing until 31% of the population from 55 to 64 years (see Figure A1-B in Appendix 1). While the 2011 employment rate for the European non-disabled population aged 15–64 is around 67%, this rate reaches only about 47.3% for the disabled population. Differences in the employment rates of these two populations range from 2.4 percentage points (pp) favouring non-disabled people in Luxembourg to 37.4 pp in Hungary and the Netherlands (see Figure A2 in Appendix 1). The literature generally underlines the negative impact of the onset of disability on different labour market outcomes, such as labour force participation (Mussida, & Sciulli, 2016; Silva, & Vall-Castelló, 2017), working hours (Müller, & Boes, 2020), and exit from the labour market (Wubulihasimu, Brouwer, & van Baal, 2015).

Income has also been considered to be a labour market outcome (Cervini-Plá, Silva, & Castelló, 2016; Dano, 2005; García-Gómez, van Kippersluis, O'Donnell, & van Doorslaer, 2013; Lechner, & Vazquez-Alvarez, 2011). Regarding both components of income (wages and compensation income), disability could have twice the influence and may lead to both mechanisms working in opposite directions. The first assumes that disability may result in a decrease in wage level. While bad health can prevent entry into the labour market due to limitations that are not compatible with some jobs, the disutility of work may also be generated by various disincentives to work, such as the arduousness of the disability or the productivity gap between disabled and healthy individuals (Silva, & Vall-Castelló, 2017), among others. Disabled workers can have a lower productivity and thus their income (based on marginal productivity) is weaker than the one of healthy population (Malo, & Pagán, 2014). In both cases, wages seem to be negatively correlated with disability. The second mechanism refers to replacement incomes. Most European countries have implemented social protection systems to prevent individuals from different social risks: unemployment; sickness and health care; disability; housing; old age; loss of spouse or parent; parental responsibilities; and social exclusion. Eurostat reports that, in 2017, European countries dedicated 7.5% of total social benefits to disability benefits, representing around 2.0% of their GDP (see Appendix 2). This proportion of GDP devoted to disability benefits ranges from 0.5% in Malta to 5.0% in Denmark. Therefore, if an individual suffers from a disability, he or she is eligible for a pension and will thus have a higher income through this compensation. Between these two mechanisms, it is difficult to know which one will be higher.

Our objective is to provide new evidence for the impact that the onset of disability can have on personal income, specifically by distinguishing between these two mechanisms. Most of the existing literature is based on the impact of disability on income level. Few decompose the income by sources, and most of them highlight the fact that public transfer incomes (e.g., disability benefits) compensate for income losses (Cervini-Plá et al., 2016; Dano, 2005; Lechner, & Vazquez-Alvarez, 2011). In order to examine this impact of disability on personal income, we can rely on health indicators that define disability in various ways (see Section 2.2). For example, Cervini-Plá et al. (2016) and Dano (2005) use accidents and road injuries to define disability, while Cervini-Plá and Vall Castelló (2018) and Lechner and Vazquez-Alvarez (2011) use an administrative definition of disability. These differences can lead to distinct results and population sizes, as well as to different issues in terms of econometrics (self-declaration biases and measurement errors). Thus, we first define disability from a general indicator of activity limitations (Global Activity Limitation Indicator) whatever the prevalence of long–term health problems and hence we combine disability with chronic/long–term health problems. . We assume that the second one refers to more severe disability.

Another issue concerns reverse causality. From a methodological point of view, the interaction between disability and income can be understood as a two-way causal relationship (Barnay, 2016; Cai, 2010; Lindeboom, & Kerkhofs, 2009). On the one hand, a high income plays a protective role for disability by allowing one to invest in health capital (through health care), thanks to having access to private health insurance or the out-of-pockets payments. On the other hand, disability can depreciate wage levels due to loss of employability and loss of productivity while also generating replacement income that can partially offset disability's adverse consequences on well-being. In a labour market model, disability may indeed be endogenous in both a structural and a statistical sense. Structurally, disability and labour market outcomes are determined simultaneously and the causality is potentially bidirectional. Statistically, unobserved heterogeneity may result from some confounding factors that can simultaneously influence both disability and socio-economic statuses such as a present-biased preference or the degree of aversion to risk. In order to raise this methodological issue, we perform panel data analysis by comparing individuals who become disabled and those who remain healthy during the same period.

Our first contribution is to disentangle changes in personal income (sum of wages and compensation incomes) following the onset of a disability. Our second contribution lies in dealing with this issue at the European level, which enables us to compare countries that are more or less generous regarding their social protection systems. Our study should provide additional evidence on changes in income due to disability, since it covers several European countries and could highlight some details regarding the role played by compensation earnings. To obtain better knowledge of the complex interactions between disability and work, it is necessary to promote occupational health risk prevention *ex ante* while also maintaining individual wealth levels by implementing compensation policies *ex post*.

We study individuals aged 50 and over from twelve countries, based on the *Survey of Health, Ageing and Retirement in Europe* (SHARE). This population is particularly concerned by disability as 31% of the 55-64 years population reports long-standing limitations (see Figure A1-B in Appendix 1).

In terms of methodology, we first perform propensity score kernel matching by building two groups (disabled and non-disabled individuals). We also implement a weighted difference-in-differences model to control for time-invariant unobserved heterogeneity. . In addition, we use both definition of disability shock, Our findings show that the onset of disability leads to a negative impact on personal income only if the disability is severe enough (onset of disability and chronic problems).

This paper is organized as follows. The next section surveys the literature on disability definitions and measures and its link with income. Section 3 concerns the database, variables, and sample selection. The empirical strategy is introduced in Section 4, and our results are reported in Section 5. We perform sensitive analyses on gender heterogeneity and social protection systems in Section 6. Finally, we discuss our results and conclude this paper in Section 7.

2. Background

2.1 Defining and measuring disability

Disability is a wide-ranging concept that refers to either physical, mental, or cognitive impairments arising from a congenital disorder, accident, disease, or the ageing process. In 2006, the Convention on the Rights of Persons with Disabilities, adopted by the United States (UN), defines disability as follows: "Persons with disabilities include those who have long-term physical, mental, intellectual, or sensory impairments which in interaction with various barriers may hinder their full and effective participation in society on an equal basis with others" (UN, 2006).

Disability is a long process resulting as the interaction between individual's health and various factors among which gender, age, habits, work (World Health Organization, 2001). Disability can be seen a the result of the progressive health deterioration, an impairment or a non-integration of the individual in the society (World Health Organization, 2001).

While most countries have adopted the 2006 UN definition, differences still remain. In Europe alone, for example, countries have different legislations, with some like Germany and Spain having created a legal framework while others like the Nordic countries refuse to define disability in order to avoid discrimination. Regarding the former countries, disability is clearly defined in the law (see, for example, the German social code of July 2001 or Spain's law no. 13/1982 on the Social Integration of Disabled Persons [LISMI][1]). In 2010, all European Union members except for Finland, Ireland, and Netherlands chose to adopt the UN's definition (European Parliament, Directorate General for Parliamentary Research Services, 2017).Two types of measures can be used to assess the nature of disability: self-reported and objective assessments.

The most common self-reported indicators of disability are, on the one hand Activity of Daily Living (ADL) and instrumental ADL (iADL), and, on the other hand, the Global Activity Limitation Indicator (GALI). ADL and iADL are thought to be relatively more indicative of irreversible impairments and more specific to age-related dependency (Cambois, Blachier, & Robine, 2013; Millán-Calenti et al., 2010) rather than to all-cause disability. GALI, which measures functional disability, is one of the most used and standardized indicators for national statistics and provides the basis for measuring disability-free life expectancy in terms of Healthy Life Years. Recently, several studies have assessed the validity of GALI for measuring disability compared to other health measures, like the ADL indicator, morbidity indicator, maximum grip strength, and others. The literature underlines that GALI sums up participation restrictions, thus making it a globally valid and reliable measure (Van Oyen, Bogaert, Yokota, & Berger 2018). Moreover, GALI correctly reports limitations captured by both subjective and objective measures that is consistent across European countries in SHARE (Jagger et al., 2010). What is more, indicators of long-term health problems can be combined with some of these previous indicators to measure disability. Indeed, even if diseases do not always lead to disability, the medical model defines disability as a direct consequence of diseases or other health problems (World Health Organization, 2001). Furthermore, disability results from the interaction between health conditions and personal and/or environmental factors (World Health Organization, 2001). Finally, this measure was already used in the literature. Kidd and his co-authors (2000) have studied the impact of disability (defined as long-term health problems) on earnings and labour force participation (Kidd, Sloane, & Ferko, 2000).

[1] For all disability laws and acts by country, see https://www.un.org/development/desa/disabilities/disability-laws-and-acts-by-country-area.html

The objective indicators forming the second group are often used to avoid the self-declaration bias and the interpersonal comparison of self-perception problem of self-reported indicators by aiming to have a more precise measure that is less affected by respondents' feelings. Physical health measures can be used, such as grip strength and the ability to get up from a chair. Objective measures can also be collected through administrative data in order to identify individuals receiving income from disability insurance. According to Bound, both types of measures present pros and cons while also leading to different biases (Bound, 1991). Consequently, both self-reported and objective measures lead to problems in terms of econometrics issues. However, for several reasons, we consider a mix of GALI and long-term illness to be the more appropriate indicators here. First, when data are derived from different countries, both indicators allow comparisons and indeed correspond to the answers to harmonized questions. Second, the UN definition accounts for all types of disability (physical, mental, etc.), which can be captured by long-term health problems, and it relates them to barriers and/or factors that limit individuals, which in turn can be captured by GALI.

2.2 Relationship between disability and income

Most studies use a clear-cut measure of disability, like administrative recognition (Angelov, & Eliason, 2016; Bhattacharya, Neuhauser, Reville, & Seabury, 2010; Cervini-Plá, & Vall Castelló, 2018; Kidd et al., 2000; Lechner, & Vazquez-Alvarez, 2011) or self-reported limitations in daily activities (Mete, Ni, & Scott, 2008; Mitra, Findley, & Sambamoorthi, 2009). As briefly explained before, self-reported measures of disability can be impacted by respondents' feelings and knowledge, among other subjective criteria. Thus, individuals can overestimate their response and, in this case, estimations can be biased. While several studies have examined this issue without arriving at any clear consensus, most find no evidence that individuals over-report disability. For example, Benítez-Silva and his co-authors (2004) use the Health and Retirement Survey (HRS) with a particular focus on disability to assess whether self-reported health measures are biased. They use the Bierens test, Ordinary Least Squares test, and several others to show that self-reported disability reports the same health status as the Social Security Administration (SSA) when deciding to grant disability insurance (Benítez-Silva, Buchinsky, Man Chan, Cheidvasser, & Rust, 2004). In Ireland, Gannon (2009) uses data from the Living in Ireland Survey and a generalized ordered response model to show that limitations in daily activities are over-reported. Nonetheless, this measurement error decreases when the author takes into account unobserved heterogeneity (Gannon, 2009). These papers reinforce our previous conclusion that self-reported disability is no more likely than administrative data to lead to more econometrics issues.

Next, we find it interesting to differentiate the results according to the nature of the disability. For example, Angelov and Eliason (2016) compare disabled and non-disabled people to study the impact of job losses on earnings and incomes (unemployment insurance, sickness insurance, disability insurance, and means-tested social assistance). By estimating a fixed effect estimator for a matched sample, they prove that the differential in earnings between disabled and non-disabled individuals one year prior to job loss varies according to disability level. For example, compared to individuals in good health, individuals with a mental disability earned less than those with a motor disability. More specifically, individuals in good health earned about 8,000€ more than those with a mental disability in the year before the onset of disability, while they earned about 7,300€ more than those with a motor disability (Angelov, & Eliason, 2016). Bhattacharya and his co-authors (2010) highlight another result: losses in earnings correspond to which part of the body is injured. Derived from California administrative data, their results suggest that psychiatric and hearing impairments lead to higher earnings losses than back injuries, which is the reference category (Bhattacharya et al., 2010). Finally, only a few studies investigate the impact relative to the degree of disability. Charles (2003) ascribes this phenomenon to the difficulty in defining disability severity because it can be multidimensional (Charles, 2003).

Even though disability shocks can be defined in various ways, the literature generally underlines the negative impact of a disability shock on income, especially on earnings (Angelov, & Eliason, 2016; Bhattacharya et al., 2010; Cervini-Plá, & Vall Castelló, 2018; Kidd et al., 2000). For example, Kidd and his co-authors (2000) use a human capital-based model of earnings determination to model labour force participation decisions, based on a sample of 16–64-year-old males derived from the British Labour Survey. Finally, by defining disability as a long-term health problem, they find that disabled individuals earn 14.1% less, on average, than the non-disabled.

This negative impact of disability on earnings emerges even before the onset of disability (Angelov, & Eliason, 2016; Cervini-Plá, & Vall Castelló, 2018). In fact, Cervini-Plá and Vall Castelló (2018) show that individuals with disability benefits earn less than those who are in good health, and these authors go further by highlighting differences before entry into the disability benefits system. Their matching and difference in differences find that, four years before entering the disability benefits system, disabled individuals earn significantly less than their counterparts without disability; and one year before entry into this system, the wage gap between these two groups represents 8.3% of the average wage of those who will become disabled. Finally, regarding global income and the combination of wages and replacement incomes, only a few papers examine both dimensions, with most of them finding a non-significant impact.

For example, Lechner and Vazquez-Alvarez (2011) use the German Socio-Economic Panel Study to quantify the loss in productivity and the evolution in labour market outcomes for individuals who had become disabled in West Germany between 1984 and 2002. Using matching methods, these authors underline that disability has a non-significant result on income. They conclude that the German social security system has been successful in mitigating the negative economic impacts of disability (Lechner, & Vazquez-Alvarez, 2011).

Other authors use different definitions of disability to reach the same conclusions. Some studies focus on unanticipated events as proxies for disability shocks, such as accidents (Cervini-Plá et al., 2016; Dano, 2005) or hospital admissions (García-Gómez et al., 2013; Lundborg, Nilsson, & Vikström, 2011). In their view, the unanticipated nature of the event ensures the true exogeneity of the shock. These studies are of particular interest to us, as their empirical strategies are similar to our intentions and because they use diversified labour market outcomes, especially various income sources. For example, by using claims data from the Spanish Social Security Administration and combining matching algorithms with difference in differences, Cervini-Plá and colleagues (2016) have estimated their theoretical wage gap model. Their results suggest that, after one year, a disability shock leads to an average monthly salary decrease of between 19% and 22% (depending on the matching used); although this decrease is essentially compensated by the disability benefits received (Cervini-Plá et al., 2016). Dano (2005) investigates the causal effect of road injuries in Denmark on disposable income, earnings, employment status, and public transfers. To study this, she implements a difference-in-differences matching method on a panel that gathers together different administrative registers. Her main finding is that public transfers compensate injured individuals for their losses in disposable income and in earnings (Dano, 2005).

3 Database, variables, and sample selection

3.1 Database

We use SHARE, a European panel survey that focuses on people aged at least 50 years old and their partners, regardless of their age (Börsch-Supan et al., 2013). Carried out every two years, this survey began in 2004 with 30,434 individuals participating from 12 European countries: Austria, Belgium, Czech Republic, Denmark, Estonia, France, Germany, Italy, Slovenia, Spain, Sweden, and Switzerland. It currently includes 27 European countries and Israel, with 139,556 individuals having been interviewed over seven waves (2004; 2006; 2008; 2011; 2013; 2015 and 2017). It covers various topics in face-to-face interviews: health; social and family networks; employment and pensions; cognition; health care; and other key areas of life.

3.1.1. Personal income

In SHARE, we have a comprehensive measure of different income types that are measured at the household and individual level, among which we find: employment and self-employment earnings; unemployment benefits; pensions; and property incomes; among others. Such information allows producing both an accurate estimate of total income and a decomposition of main sources of income. Consequently, personal income is defined as the sum of earnings from employment; earnings from self-employment; pension plans; occupational pensions; disability and sickness pension benefits; unemployment benefits; and social wages. Because of high rates of missing values, SHARE provides imputations for all these variables. We briefly describe the imputation methodology in Appendix 3.

3.1.2. Measuring disability shock through GALI and long-term health problems

The independent variable of interest in this paper is disability. We are interested in persons who declare being newly limited in the typical activities performed by people. Hence, we consider all dimension of disability, i.e., mental, physical, and cognitive limitations.

As mentioned earlier, we can measure disability through different indicators. While SHARE provides several disability measures that are objective (grip strength, chair stand test, walking speed, expiratory lung force), administrative (disability pension benefit), and self-reported (ADL, iADL, GALI), we retain the GALI for our main indicator of disability. GALI expresses the answer to a single question *"for at least the past six months, to what extent have you been limited because of a health problem in activities people usually do?"*. The three different levels of answer are the following *"severely limited", "limited, but not severely", "not limited"*. In our econometric framework, we have recoded the GALI as a binary variable that takes the value 1 if the individual declares being limited, whether severely or not. Any further mention of GALI in this paper will subsequently be in reference to this binary variable.

This GALI choice is made for several reasons. First, objective measures are related exclusively to physical limitations and consequently do not capture all types of disability. Moreover, most of these are not available in all waves of SHARE and therefore cannot be compared in a longitudinal perspective. Finally, regarding the administrative measures of disability pensions and benefits, it is difficult to achieve comparability across countries and waves.

However, as mentioned before, the GALI may be subject to self-declaration biases, by which it lacks the strength to properly identify disabled individuals. Taking this into account, we also add a second step of combining the GALI with an indicator of long-term illness. This indicator is the answer to the following question: *"Some people suffer from chronic or long-term health problems. By long-term we mean it has troubled you over a period of time or is likely to affect you over a period of time. Do you have any long-term health problems, illness, disability or infirmity? (Including mental health problems)"*. This indicator allows us to capture severe disability.

3.2 Sample selection

3.2.1. (Non-severe) disability sample

We do not use all waves of SHARE. First, we have dropped the Waves 3 and 7[2]. Moreover, in order to have a homogeneous sample and be able to compare individuals, we keep only three consecutive waves of SHARE. Bearing in mind that this study's goal is to see how the onset of disability affects personal income, we thus need at least one observation before and one after the disability onset in order to compare the situation before and after. Because we have dropped Wave 3, and because the period between Wave 2 (2006/07) and Wave 4 (2011) is longer than the period between two successive waves, we do not consider the first two waves. Consequently, we focus only on Waves 4 (2011), 5 (2013), and 6 (2015), selecting all individuals who participated in these three waves. Ultimately, we keep 30,747 individuals. We also apply the following selection criteria to identify, to the greatest extent possible, a disability shock as exogenous: being employed or self-employed in the first wave (2011); and being without activity limitation in this same wave. These two criteria select individuals who are initially healthy enough to work and without disability. With the employed/self-employed condition, we target younger people with earnings (from employment or self-employment). Moreover, we select only individuals who answered the routine questionnaire in the last wave (2015).[3] We do not consider individuals with a missing GALI in 2013 or 2015,[4] and we also exclude individuals who, at one point (at least), had a personal income equal to 0. Once having made this selection, we arrive at 5,314 individuals from 12 different European countries. Finally, we separate this sample into two groups: treatment and control. The idea is to identify the differences in situations where individuals experience a disability shock (i.e., treated individuals) and those where no such shock has been modelled (i.e., the control group). Stated simply, the treatment group covers individuals who become disabled while the control group gathers together individuals with no disability shock. Becoming disabled is defined as

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[2] These waves are based on the individual's past life events questionnaire called SHARELIFE. They do not contain routine follow up information.

[3] In addition to the main questionnaire and retrospective survey SHARELIFE, an end-of-life interview was developed for respondents who died between two waves; and it was carried out after the individual's death. A previously designated proxy for the individual was interviewed, and this person answered end-of-life questions about the individual (death, health care, estate, etc.). Here, we want only individuals who were alive during the three studied waves.

[4] At this stage "refusal" and "don't know' modalities are considered as missing.

having declared in 2013 and 2015 limitations according to the GALI criteria. Experiencing a disability shock means declaring “GALI > 0” in Waves 5 and 6. The treatment group contains 464 individuals who became disabled in 2013 and remained so in 2015, while the control group contains 3,645 individuals declaring no limitations, neither in 2013 and 2015 nor during the follow-up. Consequently, we do not take into account individuals reporting a disability only in 2013 and those reporting a disability only in 2015.

Figure A5 the Appendix 4 summarizes all these selection criteria.

3.2.2. Severe disability sample

In order to capture more severe disability, we define disability with an indicator combining GALI and the prevalence of long-term disease (see Section 3.2.2 for more details). Consequently, individuals should have neither long-term health problems nor any activity limitations in 2011, and they must be employed/self-employed. Experiencing a severe disability shock means declaring “GALI > 0” and suffering from long-term illness in Waves 5 and 6.

Ultimately, the subgroup contains 163 treated individuals who declare activity limitations and long-term health problems in 2013 and 2015, which referred to severe disability. The control group gathers together 2,391 individuals who are in good health (i.e., no activity limitations, no long-term health problems) during the entire follow-up period: 2011, 2013 and 2015.

Figure A6 in the Appendix 4 summarizes all these selection criteria.

4 Empirical strategy

We estimate the change in individual income for people who become disabled. In order to estimate the causal impact of disability on personal income, we combine a propensity score matching with a difference-in-differences approach.

Formally, we rely on the causal model of Rubin (Rubin, 1974) and thus consider the disability shock as a treatment. If we denote T as the treatment variable, we have $T = 1$ if the individual suffers a disability shock and zero otherwise.

For the outcome variable, we can proceed as follows. Let I_i^1 and I_i^0 be the income of individual i when, respectively, $T = 1$ and $T = 0$. Consequently, we do not observe I_i^1 for control individuals, and I_i^0 is not observed for disabled individuals. Nonetheless, our aim is to calculate the average treatment effect on the treated (ATET), defined as follows:

$$\Delta^{ATET} = E\left(I_i^1 - I_i^0 \mid T = 1\right) = E\left(I_i^1 \mid X, T = 1\right) - E\left(I_i^0 \mid X, T = 1\right)$$

with X being the set of observed characteristics of the individuals.

We cannot directly calculate ATET from the data. Indeed, it represents the difference in average incomes between the disabled and the non-disabled who becomes disabled. Thus, in order to obtain this mean income that is unperceived in the data, we construct a counterfactual group that becomes our control group. Nonetheless, if we simply compared treated and non-treated groups, our estimation may result in a potential bias related to differences in the compositions of both groups.

This is why, in order to control for those differences, we rely on a propensity score matching (PSM) model. The main idea of this method is to estimate, for each individual, the probability of being treated, based on a logit model. We use the following set of observed individual characteristics X: age, gender, education level, being in a couple, having at least one child, being in the private or public sector, and being self-employed. The negative impact of disability on labour market outcomes is amplified by being older, being a female, and being less educated (Lindeboom, Llena-Nozal, & van der Klaauw, 2016). Moreover, these characteristics increase the probability of being in bad health (Alexandre et al., 2012). Regarding the private/public sector, Barnay and his co-authors (2015) have highlighted a stronger negative impact of disability on private employment than on public employment. Public employment protects individuals from employment losses (Barnay, Duguet, Le Clainche, Narcy, & Videau, 2015).

In order to control for selection effect, we carry out PSM at baseline before the onset of disability, i.e., in Wave 4 (2011). Then, we match future disabled and non-disabled by using a kernel matching algorithm with a bandwidth equal to 0.01, by which all control individuals are used to construct a counterfactual (Caliendo, & Kopeinig, 2008). The goal here is to determine, by means of the Epanechnikov kernel function, the distance between the controls and their matched treated counterparts. Then, weights are given to the control persons according to this distance and to the number of times they are used as a counterfactual. The disabled individuals have a weight equal to one.

The main advantage of PSM is that it does not require making a structural hypothesis on the specification of the model because kernel matching is a non-parametric method (Härdle, & Linton, 1994). Moreover, this first step of estimating the propensity score enables us to explain what characteristics influence the probability of experiencing a disability shock.

However, one drawback is that PSM relies on the conditional independence assumption that there is no unobservable characteristics which can explain the difference in income between disabled and non-disabled individuals: $(I_i^1, I_i^0) \perp T|X$. If this assumption does not hold, the impact of disability onset on income is not causal. In other words, it implies that the income of the non-disabled group perfectly reflects the income perceived by the disabled if they do not experience a disability shock, an assumption that could be too strong. To control for unobserved characteristics, we implement difference in differences (DiD) with only individuals who are on the common support of the PSM.[5] We perform the DiD using 2011 and 2015 data, and estimate the following fixed effects panel model:

$$\begin{aligned}\ln(personal\ income)_{it} = \ & \beta_0 + \beta_1 * treatment\ group_i \\ & + \beta_2 * after\ treatment_t \\ & + \beta_3 * (treatment\ group * after\ treatment)_{it} \\ & + \beta_4 * job\_situation_{it} + \delta_i + u_{it}\end{aligned}$$

where $job\_situation_{it}$ is a four-category variable: employed or self-employed, retired, unemployed, and other situation (which groups together permanently sick or disabled individuals, homemakers, etc.); δ_i is a random individual-specific effect (an unobserved time-invariant individual effect); and u_{it} is an error term. In order to smooth the distribution of personal income, we consider the logarithm of this variable.

The variable $job\_situation_{it}$ enables controlling the effect of a change in job situation that can affect our dependent variable. In particular, we differentiate the effect of the onset of disability and that of retirement or unemployment.

Our effect of interest is given by the coefficient β_3, which is equivalent to the differences between these two waves and the two groups of individuals:

$$\begin{aligned}\beta_3 = & [E(I_i\,|X, T = 1, t = 1) - E(I_i\,|X, T = 1, t = 0)] \\ & - [E(I_i\,|X, T = 0, t = 1) - E(I_i\,|X, T = 0, t = 0)]\end{aligned}$$

where t describes the period: $t = 0$ describes the period before the treatment (i.e., 2011 in this study), while $t = 1$ corresponds to after the treatment period (i.e., 2015 in our case).

We implement the abovementioned DiD using the weights obtained by the PSM procedure. The combination of PSM and DiD allows us to account for observed and unobserved time-constant differences. This method is also used in Cervini-Plá et al. (2016) and García-Gómez et al., (2013). The main idea with this method is to attain comparability between treated and non-treated groups with the PSM and then control for unobserved characteristics with DiD.

We remove the conditional independence assumption with DiD. However, DiD relies on the parallel-trend assumption, which assumes that, in absence of treatment, individuals who became

[5] In the treated group, we can have individuals who have a propensity score very close to one or zero. When we match, these individuals are excluded because we cannot find individuals in the other group who are like these. A control individual will not have a propensity score near one and, conversely, a treated one will not have a propensity score very close to zero.

disabled would have the same trend in income as those in the control group. Nonetheless, we can verify this hypothesis more easily than the conditional independence one.

5 Results

5.1 Descriptive statistics

The proportion of newly disabled people in 2013 remaining disabled in 2015 is 11.3%. For severe disability, this rate is about 6.4% (see Table A1 in Appendix 5). At baseline (in 2011), future disabled individuals are definitively different from the non-disabled ones, with the former appearing to be slightly older and less educated. For example, future disabled individuals are 5% more likely than non-disabled individuals to have an education level lower than secondary school. Furthermore, disabled individuals are less often employed in the public sector (−4%). Concerning financial issues, the overall income of persons in the non-disabled group is 40% higher than that of the disabled. The details show the gap to be more pronounced when considering wages, with 50% higher income for non-disabled people (see Table 1). This difference is consistent with the assumption of lost productivity for the disabled, but it also potentially implies a selection effect in employment (lower-paying jobs for the disabled). Regarding severe disability, the conclusions appear to be similar (see Table 2). However, there is no age or sector gap, and we notice a slight difference in marital status. In fact, severely disabled individuals are 7% less likely to be in a couple than their non-disabled counterparts.

TABLE 1: Descriptive statistics of treatment and control groups in Wave 4 – non-severe disability sample

Individual characteristics (measured at baseline)	Disabled individuals N = 464		Non-disabled individuals N = 3,645		*t*-test diff. in means
	Mean	SD	Mean	SD	
Incomes					
Annual personal income	18,055	928	25,638	438	−7,583***
Earnings from employment	13,485	768	20,179	340	−6,695***
Earnings from self-employment	2,672	446	4,031	256	−1,358*
Old age, early retirement, survivor and war pensions	1,237	288	851	88	385
Private occupational pensions	164	67	403	167	−241
Disability/sickness pension and benefits	263	188	31	6	232***
Unemployment benefits and insurance	234	83	136	40	99
Payment from social assistance	0	0	6	3	−6

PSM variables					
Age	57.93	0.29	56.64	0.09	1.29***
Female	0.54	0.02	0.53	0.01	0.02
Education Level					
Lower secondary school	0.24	0.02	0.18	0.01	0.05***
Upper secondary school	0.47	0.02	0.45	0.01	0.01
Higher education	0.29	0.02	0.36	0.01	−0.07***
In couple	0.78	0.02	0.80	0.01	−0.02
One or more children	0.91	0.01	0.90	0.00	0.01
Occupational Sector					
Private sector	0.72	0.02	0.71	0.01	0.01
Public sector	0.11	0.01	0.14	0.01	−0.04**
Self-employment	0.17	0.01	0.15	0.01	0.02

Note: "*t*-test diff. in means" corresponds to the *p*-value of the *t*-test between the disabled and non-disabled individuals. Significance at 1% (***), 5% (**), and 10% (*). All numbers are given to the nearest hundredth (except for incomes).
Population: Individuals employed and without disability in 2011
Source: SHARE; Waves 2011, 2013, 2015

<u>TABLE 2:</u> Descriptive statistics of treatment and control group in Wave 4 – severe disability sample

Individual characteristics (measured at baseline)	Severe disabled individuals N = 163		Non-disabled individuals N = 2,391		*t*-test diff. in means
	Mean	SD	Mean	SD	
Incomes					
Annual personal income	17,976	1,504	26,523	518	−8,547***
Earnings from employment	14,366	1,341	20,719	428	−6,353***
Earnings from self-employment	2,748	702	4,524	335	−1,776
Old age, early retirement, survivor and war pensions	612	188	841	123	−230
Private occupational pensions	0	0	247	59	−247
Disability/sickness pension and benefits	19	18	23	6	−4
Unemployment benefits and insurance	231	111	164	58	67
Payment from social assistance	0	0	4	3	−4
PSM Variables					
Age	56.71	0.42	56.22	0.11	0.49
Female	0.49	0.04	0.52	0.01	−0.03

Education Level					
Lower secondary school	0.24	0.03	0.17	0.01	0.07**
Upper secondary school	0.49	0.04	0.46	0.01	0.03
Higher education	0.27	0.03	0.37	0.01	−0.10**
In couple	0.73	0.03	0.80	0.01	−0.07**
One or more children	0.93	0.02	0.90	0.01	0.02
Occupational Sector					
Private sector	0.73	0.03	0.71	0.01	0.02
Public sector	0.10	0.02	0.14	0.01	−0.04
Self-employment	0.17	0.03	0.16	0.01	0.02

***Note**:* "*t*-test diff. in means" corresponds to the *p*-value of the *t*-test between the severe disabled and non-disabled individuals. Significance at 1% (***), 5% (**), and 10% (*). All numbers are given to the nearest hundredth (except for incomes).
***Population**:* Individuals employed and without disability in 2011
***Source**:* SHARE; Waves 2011, 2013, 2015

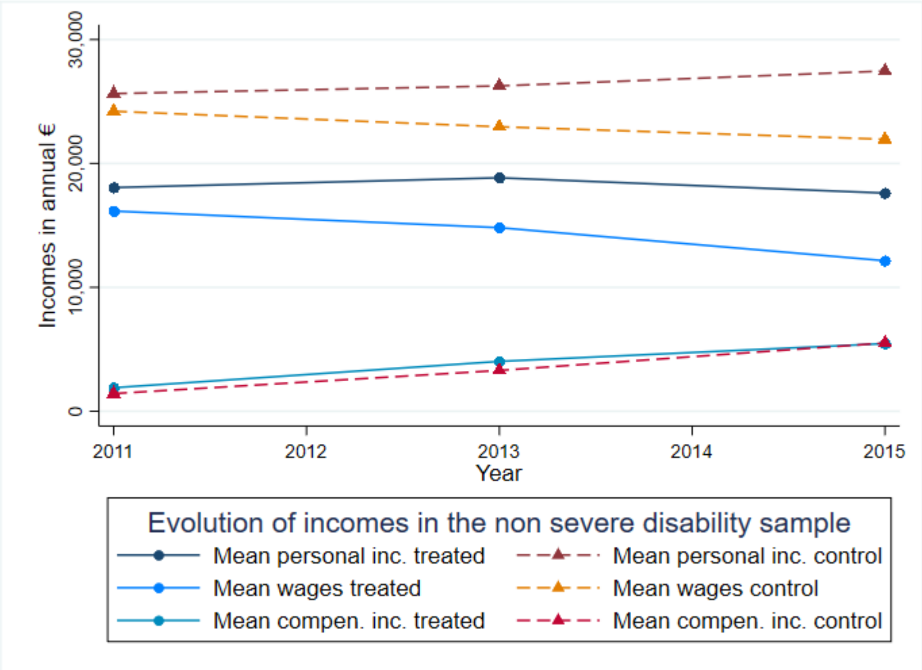
To sum up, those who become disabled later exhibit more frailty than the non-disabled in terms of health and initial socioeconomic conditions at baseline. These disparities seem to prove the non-random nature of the onset of disability. As a result, matching individuals appears to be relevant for making comparable groups. All significant differences in Tables 2 and 3 (the PSM variable parts) are therefore removed by means of propensity score matching.[6] We also perform tests on the bandwidth[7] by running the same regression with bandwidth equal to 0.001 and then to 0.1. Our results do not change.

Regarding incomes, a number of observations can be highlighted. First, we observe that between 2011 and 2015 individuals who became disabled from both samples lose personal income, from about 450€ for the non-severe disability sample to about 1,500€ for those with severe disability. This represents a decline of between 2.5% and 8.3% of their initial personal income. During the same period, non-disabled individuals gain about 2,000€ (see Figures 1 and 2 and Table A2 in Appendix 5). Let us now decompose personal income into two subgroups of income: wages and compensation revenue.[8] In control groups, wages decrease between 2011 and 2015 (around −2,000€), but the increase in retirement pensions overcompensates this decline (around +3,000€ for old-age pensions). In both disabled groups, wages decreased between 2011 and 2015. These decreases are partly compensated by the increase in compensation earnings, especially with the rise of disability/sickness benefits. For severe disability, the

[6] Comprehensive results can be provided upon request.
[7] The selection of bandwidth is related to the continuing debate between bias and precision. On the one hand, a large bandwidth allows diminishing the variance and thus increasing the precision. On the other hand, the higher the bandwidth, the more biased the estimations can be (Caliendo & Kopeinig, 2008).
[8] In Table A2 (appendix 5), we indicate the amounts of retirement pension and disability/sickness benefits. Those two items are the most interesting for us.

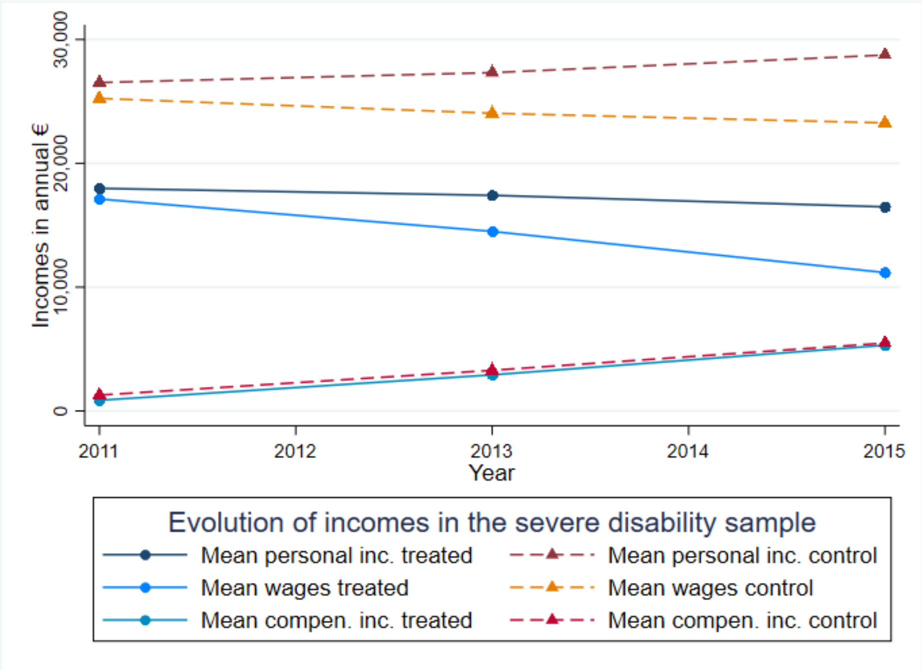
amount comes from 19€ to 945€. This multiplying factor is less important when we look at non-severe disability, for which disability/sickness benefits were multiplied by around three between 2011 and 2015. This point shows the first important difference between the two samples.

<u>FIGURE 1:</u> Trends in personal income, wages, and compensation incomes during the follow-up period in the non-severe disability sample, before matching.



***Source**:* SHARE; Waves 2011, 2013, 2015, graphic by authors

FIGURE 2: Trends in personal income, wages, and compensation incomes during the follow-up period in the severe disability sample, before matching.



Source: SHARE; Waves 2011, 2013, 2015, graphic by authors

Finally, we focus on the job situation two years after the disability onset (see Table A3 in Appendix 5). In both samples, non-disabled individuals are more likely to remain in employment, with around 70% of them still employed in 2015. We see that 58% of disabled individuals are still employed in 2015 and 4% are unemployed. However, regarding severe disability, the percent of employed individuals is 2 pp less than that of individuals with non-severe disability, while unemployed people are 2.5 pp higher.

In summarizing the key readings of these descriptive statistics, the individuals with severe disability appear to be more likely than the non-severely disabled to suffer from the adverse impact of disability onset, as they are associated with less personal income, more sickness/disability pensions, and more unemployment.

5.2 Naïve model

We first perform a naïve regression, defined as unmatched difference-in-differences (Appendix 6). These results do not take into account differences in observable characteristics between these two groups, although they do control for unobserved time constant heterogeneity. In the non-severe disability sample, results suggest a positive time effect on the three different types incomes: wages, compensation income, and personal income (the latter of which being the sum of the first two). This means that, between 2011 and 2015, incomes become higher in the control group, whatever the intensity of disability. Regarding our coefficient of interest, this naïve model suggests differences between the two samples. The differences between disabled and non-disabled in the pre-treatment versus post-treatment periods are significant only for wages in the non-severe disability sample and for the three income types when we consider severe disability. The negative coefficient in the two samples means that the onset of disability decreases wages. The same result is found for personal income in the severe disability sample, in which the onset of disability seems to increase compensation incomes. Finally, controlling for job situation with this naïve model shows that impacts are the same in the two samples, although they lack the same magnitude. Compared to being employed, the positive impacts on compensation incomes from being retired, unemployed, or in another situation are highlighted. Inversely, being retired or unemployed has a negative impact on personal income and wages, as expected.

5.3 Main results

We provide our main results in Table 4, which shows findings from the difference in differences weighted by the matching weights that consider differences in observable characteristics between both groups. These weights also control for time-invariant unobservable individual characteristics. Clearly, matching does not eliminate a notable number of people. Indeed, the sample sizes are about 99.6% and 99.7% of the initial sizes of, respectively, the non-severe and severe disability samples. This matching enables us to eliminate all the original differences between disabled and non-disabled individuals, but not only: some factors can be associated with the onset of disability. The shock may not be exogenous and is instead related to some previous characteristics, that is, some differences between the non-disabled and future disabled. Those characteristics could be independent or linked to work. In this latter case, reverse causality could arise, and we know that work can have a negative impact on health (Barnay, 2016; Bassanini, & Caroli, 2015; Robone, Jones, & Rice, 2011). Given all these points, matching at baseline is relevant.

We run two models, one without the job situation (Table 3) and the other with (Table 4). First and foremost, the first model reveals a significant positive effect on income after disability. However, this model does not take into account differences in employment status, in particular the transition to retirement or inactivity, which has affected the disabled more than the non-disabled. We want to purge the effect of disability onset on employment changes, but also the negative impact of non-employment status on global income. So, after controlling for job situation, our findings underline that non-severe disability has no impact on personal income. However, this leads to a clear 46% decrease in wages. If we look at the severe disability sample, suffering from a severe disability results in a 17% decrease in personal income. This is the result of two significant opposite effects. On the one hand, severe disability leads to an 85% decline in wages. On the other hand, it conducts to perceive benefits, pensions, that explains a 51% increase in compensation incomes. The onset of disability leads to a higher negative impact on wages than the positive one has on compensation incomes (in absolute values). It is likely that a disability does not automatically entitle one to a disability pension. Therefore, the mean amount of disability benefits is not strong enough to compensate wages losses.

TABLE 3: Weighted DiD results without controlling for the job situation

		Non-severe disability sample			Severe disability sample		
		Log personal income	**Log wages**	**Log compen. incomes**	**Log personal income**	**Log wages**	**Log compen. incomes**
After treatment	Coefficient	0.07***	−1.68***	2.51***	0.10***	−1.41***	2.35***
	SE (robust)	0.02	0.07	0.09	0.02	0.08	0.10
Treatment*After treatment	Coefficient	−0.02	−0.75***	0.42*	−0.22**	−1.44***	1.07***
	SE (robust)	0.05	0.21	0.20	0.09	0.37	0.37
No. of clusters (individuals)		4,094	4,094	4,094	2,548	2,548	2,548

***Note**:* On average, according to the weighted fixed effect model, the personal income of the non-disabled individuals increased by 7% between 2011 and 2015, in the non-severe disability sample.
***Population**:* Individuals employed and without disability in 2011
***Source**:* SHARE; Waves 2011, 2013, 2015
***Abbreviation**:* compen., compensation
****p* <0.01; ***p* <0.05; **p* <0.1.

TABLE 4: Weighted DiD controlling for job situation

		Non-severe disability sample			Severe disability sample		
		Log personal income	**Log wages**	**Log compen. incomes**	**Log personal income**	**Log wages**	**Log compen. incomes**
After treatment	Coefficient	0.17***	0.25***	0.85***	0.17***	0.34***	0.60***
	SE (robust)	0.02	0.07	0.09	0.04	0.10	0.12
Treatment*After treatment	Coefficient	0.00	−0.46***	0.16	−0.17*	−0.85***	0.51*
	SE (robust)	0.05	0.16	0.20	0.09	0.27	0.30
Job situation in 2015 *(ref: employed or self-employed)*							
Retired	Coefficient	−0.24***	−5.48***	4.62***	−0.17*	−5.80***	5.82***
	SE (robust)	0.05	0.20	0.23	0.10	0.34	0.34
Unemployed	Coefficient	−0.62***	−4.09***	3.68***	−0.62***	−3.55***	2.86***
	SE (robust)	0.18	0.74	0.72	0.21	1.07	1.01
Other†	Coefficient	−0.39**	−5.01***	4.83***	−0.39	−4.94***	5.08***
	SE (robust)	0.16	0.66	0.59	0.29	1.11	0.93
No. of clusters (individuals)		4,093	4,093	4,093	2,547	2,547	2,547

***Note**:* On average, according to the weighted fixed effect model, the personal income of the non-disabled individuals increased by 17% between 2011 and 2015, in the non-severe disability sample.
***Population**:* Individuals employed and without disability in 2011
***Source**:* SHARE; Waves 2011, 2013, 2015
***Abbreviation**:* compen., compensation
****p* <0.01; ***p* <0.05; **p* <0.1.
† This category gathers together individuals who can be permanently sick or disabled, homemakers, students, rentiers, and voluntary workers, among others.

By and large, it seems that the non–severe disability does not result in significant changes in personal income. However, a more severe shock (activity limitations combined with long-term health problems) has a negative impact on personal income. Several mechanisms may explain these findings.

First, the more intense the shock is, the more limited one becomes, meaning that the individual is less able to work and the loss in wages grows larger. At the same time, the need for care increases, thus making the disutility of work higher. In the end, these two factors point toward the probability of leaving the labour market and consequently the probability of losing wages. Regarding compensation incomes, we observe a significant impact on them from the onset of disability, but only in the severe disability sample. Once again, this result is explained by the intensity of the shock. The more intense the disability shock becomes, the greater the probability of receiving compensation incomes.

Regarding the coefficients associated with the job situation, becoming unemployed in 2015 (compared to remaining employed) leads to a loss in personal income of 62% for both samples. Regarding the retirement situation, the impact is lower in the severe disability sample due to lost wages being more greatly compensated by replacement incomes. Nonetheless, their compensation incomes are about 4.6 times higher in the non-severe disability sample, while they are about 5.8 times higher in the severe disability sample.

6 Heterogeneous effects

Due to heterogeneity in the generosity of different social welfare systems and therefore the level of compensation income received, the influence of disability on incomes could be different according to individual characteristics, such as gender (Dano, 2005; Lindeboom et al., 2016) or country. Consequently, we test for gender and the heterogeneity of social protection systems.

6.1 Gender

Gender inequality in the labour market has been largely documented in the literature. For example, Lindeboom and his co-authors study the causal effect of disability on employment, and they define disability by means of an indicator for long-term illness, disability, or infirmity. They find that the onset of disability has a negative impact on the employment rates of males but no impact for females (Lindeboom et al., 2016). Dano uses a Danish sample to show that earnings decrease after a disability shock, as measured by road injuries, and only for men (Dano, 2005). Table A5 in Appendix 7 provides results for the severe disability sample according to gender. For men, we find a negative impact of 89% on wages following the onset of disability, which is equivalent in absolute values to the positive impact on compensation income (83%). In the end, no impact on personal income is highlighted. Women suffer from a weaker decrease in wages than men do, while their compensation incomes are not impacted. The nature of disability changes by gender. For instance, severely disabled men suffer more than severely disabled women from heart problems such as heart attacks, coronary thrombosis, myocardial infarction, etc. Suffering from heart problems is more likely than other diseases to result in a low probability of participating in the labour force (Stern, 1989). This could partly explain differences between men and women.

6.2 Social welfare systems

Next, social protection systems partially allow protecting individuals against disability risk. Appendix 2 shows the differences among EU countries regarding the portions of their GDPs devoted to disability benefits. The Nordic countries (Denmark, Finland, and Sweden) dedicate a higher proportion of GDP (respectively 5%, 2.9%, 2.8%) to disability benefits than the EU-28 mean (2% of the EU-28 GDP). In contrast, the portion of GDP devoted to disability benefits in Eastern countries like Hungary, Romania, and Slovenia is more modest (respectively 1.1%, 0.9%, 1.1%) than the EU-28 mean. The same conclusions can be made after looking at the amount of social benefits devoted to disability. Consequently, we have chosen to divide our sample into two groups. The first group represents countries whose percentages of GDP dedicated to disability benefits are greater than the EU-28 mean. Germany, Sweden, France, Denmark, Switzerland, and Belgium comprise this group. The second group is Austria, Spain, Italy, Czech Republic, Slovenia, and Estonia, all of whom are below the EU-28 mean. Results for the severe disability sample are provided in Table A6 in Appendix 7. In the most generous countries, severe disability does not translate into lower income. The generosity of measures therefore seems to ensure the stability of wealth among the disabled. Conversely, in countries offering lower disability compensation, the health shock leads to a 20% drop in overall income, an 80% decrease in wages, and a 65% increase in compensation incomes. Compensation incomes do not sufficiently cover lost wages due to disability.

Among others in the group of most generous countries, we have the Nordic countries of Sweden and Denmark, as well as Germany and Switzerland. These four countries are part of the social democratic model described by the OECD. They are characterised by easy access to disability benefits, strong employment integration measures, anti-discrimination legislation, and generous compensation incomes (OCDE, 2010). For example, Denmark and Sweden have decided to freeze compensation income if a disabled individual decides to go back to work, meaning that if this person ultimately loses their job, he or she will begin to receive compensation income anew without having to reapply for it. In contrast, employment integration for disabled individuals in the second group is weakly developed and compensations are less substantial (OCDE, 2010). For example, countries like the Czech Republic and Spain impose strict conditions for receiving a combination of disability pension and other social security benefits, such as unemployment benefits (Mutual Information System on Social Protection, 2019). Estonia does not allow combination at all (Mutual Information System on Social Protection, 2019). This OECD classification adequately corresponds to our results: countries in the more generous group exhibit no impact on personal income, which could be explained by their promoting the integration of disabled individuals into the workforce and providing higher compensation incomes. These two mechanisms act as protections for people experiencing a disability shock. Conversely, countries in the less generous group lack integration policies, thus leading to lost wages that are not compensated by their low levels of replacement income.

7 Discussion and conclusion

Our study uses European panel data to measure the impact on personal income due to the onset of disability. We also take the novel approach of decomposing this personal income into wages and replacement incomes. To assess this impact, we use two different disability measures: the GALI and a combination of the GALI with an indicator of long-term health problems. Our assumption is that the onset of disability leads to a decrease in productivity and, consequently, a loss in potential wages while disabled individuals simultaneously receive a disability pension. Using combined propensity score matching and difference in differences, we are able to control not only for observed characteristics but also for unobserved heterogeneity. Our findings indicate that disability leads to a loss in wages, results that are totally in line with the previous literature. Nonetheless, impacts on compensation income and personal income are notable only when the disability shock is strong enough (i.e., when we combine the GALI with disabling diseases). In this case, personal income decreases by 17% even though replacement income increases by 51%. We contribute to the literature by decomposing global income into these two classifications, which are impacted by our treatment in a presumably inverse way. To our knowledge, ours is the first paper to take this approach using data on several countries. Consequently, we employ our method by splitting countries into two groups according to their social protection systems: more generous versus less generous. Our results highlight that the onset of disability has no impact at all in the more generous countries. Thus, we assume that disability is not a discriminatory criterion in these countries. For the less generous group, the results we find are the same as for the sample of pooled countries. We also take into account gender heterogeneity by splitting our sample into women and men. Women see their wages decrease with no effect on their replacement incomes, which ultimately leads to a negative impact on personal income from the onset of disability (29% losses). For men, the negative impact on wages is compensated by the positive impact on replacement income. These results are in line with the previous literature, which highlights that disability has a negative impact on wages only for men (Dano, 2005; Lindeboom et al., 2016).

Nevertheless, our paper suffers from several limitations. First, we rely on a database that targets individuals aged 50 years or more. Thus, our results should not be extended to younger people, since they do not have the same health status and labour market situation. Those in our sample can also be impacted by transition to retirement, thereby leading to coefficients that are higher than those that could potentially be observed in a younger sample. Health problems and early retirement are likely to be positively associated with each other (Aranki, & Macchiarelli, 2013), a result that has also been found in the Netherlands (Bernal, & Vermeulen, 2014) and particularly in the case of disability among

European countries (Wubulihasimu et al., 2015). We partly control for this by including the change in job situation in our weighted difference in differences. Second, our follow-up period is short. Therefore, we can only guess that the long-term effects become greater as disability perseveres and the intensity potentially increases. Nonetheless, the literature on disability's long-term effects on labour market outcomes shows the impact to be lower in the long term relative to the short term (Dano, 2005; García-Gómez et al., 2013; Mussida, & Sciulli, 2016). Third, our disability measure relies only on self-reported indicators, for which declaration bias can exist and questions can be interpreted differently. However, we use homogenous indicators across countries that have been reported as valid and reliable. Moreover, we have tried to cover all dimensions of the UN definition. Fourth, to ensure that the results obtained with DiD are robust, we must rely on the parallel trend assumption, which, in the absence of treatment, requires a parallel trend of incomes between disabled and non-disabled individuals. For the non-severe disability sample in Figure 1, we see that personal income, wages, and compensation incomes follow the same trend between 2011 and 2013 as they do for the treated and the control group. Indeed, while personal and compensation incomes increase in the two groups, wages also decrease for both. The same can be said for the severe disability sample in Figure 2. Finally, potential bias could remain in the heterogeneity tests. Regarding the estimates for women versus men, we know that women are more likely to leave the labour market earlier than men (Lammers, Bloemen, & Hochguertel, 2013) and to more frequently have part-time contracts (Barnay, 2016). While our model controls for exit from the labour market, these two points could potentially explain the non-effect of disability on compensation incomes. Concerning heterogeneity in the social protection system, we are perfectly aware that our two groups do not depend on all available compensation incomes, among which disability, unemployment, and old-age pension are the three most important. If we look at Eurostat's data on old-age pensions as a part of GDP during 2011–2015, we see that the proportions dedicated to old-age pensions by Denmark, France, Italy, Austria, and Sweden are greater than the EU-28 mean. Regarding unemployment during this same period, the generous countries are Belgium, Denmark, Spain, France, Italy, and Austria. If we were to look at all these compensation incomes independently, we would have created different groups from those used in our robustness checks. Nonetheless, in looking at the three compensation incomes of unemployment, disability, and old age all together, the groups that we created are quite valid. In our generous group, Denmark and France have devoted more than the EU mean to all three items; and Belgium and Austria are above the mean for two of them. Finally, we can make two comments about Austria and Italy. First, the proportions of GDP devoted by these two countries to unemployment benefits are, respectively, only 0.1 and 0.2 pp higher than the EU-28 mean during the period 2011–2015.

The second concerns old-age pensions. Because Italy and Austria are characterized by a notable level of early retirement (OCDE, 2010), they incur higher expenditures in this regard.

Our results suggest that severe disability continues to have a negative impact on labour market outcomes. In our case, the onset of disability leads to a 17% decrease in personal income, which is derived mainly from the 85% loss in wages that are not totally compensated for by the 51% raise in compensation income. These results could potentially be mitigated by social protection systems or, at least, by how disability is defined. In the more generous countries, we find no impact from our treatment on personal income, wages, and compensation incomes. These (non-)results seem to support the belief that disability could remain only a health problem with no impact on work in the presence of well-developed social protection systems. This paper's findings suggest that countries with the most generous policies do not experience disability as an impediment on the labour market. However, this should be interpreted cautiously, as "generous" here does not necessarily mean granting large compensation incomes. Instead, it implies that that these countries defined as generous exhibit zero impacts due to the important measures they take in order to integrate and maintain disabled individuals into the labour market.

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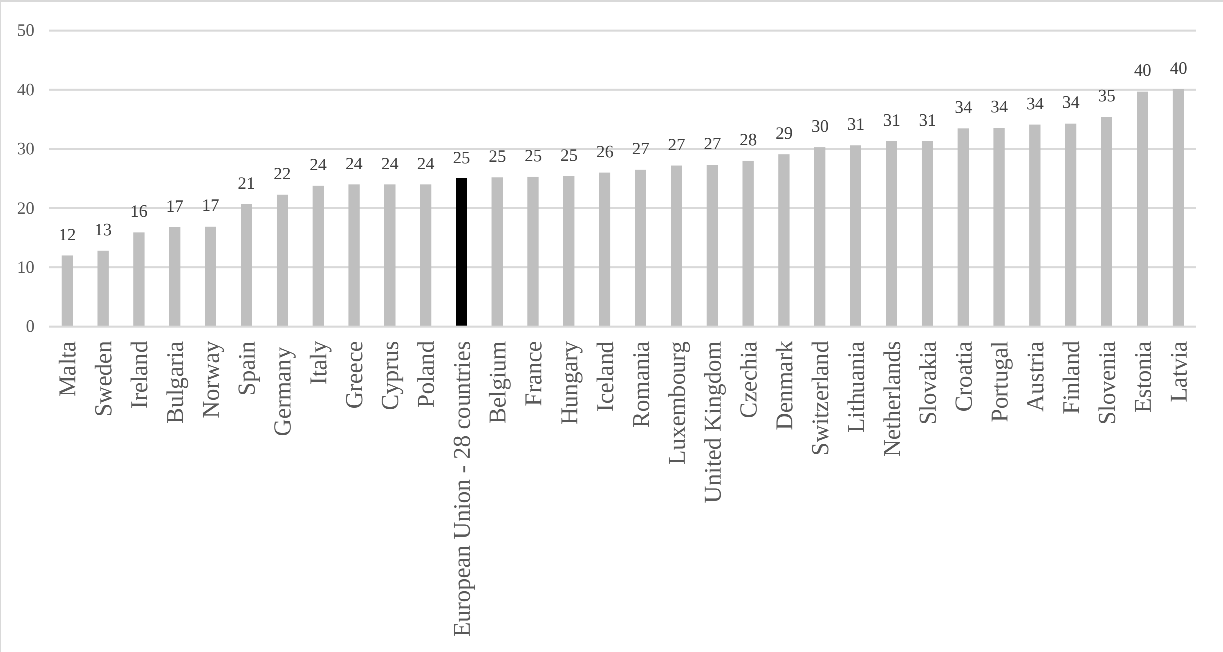
APPENDIX

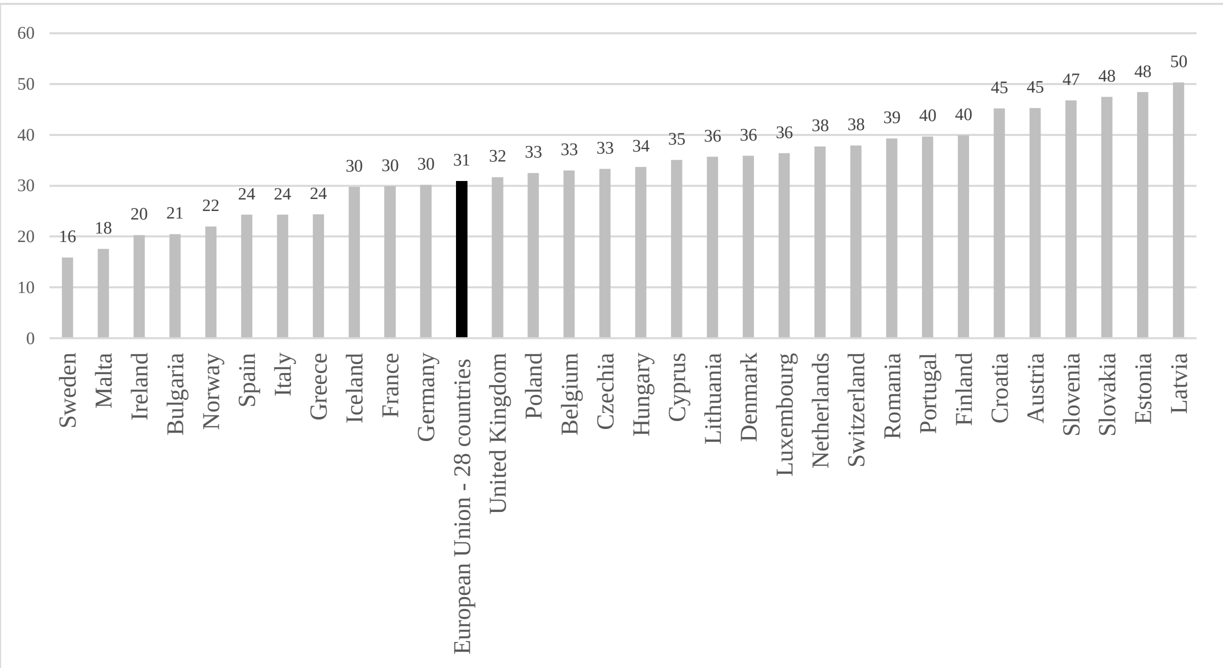
Appendix 1: Disability in Europe

FIGURE A1-A: Percentage of the population over 16 years reporting long-standing limitations in 2018



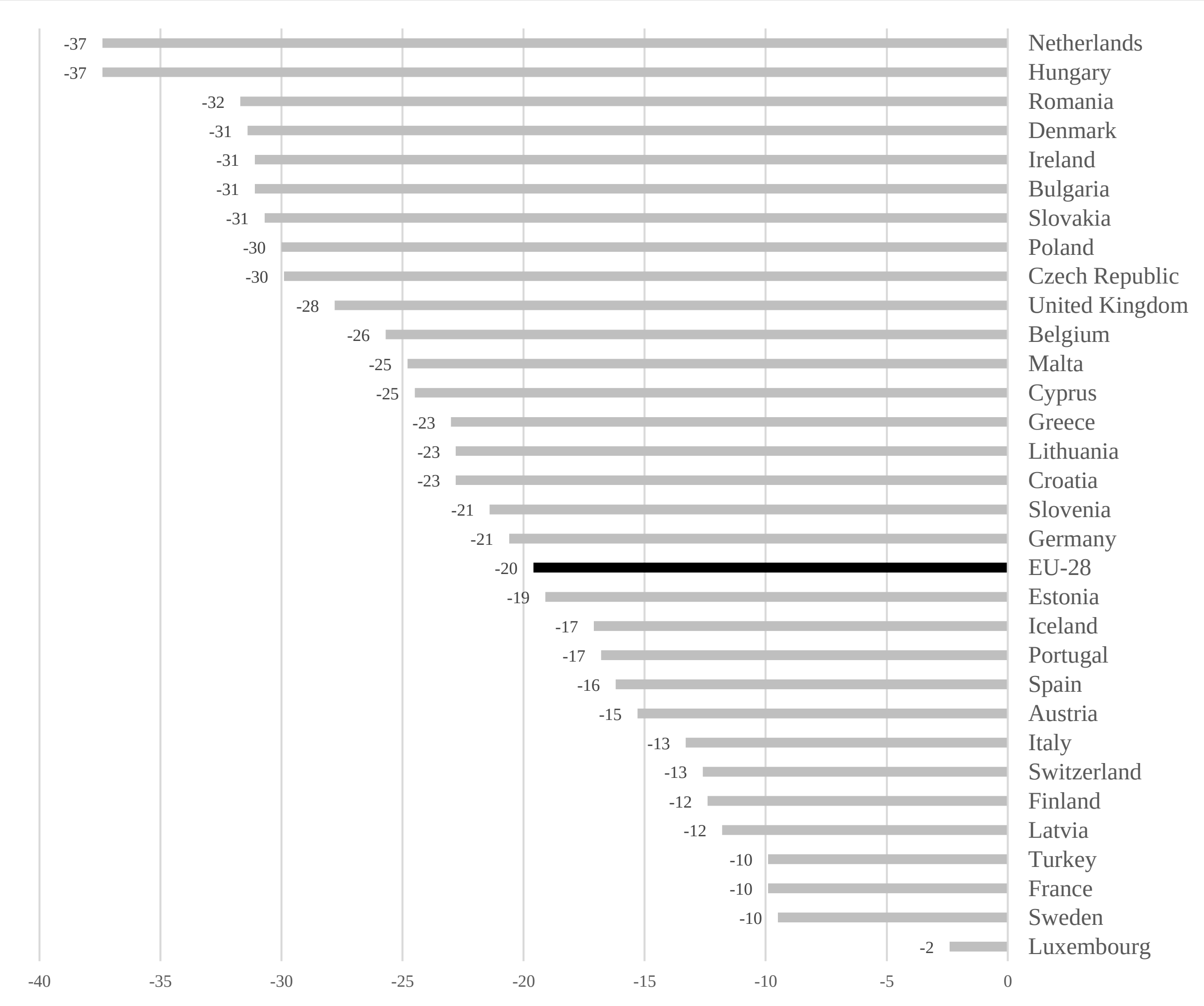
Source: 2018 Eurostat/EU-SILC data, graphic by authors

FIGURE A1-B: Percentage of the population from 55 to 64 years reporting long-standing limitations in 2018.



Source: 2018 Eurostat/EU-SILC data, graphic by authors

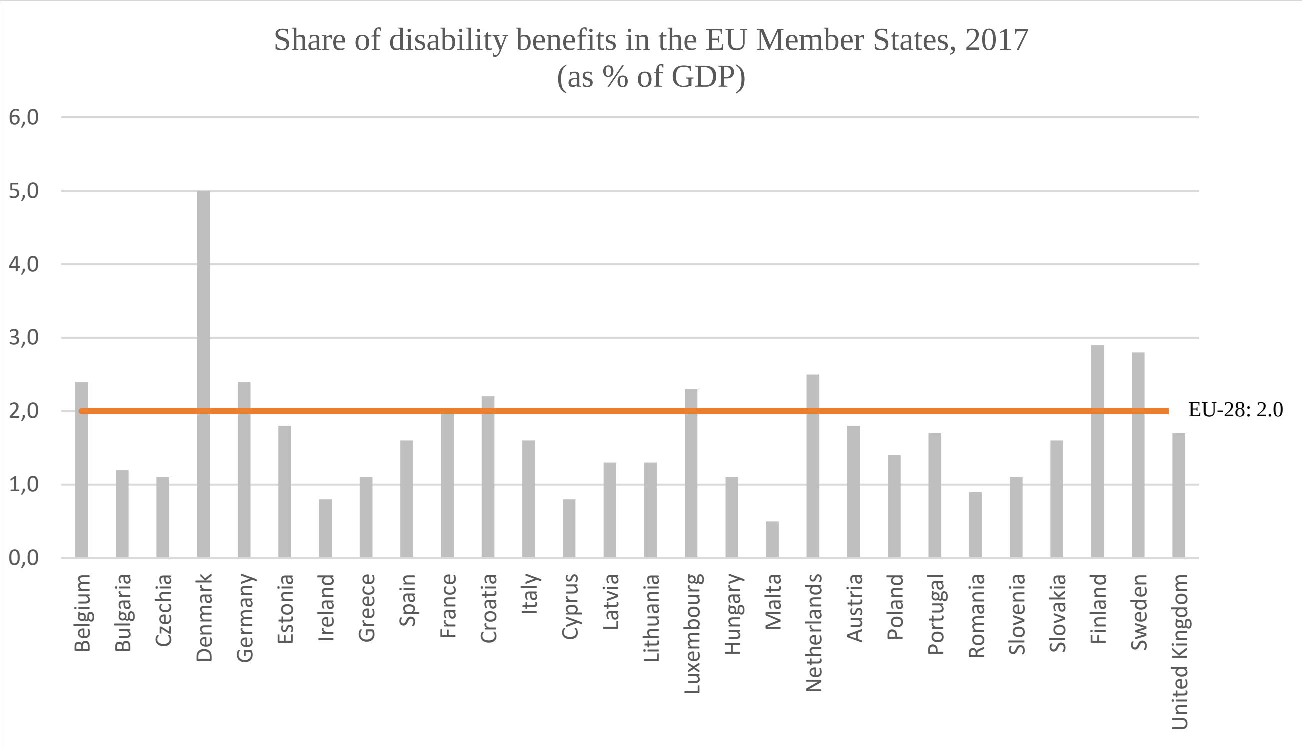
<u>FIGURE A2</u>: EU differences in employment rates for disabled and non-disabled people aged 15–64 in 2011 (in percentage points)



Note: In 2011, disabled Polish individuals were 30 percentage points less likely to be employed than non-disabled individuals.
Source: Eurostat News Release, 2014, https://ec.europa.eu/eurostat/documents/2995521/6181592/3-02122014BP-EN.pdf/aefdf716-f420-448f-8cba-893e90e6b460

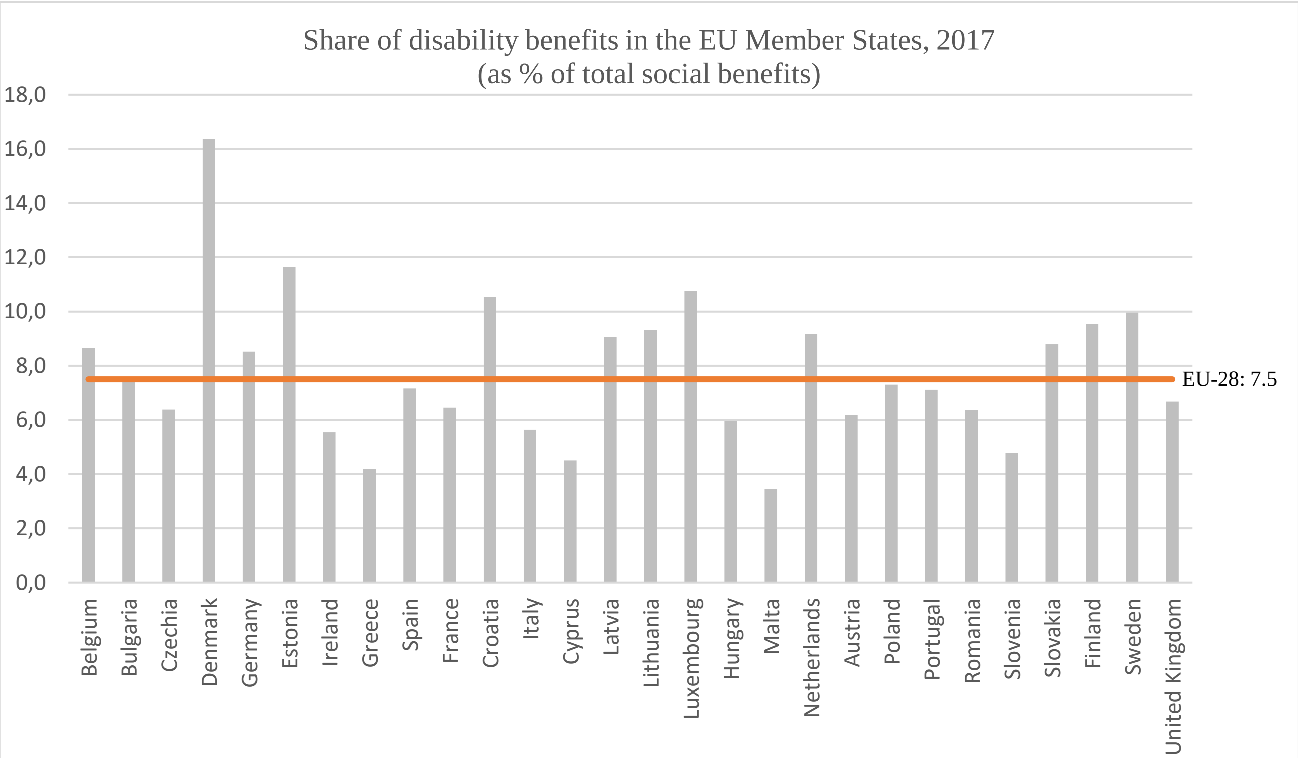
Appendix 2: Share of disability benefits in EU Member States, 2017

FIGURE A3: As a percentage of GDP



Note: Hungary dedicated 1.1% of its GDP to disability benefits in 2017.
Source: 2017 Eurostat data, graphic by authors

FIGURE A4: As a percentage of total social benefits



Note: Hungary dedicated 6% of its social benefits to disability benefits in 2017.
Source: 2017 Eurostat data, graphic by authors

Appendix 3: Imputation of income variables

The SHARE database, was compiled using two distinct methodologies to impute missing values, depending on the missing percentage contained in the variable. For variables with a small fraction of missing values (less than 5%), a hot deck method is applied. For other variables, the implementers of SHARE we use a fully conditional specification (FCS) method.

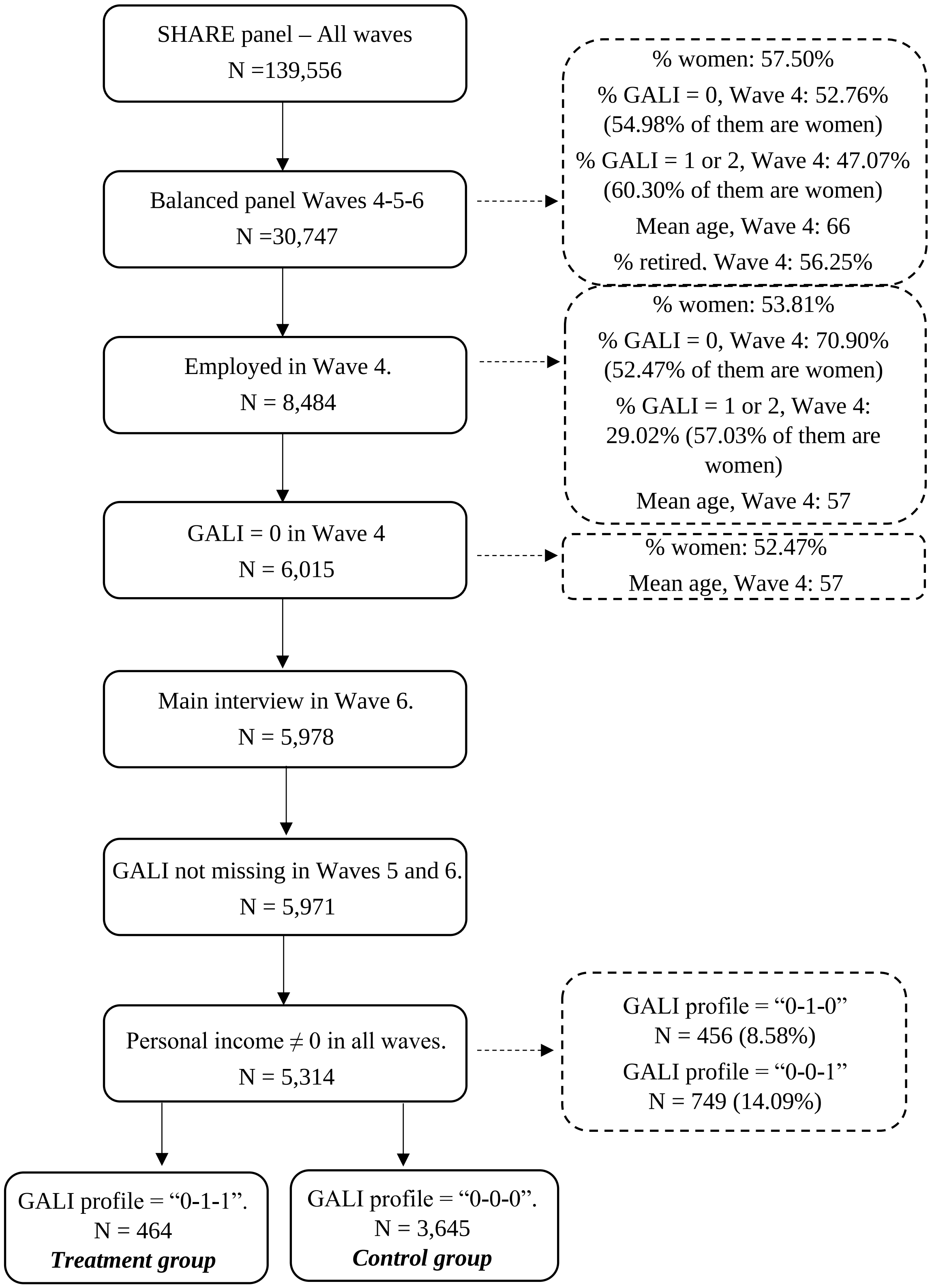
Here, we are interested in monetary variables and will thus explain only the FCS method. This method uses an algorithm that imputes several values to the same variable in order to consider the variability generated by the imputation.

Technically, the j-th variable is imputed at each step by means of the model's estimation. The predictors used are the most updated imputed values of the other variables (SHARE, 2019).

For more information, see the SHARE release guide (SHARE, 2019).

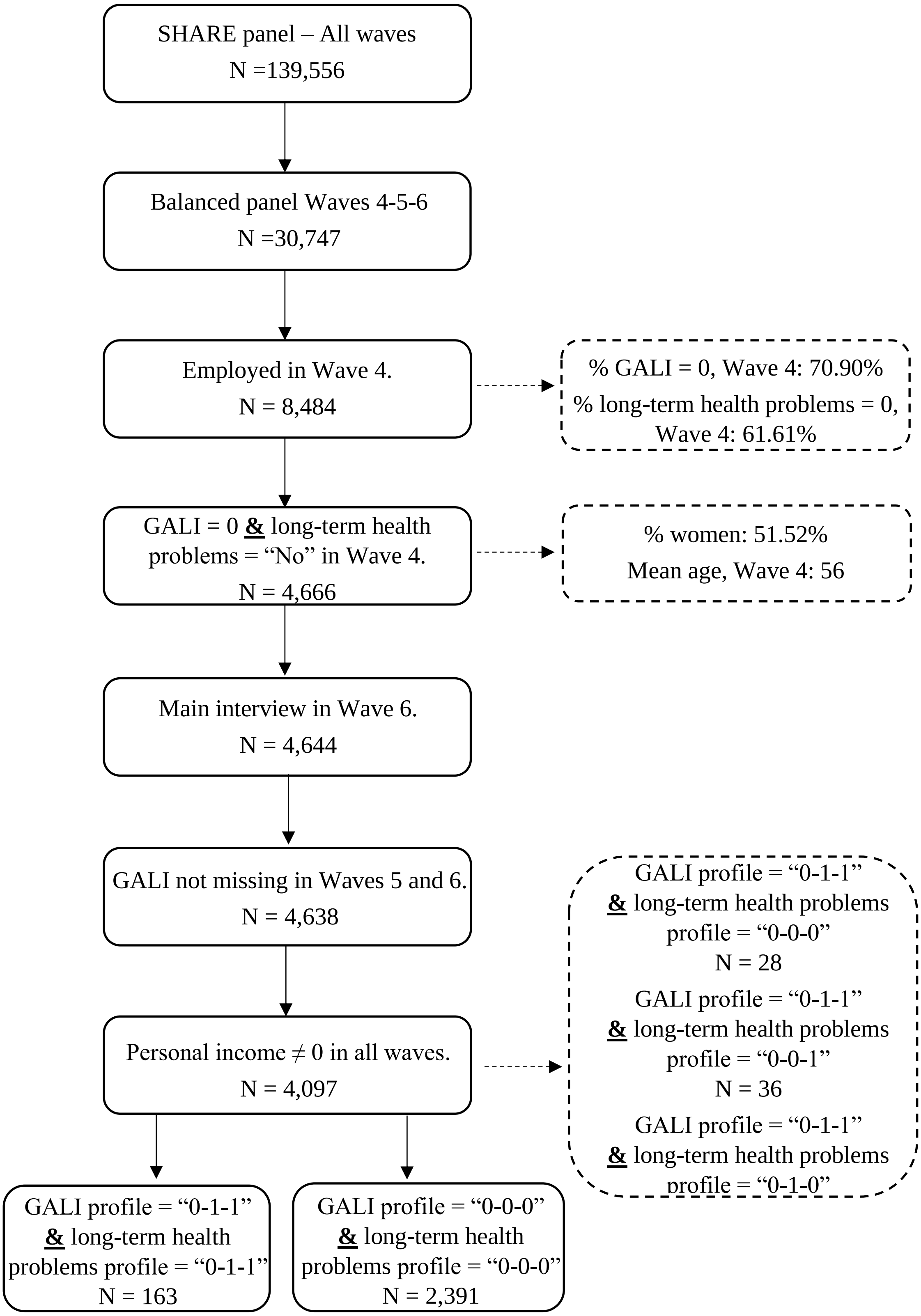
Appendix 4: Diagrams of sample selection criteria

FIGURE A5: Sample selection – non-severe disability sample



***Source**:* figure by authors
Abbreviation: GALI, Global Activity Limitation Indicator

FIGURE A6: Sample selection – severe disability sample



Source: figure by authors
Abbreviation: GALI, Global Activity Limitation Indicator

Appendix 5: Descriptive statistics.

TABLE A1: Distribution of disabled and non-disabled individuals in the samples

		Frequency	Percent
Non-severe sample	Disabled individuals	464	11.29
	Non-disabled individuals	3,645	88.71
	Total	4,109	100.00
Severe disability sample	Disabled individuals	163	6.38
	Non-disabled individuals	2,391	93.62
	Total	2,554	100.00

Population*:* Individuals employed and without disability in 2011
Source*:* SHARE; Waves 2011, 2013, 2015

TABLE A2: Incomes across waves

Sample	Group	Statistics	Personal income	Wages	Compensation	Compensation: Retirement pensions	Compensation: Disability / sickness benefits
Non-severe disability sample	**Disabled**	N	464	464	464		
		Mean in 2011	18,055	16,157	1,898	1,237	263
		Mean in 2013	18,841	14,817	4,023	2,256	806
		Mean in 2015	17,609	12,149	5,460	3,375	882
	Non-disabled	N	3,645	3,645	3,645		
		Mean in 2011	25,638	24,211	1,427	851	31
		Mean in 2013	26,255	22,961	3,294	1,959	81
		Mean in 2015	27,460	21,949	5,511	3,916	120
Severe disability sample	**Disabled**	N	163	163	163		
		Mean in 2011	17,976	17,114	862	611	19
		Mean in 2013	17,413	14,500	2,913	1,353	616
		Mean in 2015	16,483	11,176	5,307	2,790	945

	N	2,391	2,391	2,391	
	Mean in 2011	26,523	25,243	1,280	
				841	23
Non-disabled	Mean in 2013	27,321	24,042	3,279	
				1,921	87
	Mean in 2015	28,745	23,264	5,481	
				3,905	142

Note: Statistics are the annual mean in €. On average, the non-severe disabled had a personal income of 18,055€ in 2011
Population*:* Individuals employed and without disability in 2011
Source*:* SHARE; Waves 2011, 2013, 2015

<u>TABLE A3</u>: Job situation after the disability shock – 2015

Sample	Group	Job situation	Freq.	Percent
Non-severe disability sample	**Non-disabled**	N miss	7	0.19
		Employed or self-employed	2,513	68.94
		Retired	974	26.72
		Unemployed	89	2.44
		Other	62	1.70
	Disabled	N miss	3	0.65
		Employed or self-employed	267	57.54
		Retired	145	31.25
		Unemployed	17	3.66
		Other	32	6.90
Severe disability sample	**Non-disabled**	N miss	4	0.17
		Employed or self-employed	1,685	70.47
		Retired	607	25.39
		Unemployed	56	2.34
		Other	39	1.63
	Disabled	N miss	1	0.61
		Employed or self-employed	91	55.83
		Retired	48	29.45
		Unemployed	10	6.13
		Other	13	7.98

Note*:* In the non-severe disability sample, 57.5% of disabled individuals stayed employed or self-employed after their non-severe disability shock.
Population*:* Individuals employed and without disability in 2011
Source*:* SHARE; Waves 2011, 2013, 2015
Abbreviation: Freq., Frequencies

Appendix 6: Naïve results.

TABLE A4: DiD without matching

		Non-severe disability sample			Severe disability sample		
		Log personal income	**Log wages**	**Log compen. incomes**	**Log personal income**	**Log wages**	**Log compen. incomes**
After treatment	Coefficient	0.15***	0.13***	0.62***	0.15***	0.14***	0.52***
	SE (robust)	0.02	0.03	0.06	0.02	0.03	0.07
Treatment*After treatment	Coefficient	−0.00	−0.53***	0.17	−0.20**	−1.03***	0.63**
	SE (robust)	0.05	0.16	0.20	0.09	0.29	0.30
Job situation *(ref: employed or self-employed)*							
Retired	Coefficient	−0.21***	−5.35***	5.61***	−0.17***	−5.30***	6.16***
	SE (robust)	0.03	0.14	0.15	0.04	0.19	0.19
Unemployed	Coefficient	−0.40***	−3.94***	4.40***	−0.35**	−3.05***	3.73***
	SE (robust)	0.10	0.45	0.45	0.12	0.53	0.55
Other†	Coefficient	−0.19	−2.99***	3.20***	−0.15	−2.59***	2.61***
	SE (robust)	0.15	0.45	0.46	0.16	0.57	0.57
No. of clusters (i.e., individuals)		4,098	4,098	4,098	2,549	2,549	2,549

***Note**:* On average, according to the fixed effect model, the personal income of the non-disabled individuals increased by 15% between 2011 and 2015, in the non-severe disability sample.
***Population**:* Individuals employed and without disability in 2011
***Source**:* SHARE; Waves 2011, 2013, 2015
***Abbreviation**:* compen., compensation
****p* <0.01; ***p* <0.05; **p* <0.1.
† This category gathers together individuals who can be permanently sick or disabled, homemakers, students, rentiers, and voluntary workers, among others.

Appendix 7: Results of robustness checks.

1. Gender heterogeneity

Table A5: Weighted DiD for women vs. men in the severe disability sample

		Women Severe disability sample			Men Severe disability sample		
		Log personal income	**Log wages**	**Log compen. incomes**	**Log personal income**	**Log wages**	**Log compen. incomes**
After treatment	Coefficient	0.19***	0.44***	0.65***	0.15***	0.22	0.52***
	SE (robust)	0.03	0.14	0.17	0.04	0.16	0.18
Treatment*After treatment	Coefficient	−0.29*	−0.77**	0.19	−0.07	−0.89**	0.83**
	SE (robust)	0.16	0.39	0.42	0.10	0.38	0.42
Job situation in 2015 ***(ref: employed or self-employed)***							
Retired	Coefficient	−0.12	−5.81***	5.41***	−0.19*	−5.95***	6.42***
	SE (robust)	0.16	0.49	0.52	0.11	0.50	0.46
Unemployed	Coefficient	−0.68**	−3.14**	2.44*	−0.51**	−4.15**	3.48**
	SE (robust)	0.34	1.32	1.25	0.21	1.72	1.60
Other†	Coefficient	−0.51	−4.40***	3.40**	−0.28	−5.50***	6.70***
	SE (robust)	0.51	1.66	1.48	0.26	1.45	0.61
No. of clusters (i.e., individuals)		1,321	1,321	1,321	1,212	1,212	1,212

Note: On average, according to the weighted fixed effect model, the personal income of the non-disabled woman individuals increased by 19% between 2011 and 2015.
Population: Individuals employed and without disability in 2011
Source: SHARE; Waves 2011, 2013, 2015
Abbreviation: compen., compensation
****p* <0.01; ***p* <0.05; **p* <0.1.
† This category gathers together individuals who can be permanently sick or disabled, homemakers, students, rentiers, and voluntary workers, among others.

2. Heterogeneity of social protection systems

TABLE A6: Weighted DiD for more vs. less generous countries in the severe disability sample

		More generous countries Severe disability sample			Less generous countries Severe disability sample		
		Log personal income	**Log wages**	**Log compen. incomes**	**Log personal income**	**Log wages**	**Log compen. incomes**
After treatment	Coefficient	0.12**	0.32*	0.46**	0.22***	0.32**	0.59***
	SE (robust)	0.05	0.18	0.18	0.05	0.14	0.17
Treatment* After treatment	Coefficient	−0.18	−0.84	0.51	−0.20*	−0.80**	0.65*
	SE (robust)	0.17	0.52	0.52	0.11	0.32	0.37
Job situation in 2015 ***(ref: employed or self-employed)***							
Retired	Coefficient	−0.15	−5.90***	6.80***	−0.15	−5.87***	5.32***
	SE (robust)	0.15	0.69	0.61	0.13	0.40	0.42
Unemployed	Coefficient	−0.18	−0.72	0.65	−0.77***	−4.45***	3.30***
	SE (robust)	0.16	0.67	1.00	0.26	1.24	1.16
Other†	Coefficient	0.05	−4.09**	4.86***	−0.72*	−5.08***	4.85***
	SE (robust)	0.47	2.01	1.66	0.37	1.24	1.07
No. of clusters (i.e., individuals)		1,418	1,421	1,421	1,117	1,117	1,117

Note: On average, according to the weighted fixed effect model, the personal income of the non-disabled individuals increased by 12% between 2011 and 2015 in the more generous countries.
Population: Individuals employed and without disability in 2011
Source: SHARE; Waves 2011, 2013, 2015
Abbreviation: compen., compensation
****p* <0.01; ***p* <0.05; **p* <0.1.
† This category gathers together individuals who can be permanently sick or disabled, homemakers, students, rentiers, and voluntary workers, among others.