ESTIMATING THE INCOME LOSS OF DISABLED INDIVIDUALS: THE CASE OF SPAIN[†]

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Abstract

In this paper we present a theoretical model along with an empirical model to identify the effects of disability on wages. From the theoretical model we derive the hypothesis that only the temporary component of the wage gap, which is due to assimilation costs, will diminish over time, whereas the permanent element, which is due to the productivity loss after the disabling condition, will in fact persist. We test this theoretical hypothesis using an exogenous disability shock (accident) and combine propensity score matching with a difference-in-differences method to account for observed and unobserved time-constant differences. In all our specifications we find that the reduction in wages for the disabled is between 274 and 308 Euros per month, and this represents 19-22% of the average wage of a disabled worker. This gap, however, is more than offset when we count disability benefits and wages collectively as income. As predicted in the theoretical model, we observe that around 40% of the initial wage gap between disabled and non-disabled individuals is reversed once the transitory drop in productivity disappears. However, we also observe a constant wage gap that remains over time and that corresponds to the permanent fall in productivity predicted by the theoretical model (60% of the initial wage gap).

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1. Introduction

In recent years, disability policies have attracted particular attention in the OECD (Organization for Economic Co-operation and Development) countries as they represent a significant amount of government expenditure. At the same time, as a society we are becoming more and more concerned about the need to better integrate disabled individuals into the community.

Accordingly, increasing the number of disabled people working is regarded as a sound way of reducing some of the pressure on the financial stability of a social security system, while at the same time socially integrating disabled individuals.

However, a closer look into the data reveals that this objective is far from being met in most developed countries. Employment rates for the disabled are especially low in the case of Spain (around 35% in 2007) despite its GDP growth having been quite high (2% -6%) between 1996 and 2007.[1] Therefore, and in comparison to other countries, Spain has one of the lowest rates of employment for the disabled in the OECD. For instance, the employment rate for this group of workers in the UK is 45%, 40% in Australia, 50% in Luxembourg, 45% in Norway and 52% in Switzerland (OECD, 2009).[2]

In this paper we go one step further and analyse whether disabled individuals, apart from being less likely to be employed, are also suffering from other disadvantages in terms of labour market opportunities. In particular, we want to test whether the onset of an unexpected disabling condition also entails reduced earnings for the disabled and whether this wage gap between disabled and non-disabled workers is permanent or decreases over time. In other words, we want to establish whether disabled individuals are able to "make up" their lost wages in the short or long-term.

We present both a theoretical and empirical model to identify the effects of disability on wages. From the theoretical model we derive the hypothesis that only the temporary component of the wage gap, which is due to assimilation costs, will diminish over time, whereas the permanent element, which is due to the productivity loss after the disabling

[1] This refers to self-reported employment rates of disabled individuals. The general employment rate increased by 7% between 2001 and 2007.
[2] These employment rates are taken from the OECD and are, therefore, comparable for these countries. They refer to self-reported employment rates. The number of individuals receiving DI benefits has grown in Spain from 1995 to 2005 at an average annual rate of 1.4%. In 2008, 3.7% of the working-age population in Spain was receiving these benefits (as compared to an average of 5.7% in other OECD countries), (OECD, 2009).

condition, will in fact persist. We test this theoretical hypothesis using an exogenous disability shock (accident) and combine propensity score matching (PSM) with a difference-in-differences (DID) method to account for observed and unobserved time-constant differences. We find a drop in wages for disabled workers of between 274 and 308 EUR a month (expressed in constant terms at 2010 prices). We claim that this is a significant wage loss as it represents 19%-22% of the average wage of a disabled worker in Spain. However, we show that this reduction is more than compensated for when we measure both wages and disability benefits as income. With respect to the evolution of this wage gap over time, our results show that 40% of this wage gap represents a temporary component that falls over time, while the remaining 60% persists over time (associated with a permanent fall in productivity as predicted in the theoretical model). Finally, we also estimate a drop of 73 percentage points in the probability of continuing to work in the year following the accident (as a result of the disability), which is in line with the decline from 82% to 15% in the employment rate observed in the data.

There are some papers in the literature that have attempted to estimate the dynamic impact of disability on wages by specifically addressing the issue of the wage gap evolving over time. Using self-reported information about disability in the USA, Charles (2003) analyses the evolution of the expected earnings of worked-limited disabled men over time. He finds that expected earnings show a sharp drop around the date of onset and then subsequently recover.[3] This same characteristic is also analysed in other countries but the results are ambiguous. While some of the studies find significant reductions in income due to the onset of a disabling condition (Contoyannis and Rice (2001) and Kidd et al. (2000) for the UK and Lundborg et al. (2011) for Sweden), there are also a number of authors that find very mild or even insignificant effects of disability on income (Lechner and Vazquez-Alvarez (2011) for Germany and Walker and Thomson (1996) for the UK).

In any case, because of the characteristics of the datasets they use, none of the previously mentioned papers are able to distinguish between different types of disability. As Charles (2003) mentioned, the type of disability (accident or common

3 In a more recent study using the same database, Mok et al. (2008) find much greater losses from disability than those published in Charles (2003). This result is in line with the evidence found by Meyer and Mok (2006) in a previous study.

illness) may have different effects on the temporal pattern of earning losses. Furthermore, some types of disability may not be exogenous and may raise some key concerns about endogeneity problems in the estimates.

Therefore, and in order to overcome any potential endogeneity problem, a number of papers in the literature have used accidents as an exogenous health shock in order to clearly identify the effects of disability on income and employment. Along this line of research, Moller (2005) combines PSM and DID to find that older individuals and those in the lower income distribution bracket suffer from significantly lower disposable incomes than non-injured persons. Using a similar technique, Halla and Zweimüller (2011) show the negative and persistent effect of Commuting Accidents on subsequent employment and income for Austria.

We are aware of only one study (Garcia-Gomez and Lopez-Nicolás, 2006) that focuses on the effects of disability on income for the case of Spain. In this particular study, the authors make use of the European Community Household Panel dataset to estimate the effect of past health events on current changes in labour status. Their results show a reduction in personal income of 1,648 Euros (EUR) in the year of the disability shock and 1,740 EUR for the second year. They also find that the drop in labour income is not fully compensated by social security support. As the sample sizes for the treated and control groups are small, the authors are unable to estimate the effects on subsequent periods. Furthermore, as they use a self-assessed health measure to define the health shock, the presence of endogeneity problems may not be ruled out.

The up-to-date administrative database that we use allows us to go one step further than the work of Garcia-Gomez and Lopez-Nicolás. Firstly, we present a more updated study of the effects of disability on wages (from 1996-2010) than that in the paper by Garcia-Gomez and Lopez-Nicolás (1994-2001) and secondly, thanks to the longer time span of our data, we are able to determine whether disabled individuals are able to, in wage terms, “catch up” to non-disabled workers. Finally, we employ a measure of disability that is clearly exogenous (accidents) as our administrative dataset allows us to identify the source of the disabling condition.

2. The Spanish Disability System

The disability system in Spain distinguishes between two types of permanent disability benefit: i) contributory, which are awarded to individuals who have generally contributed to the social security system before the onset of their disabling condition and ii) non-contributory, which are awarded to individuals who are assessed as disabled but have never contributed to Social Security (or have not reached the minimum contributory requirement which would enable access to the contributory system). Non-contributory disability benefits are means-tested and managed on a regional level.[4]

The size of the non-contributory system is relatively small compared to the contributory system and the amount of benefits received is also smaller in the non-contributory case.[5] As we only have data on contributory disability benefits, in the remainder of the paper we will focus only on the contributory disability system in Spain.[6]

Social Security defines permanent contributive disability insurance as an economic benefit compensating an individual for the loss of a specified amount of wages or professional earnings when affected by a permanent reduction in or a complete loss of his/her working ability due to the effects of a pathologic or a traumatic process resulting from illness or accident.

To capture the various situations someone with a disabling condition can find themselves in, the Spanish Social Security Administration uses a classification of three central degrees of disability that depend on lost working capacity:[7]

(i) Partial disability (57% of claimants): The individual is unable to perform the fundamental tasks of his/her regular job or professional activity, but he/she is still capable of doing a different job or professional activity.

(ii) Total disability (40% of claimants): The individual is unable to hold down any kind of job or do any kind of professional activity.

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[4] Income is evaluated yearly. The income threshold in 2010 was set at 4,755.80 Euros/year for an individual living alone. This amount is adjusted if the individual lives with other household members.

[5] 197,126 individuals received non-contributory disability benefits in 2009, while 920,860 received contributory benefits that same year. The average non-contributory pension is 417.09 Euros/month, compared to an average contributory disability pension of 831.49 Euros/month.

[6] Furthermore, there are disincentives to working because of the means-testing requirement for non-contributory DI benefits that cannot be disentangled from the effects of the health shock on income.

[7] There was a fourth level of benefit (permanent limited disability) which now no longer exists.

(iii) Severe Disability (3% of claimants): Individuals, who as a result of anatomic or functional loses, need the assistance of a third person to accomplish essential daily activities such as eating, moving, etc.

The pension total is obtained by multiplying a percentage by the regulatory base. Note that, the percentage varies depending on the type of pension and the degree of disability (see Table A1.1 in Appendix 1), and the regulatory base differs depending on the cause of the disability and on previous salaries.[8] The percentage is 55% or 75% for partial disability beneficiaries, 100% for total disability and 150% for severe disability.

The number of years included in the regulatory base depends on the cause of the disability; for a common illness the regulatory base is calculated by dividing the wages received in the final 96 months (8 years) before becoming disabled by 112. When the cause of the disability is an accident unrelated to work, the regulatory base is calculated by dividing the wages of the 24 months previous to becoming disabled by 28. The individual can choose which 24 months (from the last 7 years of work) they wish the amount to be calculated on. For a work-related accident or illness, the regulatory base is calculated by dividing the wages of the last 365 days before becoming disabled by 12.[9]

3. Theoretical Model: A wage gap model between non-disabled and disabled workers

We consider a wage determination setting for both non-disabled (*n*) and for partially disabled individuals (*d*). The total production output generated by a non-disabled worker is p_t, where the subscript *t* refers to time. The labour productivity of a disabled worker is consecutively reduced by a constant proportion ε. According to the Spanish disability system legislation, a partially disabled individual must work in a job or professional activity different to that before becoming disabled. Along the same lines, we also assume the presence of a productivity gap, θ_t, related to the assimilation costs

[8] Benefit=Regulatory Base * Percentage.
[9] There was a reform in the calculation of the level of disability benefits for ordinary illness introduced in 2008. After the reform, there was a percentage that depended on the number of years contributed to the system that was multiplied by the regulatory base. However, this change only affects individuals whose cause of disability is an ordinary illness and, in our sample, we only include individuals disabled due to accident. Therefore, this reform does not affect our sample.

of working in a new and different job or professional activity.[10] This gap may disappear after a certain period spent working in the new job. The Company pays wages w_t^d and w_t^n for each type of worker. As long as the firm employs a worker, the total payoff for the firm is $p_t - w_t^n$ for a non-disabled worker and $p_t(1-\varepsilon-\theta_t) - w_t^d$ for a disabled worker.

An employer and a worker are matched together through labour market frictions. Thus, if the company and the worker separate, they will both have to go through an expensive search process before finding another employer or employee. Because of the presence of these labour market frictions, the worker and the firm bargain over the worker's wage. If they disagree, both disabled and non-disabled workers receive an outside income, b_t, and the firm produces nothing. The parameter b_t includes unemployment benefits and the home production net value of search costs. Moreover, disabled individuals also receive partial disability pensions that are non-contingent to working status. This pension is equivalent to a proportion, α, of their average wage for the years previous to the exogenous disability shock, w_0^d.

We assume that wages are determined by Nash bargaining, where the worker has bargaining power β. The wages derived from the Nash bargaining solution are the w_t^d and w_t^n which maximize the weighted product of the worker's and the firm's net return from the job match. Therefore, wages must satisfy the following conditions:

$$w_t^n = \arg\max\,(p_t - w_t^n)^{1-\beta}(w_t^n - b_t)^{\beta} \tag{1}$$

$$\mathrm{w}_\mathrm{t}^d = \arg\max\left(p_t(1-\varepsilon-\theta_t) - w_t^d\right)^{1-\beta}\left(w_t^d + \alpha w_0^d - b_t - \alpha w_0^d\right)^{\beta} \tag{2}$$

Note that the disability pension, αw_0^d, appears in the payoff, $w_t^d + \alpha w_0^d$, as well as in the outside option, $b_t + \alpha w_0^d$, of the weighted net return of the disabled worker because disability benefits are not contingent to working status.

In the case of agreement, the negotiated wages will be

$$w_t^n = \beta p_t + (1-\beta) b_t \tag{3}$$

[10]The temporary component of the wage loss can also be related to the ability to adapt to the disability condition. For a discussion, see for example Wu (2001), Oswald and Powdthavee (2008) and more recently Braakmann (2012) and Bayer and Juessen (2012).

$$w_t^d = \beta p_t(1 - \varepsilon - \theta_t) + (1 - \beta)b_t \quad (4)$$

Note that when the pension is not contingent to working status, it does not affect the wage. The difference between expression (3) and (4) generates the following wage gap

$$w_t^n - w_t^d = \beta p_t(\varepsilon + \theta_t) \quad (5)$$

Expression (5) shows that the wage gap of a disabled worker depends on a permanent and a transitory productivity gap. The permanent component ε is due to the disability condition after the disability shock, while the transitory component is related to the presence of assimilation costs for being in a different job or professional activity, which in turn reduces the implicit bargaining power of the disabled employee.[11] Thus, equation (5) suggests that the wage gap will be lower after some work experience in the new job. In particular, we expect that $lim_{t \to \propto} \theta_t = 0$. However, the permanent wage gap will remain over time.

4. Database and sample selection

We use the Continuous Sample of Working Lives ("Muestra Continua de Vidas Laborales", MCVL) which is a microeconomic dataset based on administrative records provided by the Spanish Social Security Administration. It contains a random sample of 4% of all the individuals who, at some point during 2010, contributed to the social security system (either by working or being on an unemployment scheme) or who received a contributory pension.[12] The random sample selected contains over one million people. There is information available on the entire employment and pension history of the workers, including the exact duration of employment, unemployment and disability pension spells, and for each spell, several variables that describe the

[11]This permanent component of the wage gap can also include discrimination related to disability status (see, for example, Malo and Pagán (2012)). According to these authors, 80 percent of the wage gap between non-disabled and disabled workers not hampered by their daily activities is explained by differences in workers' characteristics (productivity gap) while 20 percent can be explained by job discrimination.

[12] This means that the only individuals missing from this database are those who were inactive in 2010 and did not receive any kind of contributory benefit (such as disability, orphan, widow, etc.). Furthermore, the sample is representative for 2010 but, as exit from the disability system is extremely low (1.1%), we are confident that the sample is also representative for the other years included in the analysis.

characteristics of the job or the unemployment/disability benefits. There is also information on personal characteristics such as age, gender, nationality and level of education.

For the treatment group, we select all individuals that become partially disabled due to an exogenous disability shock (accident) between 1996 and 2010.[13] We do not include individuals that become totally disabled as the definition of total disability stresses that this group of individuals is not able to do any kind of job. As our interest lies in estimating the wage (or productivity) lost as a result of the disability shock, we exclude individuals with total disability from our sample. Furthermore, in order to solve the endogeneity problem between receiving a benefit and labour market status, we only include individuals who are disabled because of an accident.[14] In the control group we include a 10% random sample of everybody who is in our database between 1996 and 2010 and who never received a disability benefit (for either common illness or accident).[15]

The selected sample contains 125,717 individuals (1,120,607 person-year observations in total), 71,917 are men, while 53,800 are women. 2,762 of these individuals in our sample move to disability benefits due to an exogenous disability shock at some point between 1996 and 2010 and are, thus, our treatment group, while 122,955 individuals never become disabled in our sample period and constitute our control group. We have selected such a large control group in order to ensure a good matching process and to maximize the options of finding a similar individual in our control group for each individual in the treatment group.

5. Empirical strategy: Average Treatment Effect on the Treated

As explained above, we want to estimate how much wages change, on average, for those individuals who become disabled as a result of an exogenous disability shock, compared to the hypothetical state of having not received a disability shock. We make

[13] Note that we identify if an individual has had an accident only if he/she receives disability benefits. Therefore, we have a number of milder accidents that we will not be able to capture in our database. Furthermore, individuals who have suffered an accident but that do not want to claim disability benefits, because this would entail changing jobs, are also not in our database.
[14] We claim that an accident is an unexpected event that has to be externally assessed by a medical team in order to be eligible for disability benefits.
[15] We take a 10% random sample as we had too many individuals in the original sample.

use of matching methods to allow for the counterfactual approach associated with treatment effect techniques for program evaluation.

Formally, let $D = 1{,}0$ indicate if the individual is actually treated or not. In our case, if the individual becomes disabled or not. Let X be the set of observed characteristics and W_{1i} and W_{0i} be the potential salaries of interest if the individual is treated or not, respectively. The notion of "potential" is used to emphasize that only one of W_{1i} or W_{0i} is observed for every individual in the sample.

In this context we want to measure the Average Treatment Effect on the Treated (ATET) and which is given by the following expression:

$$ATET = \vartheta = E\lfloor W_{1i} - W_{0i} |\, D_i = 1\rfloor = E\lfloor W_{1i} |\, X, D_i = 1\rfloor - E\lfloor W_{0i} |\, X, D_i = 1\rfloor$$

Clearly ϑ is not identified by the data, since we observe each individual in one of the possible states in each moment in time. If we assume that the probability of becoming disabled is random, we could solve this problem by using the control group as a counterfactual. However, even though we have only taken those individuals that became disabled because of a work-related accident, the case could be that the types of accidents that leave the individual impaired may occur more frequently in certain professions or sectors than in others.

Therefore, we will control for those differences observed between the treatment and control groups with a Propensity Score Matching (PSM) model that will create subgroups of individuals where treated and control group workers do not differ before the shock. Our administrative dataset is rich with information on the characteristics of the individual and the type of job that he/she had before the disabling condition. We estimate the PSM separately for each subsample in order to estimate heterogeneous effects by working status. Next, we use different matching techniques to compare the individual in the treated group that is most similar to an individual in the control group. Such a method is attractive because it represents an improvement on other parametric and semi-parametric approaches to program evaluation since it avoids many potential biases due to the model specification.[16] However, this method relies on the conditional independence assumption:

$$(W_{1i}, W_{0i}) \perp D|X$$

This strong assumption, which is known as selection on observables, was introduced by Rubin (1973, 1974) and Rosenbaum and Rubin (1983, 1984).

The idea is that using this method, the ATET is identified under the assumption that observable controls and the pre-treatment outcomes include all factors that determine both the probability that an individual becomes disabled, as well as their potential wage in the absence of disability.

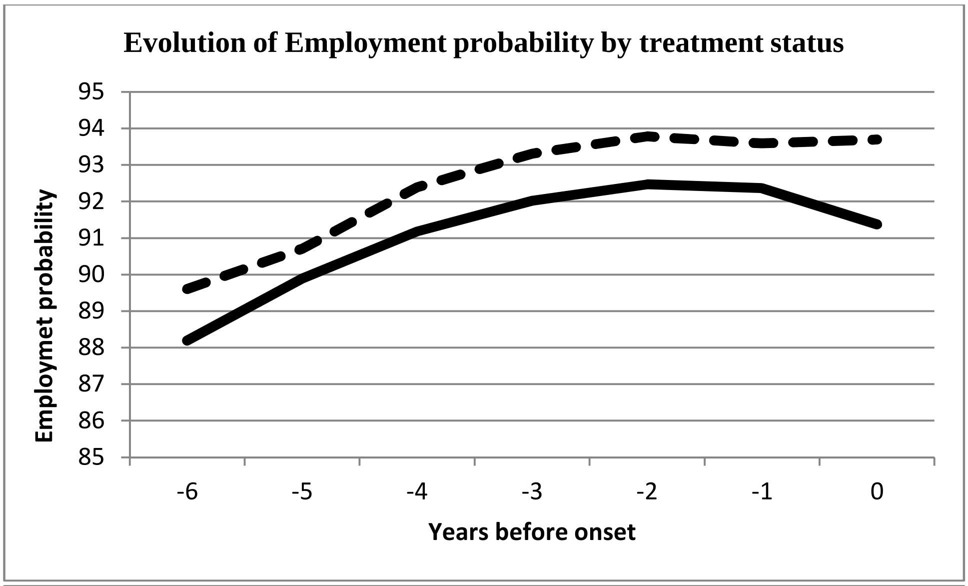
Therefore, in an attempt to relax this strong hypothesis, we estimate the effect of interest by using a combination of Difference-in-Differences (DID) with PSM. More specifically, we estimate a DID model using weights obtained from the PSM.[17] The main idea of this new technique is to use PSM to obtain a comparable set of treated and control individuals and estimate a DID model to control for fixed unobservable characteristics. In the DID regression we include the same explanatory variables measured in *t=1* included in the PSM. However, our results did not change if we did not include these covariates. Essentially, by running this weighted DID regression we weaken the identifying assumption of the matching estimator (conditional independence assumption). Therefore, this technique only requires that, conditional on observables, in the absence of the shock the evolution (not levels) of wages before and after the shock would have been the same for the treated and their matched controls (Heckman et al. (1997); Blundell and Costa-Dias (2002)).

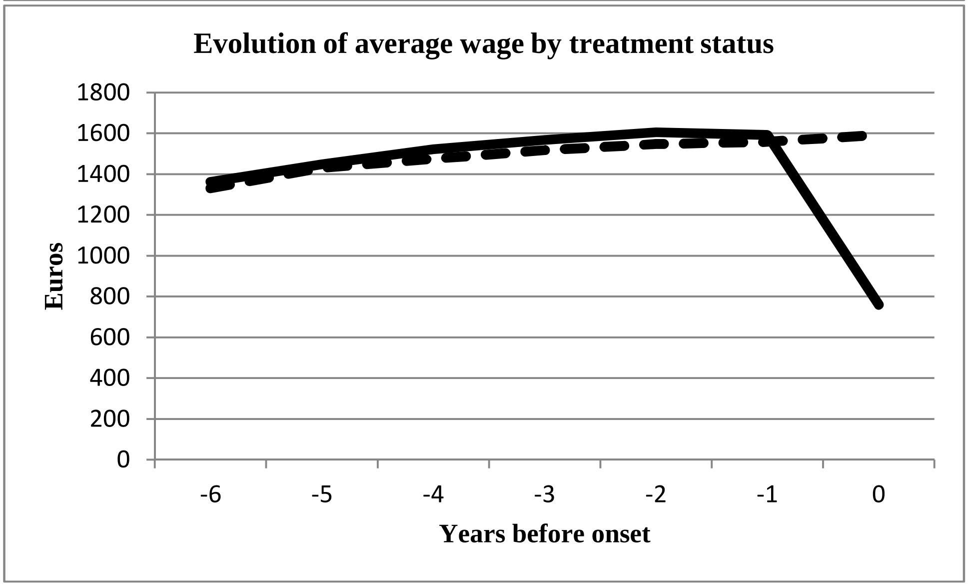
To analyse the parallel-trend assumption, we present Figure 1 to show pre-treatment outcomes (employment and average wages) during the six years before onset. As we can observe in both graphs, although levels are slightly different, trends are parallel before the onset.

[16] See Heckman and Horz (1989), Heckman, Ichimura and Todd (1997) and Blundell and Costa Dias (2002) are just some of the articles that explain how to evaluate certain treatments (in our case disability) using matching procedures.

[17] Following García-Gómez et al. (2013), treated individuals are weighted as 1 and individuals in the control group receive a weight depending on the number of times the individual is used as a control and on the distance to the propensity score of their matched treated peer on the Epanechnikov kernel.

Figure 1: Employment probability and average wages in pre-treatment period





Note: Treatment group (solid lines) and control group (dashed lines). Amounts are expressed in 2010 Euros.

6. Constructing the treatment and control groups

To construct the treatment and control groups we use the MCVL and follow a similar methodology as in Lechner and Vazquez-Alvarez (2004) and García-Gomez and López-Nicolás (2006). In particular, our treated group includes individuals who were non-disabled in *t=1*, become partially disabled due to an exogenous disability shock (accident) in *t=2* and continue being partially disabled in *t=3*.[18] For our control group, we want individuals similar to those in the treatment group in *t=1*, the moment in which we construct the propensity score. Thus, we implement a sequential strategy in which we first consider a window of three years for each observed individual. Hence, with annual data we require at least three waves with which to generate a sequence. As our dataset covers the period 1996-2010, we have 14 possible sequences of three years. Then, for each sequence we select individuals who are healthy (not disabled) and are employed at *t=1*. Therefore, our treatment group includes individuals who meet the above-mentioned selection criteria, become disabled as a result of an exogenous disability shock at *t=2* and remain disabled at *t=3*. The sequence of health status for these individuals is No Disabled, Disabled, Disabled (ND,D,D). On the other hand, the control group includes individuals who meet the aforementioned selection criteria and continue being non-disabled both in *t=2* and in *t=3*. Therefore, they experience the sequence No Disabled, No Disabled, No Disabled (ND,ND,ND).[19] Finally, we match individuals in the treated and control groups with the propensity score in *t=1*, where both individuals are non-disabled. Since we have a longitudinal database we can use the outcomes before the individual becomes (or does not become) disabled in the vector of conditioning variables (for example, wages in *t=1*).

7. Descriptive statistics

The first panel in Table 1 presents samples sizes for the treated and control groups for the different subsamples that we consider in our estimations.

[18] Only 1.1% of individuals stop receiving partial disability benefits in our sample. Therefore, we consider partial disability as an absorbing state as exit from the partial disability system is very low.

[19] An individual who is in the control group in one sequence can be a control unit for any given sequence and count as independent observation for each of the different sequences. However, individuals who appear as a treatment unit can only appear in one sequence as treated because, once he/she becomes disabled, he/she will remain disabled permanently. The sequence ND,D,D can only be experienced once. But a treated individual can appear in a previous sequence as a prior control if he becomes disabled in the final years of our sample.

As we can observe, we have a high number of observations in the control group (non-disabled workers) which allows us to choose the individual in the control group that is most similar in characteristics to each individual in the treatment group before the shock occurs.

The first row in Table 1 shows the number of observations that we have when we analyse the effects of the disabling condition independently of whether the individual works or not after the occurrence of the shock. In this case, we only condition on working before the shock and we analyse the effects of disability on income as defined by wages plus disability benefits. The second row shows the number of observations that we have when we restrict the sample to include only those individuals who work in the year before and the year after the shock occurs. Finally, in the third row we have the number of observations when we restrict the sample to include only those individuals observed as working in all periods. We use this last sample to explore the evolution of the wage gap over time. In this case, the number of treated individuals is small because the condition is very restrictive.

The second and third panels in Table 1 show the descriptive statistics of the employment and income measures that we use as dependent variables in the estimations.[20] We consider an individual to be employed if he/she is observed as working on June 15 of that year. Therefore, if he/she is reported as working we calculate his/her wage as the monthly average wage in June. In order to take into account that some individuals may not work the entire month, we divide the wage received in June by the total number of days worked in that month. Following this, we multiply the figure by 30 so as to have an adjusted measure of the monthly wage.[21]

As seen in the fourth and fifth rows in Table 1, in $t=1$ (before the accident) the percentage of individuals that are employed is almost identical in the treated and control groups. However, in $t=3$ (after the shock) the share of individuals working is substantially different between the two groups. Only 15.32% of treated individuals are employed, as opposed to 87.36% in the control group. If we consider wages instead of

[20] In fact, we use a proxy for wages, the contributory base, which is equivalent to wages except for the fact that they are top and bottom-coded (censored). Although for the entire MCVL this is a significant problem as Bonhomme and Hospido (2009) mention, such an issue is not likely to be relevant in our case as wages are censored only for very few observations (less than 0,1% of the sample).

[21] We have also estimated our results with another measure of the wage variable. These results are presented in Appendix 2.

employment, we observe the same pattern; a very similar average monthly wage in the two groups before the accident, but a sizeable difference in wages between the two groups the year after the accident (in *t=3)*. More specifically, subsequent to the accident the wages for the treated group are substantially lower than wages for the control group. When we add disability benefits and wage together, we observe a very different picture depending on whether we condition the sample to include only those individuals who work at *t=3* or not. If we condition working at *t=3,* we can see that the sum of the benefits and wages is considerably greater for the treated group than for the control group (who, as they do not have a disability, only receive wages). However, if we take all disabled individuals in the sample into account (independent of whether they work or not after the disability); the total sum of wages plus social security benefits for disabled individuals is lower than the wage of non-disabled workers. This result suggests that a large number of disabled people decide either not to work or are unable to find a job even though legally they are able to work. Those individuals then have to live on only the support that they receive from the disability system which corresponds to only a percentage (55 or 75%) of their previous earnings.

Table 1: Descriptive statistics of employment and income measures.

	Treated		**Control**	
Sample size if:	Individuals		Individuals	
Working in *t=1*	1718		530759	
Working in *t=1* and *t=3*	356		473627	
Working in *t=1, t=3…t=7*	189		310536	
	Percentage		Percentage	
Employment in *t=1*	82.30		84.37	
Employment in *t=3*	15.32		87.36	
Conditional on working in t=3	Mean	Std Dev	Mean	Std Dev
Wage in *t*=1	1318.76	839.76	1346.61	1064.54
Wage in *t*=3	1389.15	1267.22	1584.55	995.76
Wage + Pension	2282.19	1390.74	1584.55	995.76
Independently if they work in t=3				
Wage + Pension	1283.2	869.89	1502.63	1026.02

Note: amounts are expressed in 2010 Euros.

8. Results

In this section we calculate the impact of becoming disabled on employment and on different measures of income. Thus, we estimate the ATET by first only using PSM and then by using a combination of PSM and DID. Initially, following Becker and Ichino (2002), Abadie and Imbens (2002) and Abadie et al. (2004), we estimate the propensity score (the probability of being in the treatment group) with a probit specification (as we have two possible states (ND,D,D versus ND,ND,ND). In all our regressions we include as regressors all the relevant and available variables that we have: age, age squared, professional category, sector of activity, region, sequence, sex, nationality and wages at t=1.[22] The specification passes the "balancing hypothesis". This means that there are no systematic differences in observable characteristics between the treated and control groups once we condition on the propensity score. After this, we match treated and control individuals using different approaches. Specifically we use the nearest neighbour matching and the kernel matching method. There is no element (a priori) for favouring either of these approaches. Therefore, we present the results of both estimates to assess the robustness of our findings. Next, we follow García-Gómez et al. (2013) and estimate the effect with DID using the weights obtained from PSM.

8.1 Effects of becoming disabled on employment and wages.

The first row in Table 2 presents the estimates of the ATET of disability on the probability of working in *t=3* (the year after the accident) using both PSM, as well as PSM combined with DID. The coefficient can be interpreted as the percentage point difference in the probability of working between individuals in the treatment and control groups. With both methods we obtain a fall of around 73 percentage points in the probability of working due to the accident. This drop corresponds to the difference in the percentage of individuals working at *t=3* between the control (87.36%) and the treatment groups (15.32%) reported in the descriptive statistics table (Table 1). With the two econometric models estimated in this section, we can now attribute this drop to the health shock that causes the disabling condition.

[22] We do not use education because this variable is measured incorrectly in this database. Instead, we use professional category that captures very well the educational level and it is the variable that in general is used as a proxy of education in this database. Unfortunately and due to the nature of our data (administrative records), we do not have any other personal information that would have been interesting to include in the propensity score (such as spousal earnings).

The second row in Table 2 presents the estimates of the ATET of disability on earnings in *t=3*. Both methods show a significant reduction in the monthly wage for the disabled as a result of the onset of the disabling condition. For instance, estimating the ATET with PSM and the nearest neighbour matching method, the wage reduction of a disabled person is 293 EUR per month; expressed in constant terms at 2010 prices. If we use the kernel matching method, the reduction is slightly higher, 342 EUR per month. The reduction is a similar size to when we combine PSM and DID. In this case, the wage gap is estimated to be 308 or 274 EUR per month; depending on the matching technique used.[23]

As the average wage for disabled individuals working at *t=3* is 1,389.15 EUR per month (see Table 1 above), this wage gap represents between 19% and 22% of the wage of a representative disabled worker (depending on the matching method applied).

Table 2: Effects of disability on employment and income at t=3

	Propensity Score Matching		**Propensity Score Matching with Diff-in-Diff**	
	Nearest-Neighbour Matching	Kernel matching	Nearest-Neighbour Matching	Kernel matching
Employment	-0.742 (0.013)	-0.731 (0.011)	-0.742 (0.013)	-0.723 (0.014)
Wage	-293.38 (97.83)	-342.21 (81.99)	-308.74 (87.63)	-274.18 (80.15)
Wage + Pension if they work in t=3	607.63 (104.50)	558.81 (85.99)	592.26 (86.82)	626.83 (81.28)
Wage + Pension indep. if they work in t=3	-287.87 (32.09)	-359.74 (25.41)	-331.15 (26.04)	-345.87 (23.14)

Note: amounts are expressed in 2010 EUR. Bootstrapped standard errors in parentheses.

[23] We also estimate the effects using Difference in Differences without Propensity Score Matching (comparing the distance between the treated group and the control group before and after the shock) and we obtain a reduction in the wage of 273 EUR per month. Furthermore, we estimate the effect using Event Study. With this methodology we assume that the treatment is totally random and we predict the wages for treated individuals as if they had been in the control group. We then calculate the difference between that prediction and their actual wage and we obtain what is labelled in Event Study literature as the “abnormal return”. In particular, we obtain a reduction of wages of 296 EUR per month.

As our theoretical model in Section 4 suggests, this estimated wage gap is probably due to two productivity shocks: a permanent productivity shock generated by becoming disabled and a temporary productivity shock related to the fact that these individuals have to change jobs and have, therefore, a learning process in the new job. In section 8.3 we will develop this point further.

8.2 Are disability benefits able to offset the wage gap?

An important question to be answered from a policy point of view is whether the benefits that are received by these disabled individuals are able to compensate the lower wages that they earn after the shock. Therefore, in the third and fourth rows in Table 2 we attempt to analyse the extent to which the social security provisions compensate for the loss of wage that we observe in the first row. In other words, we try, once we have considered income as both the wages earned and the amount received in disability benefits, to see if the income gap between our treated and control groups is still present.

Since disability benefits can be received independently of the working status of an individual, we carry out the exercise for two subsamples. In the third row in Table 2, we work with the subsample of disabled individuals who continue working after the shock. Thus, we have a sample of individuals (in the treated and control groups) that work in $t=3$. Instead, in the fourth row in Table 2 we do not condition the disabled to work in $t=3$. Therefore, our sample of disabled individuals includes individuals that may or may not work in $t=3$. In both rows we consider the sum of their wages, if they work, plus the disability benefits.

In the third row we note that, when we condition the subsample of individuals working in $t=3$, the sum of the wage plus the disability pension is greater in the treated group than in the control group. This means that the benefits for this subgroup of disabled workers more than offsets the drop in wages, regardless of the matching method or the estimation method that we use.

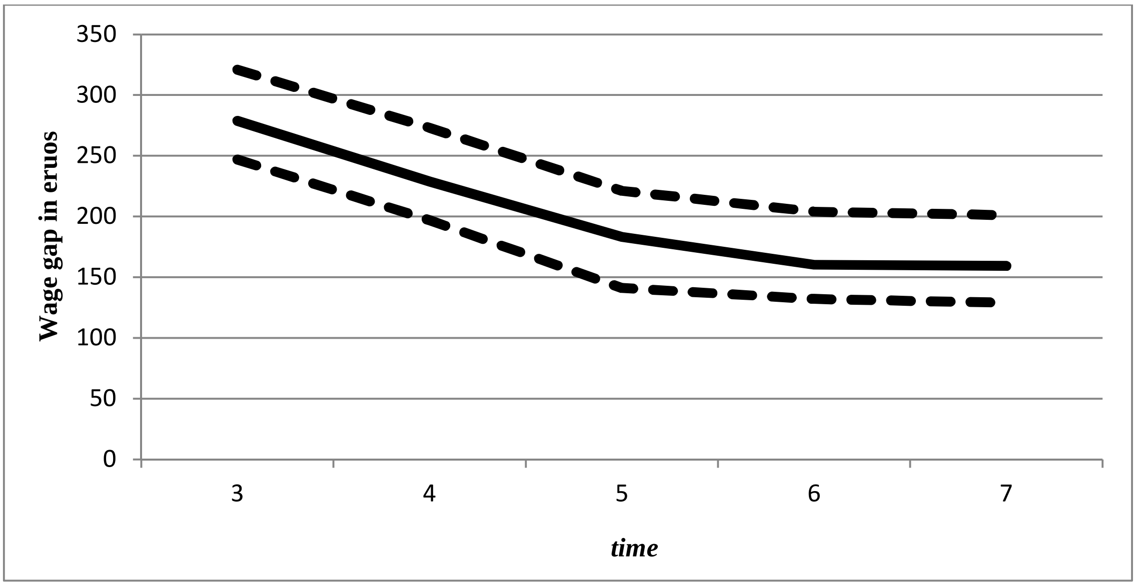
However, row four in Table 2 indicates that when we do not condition on working in $t=3$, benefits are not able to entirely offset the fall in wages. This result is due to the fact that disability benefits obtained by this group of individuals are lower than previous wages. It is important to note that, even if this group of individuals can continue working after the onset of the disabling condition, a large number of them do not actually work after onset. Therefore, as the disability benefits are the only income source that they have, average incomes are lower for this group of individuals when we calculate average incomes including both workers and non-workers.

8.3 What happens with the wage gap over time?

In this subsection we consider a longer period in order to test the hypothesis (derived from the theoretical model) that part of the wage gap between our treated and control groups will decrease over time due to the reduction in the temporary productivity gap.

As explained earlier, partially disabled individuals are allowed to work but they must do so in a job different to the one they had before becoming disabled. Therefore, they have to change jobs once they have been accepted into the disability system. In the new job we would expect a drop in productivity and, accordingly, a drop in wages. This drop in productivity can be broken down into two elements: i) a permanent reduction due to the disability itself and; ii) a transitory reduction in productivity caused by the fact that any new job requires an initial learning process. We expect the transitory fall in productivity, and consequently in wages, to disappear over time as the disabled worker adjusts to the requirements of the new job. The aim of this section, thus, is to measure how much of the wage gap observed in Table 2 is due to a permanent or to a transitory fall in productivity. In order to do that, we restrict our sample to individuals that work from $t=3$ to $t=7$ to make sure that we are analysing the fall in wages for the same group of individuals. We present in Figure 2 the results of our preferred model (PSM with DID regression, Nearest-Neighbour Matching) which show that wages for disabled workers are lower than wages in the control group and this holds true for all the periods included in the analysis. At the same time, we also observe that the pay gap between disabled and non-disabled individuals falls over time. We interpret this as evidence of the existence of a transitory drop in productivity that vanishes over time. However, we also observe a constant wage gap associated with the permanent fall in productivity that becomes stable and remains relatively constant 4 and 5 years after becoming disabled (from $t=6$ to $t=7$ in Figure 2 the wage gap stops decreasing and becomes permanent). Therefore, there is a difference in wages of around 160 EUR per month between disabled and non-disabled individuals that becomes permanent. In other words, 57%-59% of the wage gap between non-disabled and disabled workers is permanent.[24]

Figure 2: Wage gap over time: permanent and transitory fall in productivity



Note: Wage gap estimated from PSM with DID regression (Nearest-Neighbour Matching). Confidence intervals at 0.95 percent (dashed lines). Amounts are expressed in 2010 EUR.

9. Conclusions

Despite several policies that aim at ensuring that disabled individuals have the same labour market opportunities as their non-disabled counterparts (such as anti-discrimination and labour promotion policies), Spain is characterized by having very low employment rates for disabled individuals when compared to other OECD countries. In this paper, however, we focus on another potential disadvantage in terms of labour market opportunities by testing whether the onset of an unexpected disabling condition also entails reduced earnings. At the same time, we are also interested in analysing if this wage gap between disabled and non-disabled workers is permanent or is reduced over time. In other words, we want to know if disabled individuals are able to "catch up" in terms of wages lost due to their disability.

In order to do that, we focus on individuals in the partial disability system so as to ensure that disabled individuals in our sample are able to work and present both a theoretical and an empirical model that allows us to identify the effects of disability on

[24] We observe the same pattern when we apply a different estimation method. This can be observed in Table A3.1 in the Appendix (sensitivity check).

wages and the sources underlying this relationship. In the theoretical model, we assume that the wage gap of a disabled worker depends on a permanent and a transitory productivity gap. The permanent component is due to the disabling condition after the disability shock, while the transitory component is related to the presence of assimilation costs for being in a different job or professional activity which, in turn, reduces the implicit bargaining power of the disabled employee. Thus, the model predicts that the wage gap will be lower after some work experience in the new job (reduction of the temporary component) but that the permanent component will remain.

We proceed by testing this theoretical hypothesis with an empirical model in which we estimate how much, on average, wages change for those individuals who become disabled due to an exogenous disability shock, compared to the hypothetical state of not having received the disability shock that causes the disabling condition. We also empirically estimate the evolution of this wage gap over time in order to check whether the predictions of the theoretical model are fulfilled. As one of the main problems in measuring this change is the endogeneity between the disability status and wages, we only include in our sample those individuals that become disabled due to an accident and estimate a model that combines propensity score matching with a difference-in-differences model. In all our specifications, we find that the reduction of the wage for the disabled is between 274 and 308 EUR per month (expressed in constant terms at 2010 prices), which is between 19 and 22% of the average wage of a disabled worker. However, this reduction is more than offset when we take both wages and disability benefits as the income measure for the group of disabled individuals that work. For the entire group of partially disabled individuals (those who work and those who do not have a job), we still find a fall in income, even when adding the wage and the benefits together (as a large number of these individuals do not work). When we analyse the temporal evolution of the wage gap, we observe that, as predicted in the theoretical model, the wage gap between disabled and non-disabled individuals falls over time (the transitory drop in productivity is evaporating). However, we observe a constant wage gap of 153-159 EUR per month (between 57-59% of the initial wage gap) associated with a permanent fall in productivity (predicted in the theoretical model) that remains constant over time. Finally, our results show a large drop of 73 percentage points in employment probabilities the year after the accident which is attributable to the onset of the disabling condition. Our results point towards the same direction as those found in the literature do. However, as we are able to use a broader definition of accidents than the usual one (Commuting Accidents) and our sample includes those individuals that receive a disability benefit due to an accident, our results are quantitatively higher than previous results both for Spain (Garcia-Gomez and Lopez-Nicolás, 2006) as well as for other countries (Moller (2005) and Halla and Zweimüller (2011)).

Our results prove that there are significant and permanent wage losses for disabled workers. Therefore, we believe that there is room for policymakers to introduce new incentives for employers to provide training courses for disabled workers to upgrade their skills and increase their productivity in an attempt to close (or at least reduce) this permanent wage gap. Furthermore, as part of the wage gap is temporary, policymakers should discuss whether the formulas used to calculate a disability benefit should be constant (as they are now) or should include some conditionality depending on time since onset of the disabling condition. Nevertheless, a note of caution should be made when trying to extend our results to the group of disabled workers whose disability is not derived from an accident. As the mean DI benefit is somewhat lower for non-accident related DI beneficiaries, when we take both wages and disability benefits as income, the results may not be exactly the same as those estimated in this paper.

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Appendix 1: The Spanish Disability System

Table A1. 1: Parameters for calculating permanent disability benefits in Spain.

	Ordinary Illness	Work-unrelated Accident	Work-related Accident or Professional Illness
Eligibility	Age >= 31: Contributed 1/4 time between 20 years old and disabling condition. Minimum of 5 years Age < 30: Contributed 1/3 time between 16 years old and disabling condition. No minimum number of years required	No minimum contributory period required	No minimum contributory period required
Regulatory Base	Average wage last 8 years of work	Average annual wage of 24 months within the last 7 years of work	Average wage last year of work
Percentage applied to the regulatory base	Partial Disability: 55% Individuals older than 55 with difficulties finding a job due to lack of education or the characteristics of the social and labour market of the region where they live: 75% Total Disability: 100% Severe Disability: 100%+50%		

Appendix 2: Estimations with a different wage measure

Alternatively, we consider a second measure of wages. Wage 2 is the monthly average of the wages for the whole year. In this case, we add together the wages received in all months worked and then we divide it by the total number of months worked in order to obtain a monthly measure. Tables A2.1, A2.2 and A2.3 present the same descriptive statistics and estimates as our baseline results but using this new definition of wages (Wage 2). Although the figures are slightly higher, all results are akin to those we obtain with our baseline wage measure.

Table A2.1: Descriptive statistics for wage 2.

	Treated		Control	
	Mean	Std Dev	Mean	Std Dev
Conditional on working in t=3				
Wage2 in t=1	1304.63	828.59	1253.74	988.45
Wage2 in t=3	1204.43	658.99	1322.42	1041.28
Wage2 + Pension	2097.46	873.95	1322.42	1041.28
Independently if they work in t=3				
Wage2 + Pension	1244.5	728.21	1292.9	1020.69

Table A2.2: Effects of disability on wage 2 and wage 2 plus pension at *t*=3

	Propensity Score Matching		**Propensity Score Matching with Difference in Differences**	
	Nearest-Neighbour Matching	Kernel matching method	Nearest-Neighbour Matching	Kernel matching method
Wage 2	-516.37 (69,41)	-495.83 (46.19)	-434.48 (47.57)	-468.71 (43.47)
Wage 2 + Pension if they work in t=3	384.63 (78.57)	405.18 (57.08)	466.53 (45.67)	432.31 (50.11)
Wage 2 + Pension if they work in t=3	-320.54 (29.14)	-404.64 (24.13)	-390.23 (18.51)	-422.88 (23.78)

Table A2.3: Wage 2 gap over time: permanent and transitory fall in productivity

	Propensity Score Matching		**Propensity Score Matching with Difference in Differences**	
	Nearest-neighbour Matching	Kernel matching method	Nearest-neighbour Matching	Kernel matching method
t=3	-409.57	-480.03	-369.72	-392.25
	(106.17)	(65.44)	(78.68)	(66.15)
t=4	-392.24	-453.05	-352.39	-377.56
	(110.78)	(88.74)	(83.65)	(81.23)
t=5	-379.58	-421.74	-339.73	-325.95
	(106.68)	(70.90)	(83.65)	(102.34)
t=6	-231.9	-372.84	-204.4	-245.88
	(110.63)	(72.47)	(86.48)	(74.35)
t=7	-230.94	-371.72	-202.9	-244.78
	(111.25)	(98.91)	(88.76)	(96.56)

Note: amounts are expressed in 2010 EUR. Bootstrapped standard errors in parentheses.

Appendix 3: Sensitivity check; Wage gap over time with alternative estimation methods.

Table A3.1: Wage gap over time: permanent and transitory fall in productivity

	Propensity Score Matching		**Propensity Score Matching with Diff-in-Diffs**	
	Nearest-Neighbour Matching	Kernel matching	Nearest-Neighbour Matching	Kernel matching
t=3	-261.02	-361.84	-278.86	-262.03
	(101.84)	(78.19)	(81.5)	(79.21)
t=4	-210.79	-353.79	-228.63	-212.08
	(105.03)	(88.56)	(87.34)	(84.12)
t=5	-172.36	-289.98	-183.2	-178.23
	(106.3)	(105.42)	(84.82)	(101.46)
t=6	-152.13	-215.81	-160.2	-154.06
	(110.93)	(84.87)	(110.93)	(89.78)
t=7	-151.46	-215.03	-159.2	-153.25
	(106.15)	(93.59)	(106.15)	(98.12)

Note: amounts are expressed in 2010 EUR. Bootstrapped standard errors in parentheses.