Personality and Disability Employment Gap in the United States: Evidence from the Disability and Use of Time Supplement

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Abstract

Understanding the factors contributing to the disability employment gap is critical for improving the employment opportunities for people with disabilities. Personal characteristics like age and gender have been studied but little is known about the role of personality and employment for those with and without disabilities. Differences in these factors are also expected for individuals who identify as work-limited disabled. This paper examines the role of personality traits in explaining the disability employment gap in the United States by applying a structural equation model followed by a tailored decomposition technique and taking advantage of uniquely rich data from the Disability and Use of Time Supplement in 2013. Age and female were significant predictors of employment only for those without disabilities. Personality predicted employment for those without disabilities and non-work-limited disabled, but not for the work-limited disabled. The employment gap between those without disabilities and work-limited disabled was significant but not in comparison to those individuals who consider themselves non-work-limited disabled. The findings highlight the importance of controlling for personality traits when estimating the employment gap between those with and without disabilities and understanding its determinants.

1. Introduction

People with disabilities are persistently in a worse labor market position than those without disabilities, particularly with respect to employment (Vornholt et al., 2018). In the United States, recent statistics show a significant employment gap of 35.9% points between those with and without disabilities ages 18-64 living in the community (Houtenville et al., 2023).

Estimating the magnitude of the disability employment gap is crucial but identifying the factors contributing to this gap is equally important for improving the employment opportunities for people with disabilities. Limited evidence examining the reasons behind the disability employment gap distinguishes between differences in observable factors such as gender, age, education, race/ethnicity (i.e. explained part), and unobservable factors (i.e. unexplained part) – the latter, typically relating to discrimination against those with disabilities (see Jones, 2021 for a review). Despite the focus on discrimination, unobserved differences in productivity have also been acknowledged as significantly contributing to the disability employment gap, reducing the amount of the gap attributed to discrimination (Jones, 2006).

Observable factors, including gender, age, race and ethnicity are commonly included in studies of employment outcomes for those with disabilities. Gender (Rabren et al., 2002), race and ethnicity (Prince et al., 2018; Salkever et al., 2007; Simonsen & Neubert, 2012; Wehman et al., 2015), and age (Mitchell et al., 2006; Prince et al., 2018; Salkever et al., 2007) have all been shown to correlate with employment status, as does education (Ohl et al., 2017). All these studies focused on particular populations, such as individuals with schizophrenia (Salkever et al., 2007) or developmental disabilities (Simonsen & Neubert, 2012). However, even when all populations were considered in other studies (see for example, Geiger Baumberg et al., 2019; Jones 2021; Sevak et al., 2018), all these observable factors predicted employment outcomes.

The availability of more nuanced data and an ongoing interest in identifying and controlling for as many unobservable factors as possible, which can reduce further the part of the gap attributed to discrimination, has led economists into examining the effect of noncognitive skills (such as personality and preferences) on differences in labor market outcomes (Blau & Khan, 2017; Neumark, 2018). For example, personality traits (measured by the Big Five) have been found to explain up to 4% of the gender wage gap (Braakmann, 2010; Mueller & Plug, 2006; Nyhus & Pons, 2012; Risse et al., 2018; Schäfer & Schwiebert, 2018; for a review see Roethlisberger et al., 2022) – with the exception of Kamal and Blacklow (2022) where no significant effect was found – and 8% of the gender employment gap (Braakmann, 2010). Although the role of personality traits has gained popularity among gender related studies, to our knowledge, it has not been used to directly explain differences in labor market outcomes by disability status.

It is known that personality traits measured before acquiring a disability can signify disability adaptation (Boyce & Wood, 2011), indicating a direct link between personality and disability. The difficulty in controlling for this direct link, for example, in the employment equation may have contributed further to the impact of personality on the disability employment gap not being explored. Instead, existing studies have rather focused on the role of disability in determining absenteeism while controlling for personality (Vlasveld et al., 2012), and the role of personality on the length of prior employment for people with disabilities (O'Sullivan et al., 2012). Nevertheless, certain personality characteristics – including neuroticism and conscientiousness – have been found to be associated with higher job performance and satisfaction (Bono & Judge, 2003). Further, it is known that having certain personality characteristics can make someone more prone to specific disability types (such as depression) than others without such characteristics (see Koford & Cseh, 2015 for a review). Therefore, it can be that personality contributes to the lower labor market outcomes of people with disabilities, including employment rates. This is consistent with growing recognition in the literature that further research examining the relationship between personality and employment outcomes for people with disabilities is needed (O'Sullivan et al., 2012).

Beyond the observable and unobservable factors already mentioned, disability status alone is not sufficient. According to DeLeire (2001), an individual with a disability is likely to be less productive than someone without a disability, which makes it impossible to separate the effect of health from the effect of unobserved productivity. As such, a simple variance decomposition of the employment gap by disability status would overestimate the gap between those with and without disabilities. Instead, work limitations caused by the disability should be considered and the employment gap decomposed separately for each disability group. DeLeire's (2001) approach assumes that: (a) individuals with disabilities, irrespective of them being work-limiting or not, face the same level of discrimination and (b) individuals without disabilities and non-work-limited disabled have the same unobserved productivity. Then, the unexplained part of the employment gap between the work-limited disabled and those without disabilities is not only attributed to discrimination but also to unobserved differences in productivity, unravelling the actual magnitude of discrimination against those with disabilities (see Figure 1 for an illustration).

[Figure 1 about here]

Our study aims to examine the role of personality traits in explaining the disability employment gap in the United States. We utilized data from the Disability and Use of Time (DUST) supplement (2013) to the Panel Study of Income Dynamics (PSID) and employed a structural equation model to account first for the potential direct link between personality and disability, followed by a decomposition technique. We defined disability using a set of specific items extensively used to define Americans with disabilities (see for example, Altman et al., 2017) and further distinguished between work-limiting and non-work-limiting disability, characterized as an important step in finding the actual effect of discrimination against those with disabilities on employment. (DeLeire, 2001; Jones, 2006).

2. Methods

2.1 Data

The DUST is a supplement to the PSID, the largest nationally representative household panel survey in the United States (Panel Study of Income Dynamics, public use dataset). The supplement was primarily designed to investigate connections between disability, time use, and wellbeing for older adults. In this study we used information obtained in the second wave of DUST in 2013, as it includes a larger sample and is also the only wave where information on personality traits was collected. The second wave of DUST was carried out following the 2013 core PSID interview to single and married or partnered adults age 60 or older. In contrast to the first wave, there was no age restriction on the spouse or partner's age. The DUST supplement included information for example, on impairments and limitations, behavior change, cognitive functioning, and participation activities. The supplement data can be linked to the core PSID data in the same year (and previous years) using the unique PSID family and sequence identifiers (Freedman & Cornman, 2015), and we followed this approach for variables of interest not in the supplement (for example, race, home ownership, presence of dependent children in the household and state of residence).

2.2 Disability

To identify people with disabilities, we used a set of standardized six items – developed for the U.S. Census and the American Community Survey (ACS) – that relate to having (a) serious difficulty hearing, (b) difficulty seeing even when wearing glasses, (c) serious difficulty concentrating, remembering or making decisions, (d) serious difficulty walking or climbing stairs, (e) difficulty dressing or bathing, or (f) difficulty doing errands alone such as visiting a doctor's office or shopping (Brault et al., 2007; Center for Disease Control and Prevention, 2010). Individuals who responded positively to at least one of the six items were identified as having a disability. To account for work limitations caused by the disability, we used responses to the question ‘Do you have any physical or nervous condition that limits the type of work or the amount of work you can do?’, included in the core PSID. We identified someone with a work-limiting disability if they also responded affirmatively to the work-limitation question. If they responded negatively to the work-limitation question but have a disability, they were considered as non-work-limited disabled. The definition of work-limiting disability is largely consistent with existing literature (see for example, DeLeire, 2001; Jones, 2021), albeit a single question was typically used to define those with disabilities, and both questions relating to disability and work-limitation were asked consecutively in the same questionnaire.

2.3 Personality

For personality, DUST includes a set of 15 items that can be used to assess the respondents' Big Five personality traits, i.e. agreeableness, conscientiousness, extraversion, neuroticism, openness to experience (Gosling et al., 2003). The respondents were asked how much they agreed with different statements about themselves (see Supplemental Material Table S1 for exact wording of the questions) on 4-point Likert-type scales (‘Not at all’, ‘A little’, ‘Some’, ‘A lot’). We obtained a respondent’s score for each personality trait by averaging the scores from the different statements referring to that trait – for some items, the scales were reversed following Kankaraš (2017) (see Supplemental Material Table S1 for more details on these items). Similar to existing literature (Caliendo et al., 2014), two items (namely, ‘reserved’ and ‘sometimes rude to others’) were excluded due to low factor loadings.

2.4 Socio-demographic and socio-economic factors

An individual was considered employed if they have responded positively to the question ‘Do you work for pay right now? This includes having a job, being self-employed, or owning your own business.’, asked in the supplement. Additional variables included in the supplement were the individual’s marital status, years of age, gender and season – latter derived from the supplement interview date. The analysis further considered information from the 2013 core PSID on a number of largely time-invariant variables that can be uniquely linked back to the individuals who responded to the supplement. These include highest education qualification, minority status derived from responses to race and ethnicity questions, presence of dependent children under 18 years old, home ownership, and region derived from the state of residence.

The core PSID also included an interview date variable, which combined with that from the supplement was useful to help identify the number of days between the two interviews.

2.5 Sample

After the exclusion of missing data for the variables of interest resulting in the loss of 31 cases (3.5%), the main analysis considered 845 men and women mainly of late working age up to 65 years old. As a sensitivity analysis, we further increased the upper age bound to 70 years to capture those working past retirement age. Table 1 reports (unweighted) summary statistics of the main variables included in the analysis. In line with existing literature, people with disabilities (work-limiting or not) are significantly less educated than those without disabilities. At the same time, people with disabilities have, on average, significantly lower scores on conscientiousness but significantly higher scores on neuroticism than those without disabilities (Vlasveld et al., 2012). These findings are consistent with a body of evidence looking at correlations between personality traits and (risk of or reporting) disability (Jang et al., 2002; Rosmalen et al., 2007).

[Table 1 about here]

2.6 Analysis

Typically, studies looking into gaps in labor market outcomes (including employment) and their determinants use a variance decomposition method to unravel the explained and unexplained part of the gap. In this paper, while the intention is to estimate the association between disability and employment, we further wish to control for the effect personality has on disability either within the decomposition itself or separately. To our knowledge, no existing variance decomposition method can accommodate such interdependency between personality and disability. For this reason, we chose to manually perform the decomposition using the estimates obtained from a structural equation model, the latter allowing for modelling simultaneously this complex relationship between personality and disability.

As a first step, we estimated a structural equation model with robust weighted least squares (WLSMV) while controlling for the binary nature of the employment indicator (i.e. probit) using the following formula:

$$Employment = \beta_0 + \beta_k known\_determinants + \beta_p personality + e_1 \qquad (1)$$

where e_1 is the error term.

The models were estimated simultaneously for three groups: those with disabilities; non-work-limited disabled; work-limited disabled. We controlled for *known_determinants*, i.e. characteristics that have been found to be observable factors of employment (see for example, Jones, 2006), including gender, centered age and its square, education, marital status, ethnicity, presence of dependent children, home ownership, season and region ($\beta_1 - \beta_{15}$), and *personality*, indicated by the five personality traits (β_{16} – β_{20}). For a comparison, we separately ran a specification of (1) without the personality traits. Mplus 8.4 (Muthén & Muthén, 1998-2017) was used to estimate the multiple group models with the weight *famwt* (to account for the complex sample design) and cluster *pair* (to account for individuals from the same household being interviewed in the supplement).

As a second step, using the structural equation estimates, we manually decomposed the employment gap between those with and without disabilities using an extension of the well-established Blinder-Oaxaca (1973) decomposition, namely the Fairlie (2006) decomposition method, which accounts for the discrete nature of the employment indicator. According to the Fairlie decomposition, the employment gap was decomposed into a part explained by differences in observable characteristics between those with and without disabilities and an unexplained part, latter referred to as discrimination effect. Given the ‘index number’ problem with this type of decomposition, i.e. the results may vary depending on the reference group, we used a pooled model to form the non-discriminatory group (Neumark, 1988), which has been extensively used in the literature with this type of decomposition. The decomposition analysis was done in Stata SE 15.1 (StataCorp, 2017) using the model output from Mplus (Muthén & Muthén, 1998-2017).

3. Results and Discussion

Table 2 reports the results from the structural equation models estimated simultaneously for those without disabilities and the two groups of those with disabilities. The first model contained the observable factors, and the second model contained the observable factors and the Big Five personality traits. For the observable factors, only squared (centered) age and female were negatively related to predicted employment in the without disabilities group. These coefficients were statistically significant at 1% significance level in the models with and without traits. Among the traits, conscientiousness is significantly positively related to the predicted employment probability for two out of the three groups under consideration (i.e.

without disabilities, non-work-limited disabled) while extraversion is negatively related to the employment probability for those without disabilities – the strong influence of these traits is consistent with existing evidence on employment differentials by gender (Braakmann, 2010). The direction of these relationships remains in the pooled model, used as a reference group in the employment gap decomposition (findings not reported here but available upon request), albeit the effect becomes not significant for extraversion.

[Table 2 about here]

Table 3 presents the results from the disability employment gap decomposition, which is done separately by disability group. The first column reports findings from the specification without personality traits. The results show a 3% predicted employment gap between the non-work-limited disabled and those without disabilities, which rises to a significant 31% between work-limited disabled and those without disabilities. The small and insignificant difference in predicted employment probability between non-work-limited disabled individuals and those without disabilities is consistent with existing UK and US evidence (DeLeire 2001; Madden 2004). When focusing on the employment differences between work-limited disabled and those without disabilities, almost a quarter (22%) of the gap can be explained by differences in disability observable characteristics, rising to over a third (43%) when further controlling for personality. At the same time, over three-fourths (80%) of the gap are due to unobserved differences in productivity between work-limited disabled and those without disabilities, which remains high even after controlling for personality (67%). Importantly, the results indicate that discrimination does not account for the difference in predicted employment rates between work-limited disabled and those without disabilities, which is consistent with scarce UK evidence (Jones, 2006). The results are qualitatively similar when considering those working past retirement age, albeit the decomposition effects are slightly larger in magnitude (see Supplemental Material Table S2 for more details).

[Table 3 about here]

The DeLeire (2001) assumptions may be argued to be very strong but are difficult to test directly, especially that of the same amount of discrimination among the two disability groups. The assumption with regards to the common productivity between those without disabilities and the non-work-limited disabled can be tested indirectly by using for example, a measure of severity as an additional determinant in the models (Jones, 2006) – we defined severity as the number of health problems that limited activities (i.e. breathing; health/circulation; stomach; back/neck; shoulders/arms/hands; hips/legs/knees/feet; low energy/exhaustion; memory) in the last seven days, derived from individual questions in the supplement. The chosen severity measure might be imperfect conceptually, and in the absence of a standardized measure, illustrative. Severity, in linear or quadratic form, was not a statistically significant predictor of employment for either disability group.

Our analysis showed the important role that work-limitation had on the results. Considering the criticisms mentioned earlier in terms of the reference group (Neumark, 1988) and the unexplained part in the standard Oaxaca-Blinder decomposition itself (Fairlie, 2006) as well as the difficulty in testing the discrimination assumption, if violated, then the discriminatory component we identify in this study is only a low bound of discrimination.

3.1 Limitations and Future Research

We should acknowledge that this study is not without limitations. First, the preferred pooled approach, used in this analysis, has been criticized by Edler et al. (2010) as potentially leading to an underestimation of the unexplained part. The alternative is to instead estimate a pooled model with a disability status indicator as one of the control variables whereby the coefficient would be an indicator of the unexplained part of the gap. Even with this shortcoming, we chose to create two models, a pooled model and a multiple group model by disability status. The multiple group model provided estimates that are fully moderated by the group membership so any interactions between any variable and disability status was estimated, something not possible if disability status was included just as a control variable. Second, we did not account for potential measurement error in reporting disability. Although existing literature (Gosling & Saloniki, 2014) has identified that disabled individuals are more likely to misreport their status in surveys, the subsequent bias in the employment gap estimates does not only vary significantly depending on the disability measure but also relies heavily on the discrete nature of such a measure (Liu and Millimet, 2021).

Future avenues for research could be the homogenous collection of longitudinal data on employment, personality and disability – the latter, incorporating both the standardized six items definition as well as the work limitation question – in the United States. Such a focus could facilitate the exploration not only of acquired disability and its impact on personality, but also allow for distinguishing by disability type, which can lead to more targeted policy recommendations in this area.

4. Conclusion

The findings of this paper highlight the importance of controlling for personality traits when estimating the employment gap between those with and without disabilities and understanding its contributors. Unobserved differences in productivity between work-limited-disabled and those without disabilities contribute to over 50% of the gap, regardless of controlling for personality traits, signifying that productivity, and specific policies towards increasing this for the work-limited-disabled, is key. Although the recent policy focus has been mainly on employer accommodations and adjustments for people with disabilities (Blanck, 2020), it may be that increased productivity is also achieved by alleviating individuals' stress and fatigue – both impacting on efficiency and quality of work performed, and subsequently leading to reduced productivity – as so the focus on different disability types to pave the way forward.

Data availability statement

The collection of data used in this study was partly supported by the National Institutes of Health under grant number R01 HD069609 and R01 AG040213, and the National Science Foundation under award numbers SES 1157698 and 1623684. The data used in this paper are available to download to registered users via the PSID Data Center (https://simba.isr.umich.edu/data/data.aspx).

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Table 1

Summary Statistics of Main Variables

Characteristic	Pooled	Without disability	Non-work-limited disability	Work-limited disability	Significance of disability differential	
	(1)	(2)	(3)	(4)	(2) – (3)	(2) – (4)
Employed	0.491	0.554	0.531	0.219	NS	**
Age	61.212	61.136	61.158	61.548	NS	NS
Female	0.614	0.596	0.638	0.651	NS	NS
Minority	0.284	0.255	0.322	0.342	+	*
Married	0.743	0.782	0.729	0.623	NS	**
Presence of dependent children	0.086	0.067	0.119	0.116	*	*
Non-homeowner	0.169	0.138	0.220	0.219	**	**
Masters	0.127	0.159	0.096	0.048	*	**
Degree	0.219	0.251	0.158	0.178	*	+
Associate degree	0.176	0.174	0.147	0.219	NS	NS
Openness	3.025	3.048	2.996	2.979	NS	NS
Conscientiousness	3.521	3.614	3.441	3.283	**	**
Extraversion	3.120	3.152	3.085	3.048	NS	NS
Agreeableness	3.560	3.581	3.483	3.575	*	NS
Neuroticism	2.201	2.083	2.352	2.438	**	**
N	845	522	177	146		

Note. Figures are (unweighted) mean values. *NS*, not significant. ***p* < .01. **p* < .05. +*p* < .10.

Table 2

Probit Estimates (Standard Errors) from Structural Equation Models with Observable Factors List and with Observable Factors and Personality

	Observable factors			Observable factors and personality		
	Without disability	Non-work-limited disability	Work-limited disability	Without disability	Non-work-limited disability	Work-limited disability
Age (centered)	-0.115**	-0.071	-0.001	-0.115**	-0.083	0.008
	(0.024)	(0.054)	(0.015)	(0.024)	(0.052)	(0.075)
Age (centered)	-0.004**	0.016	-0.001	-0.004**	0.010	-0.001
squared	(0.001)	(0.015)	(0.015)	(0.001)	(0.014)	(0.016)
Female	-0.335*	-0.290	0.140	-0.344*	-0.055	0.215
	(0.132)	(0.276)	(0.324)	(0.142)	(0.313)	(0.380)
Married	0.057	-0.247	-0.393	0.108	-0.328	-0.557
	(0.174)	(0.346)	(0.364)	(0.180)	(0.389)	(0.435)
Masters	0.205	0.327	0.665	0.260	0.488	0.208
	(0.192)	(0.481)	(0.699)	(0.194)	(0.558)	(0.843)
Degree	0.169	0.326	0.531	0.176	0.413	0.493
	(0.162)	(0.385)	(0.420)	(0.165)	(0.403)	(0.419)
Associate degree	0.218	0.388	-0.028	0.244	0.400	-0.285
	(0.199)	(0.314)	(0.414)	(0.202)	(0.341)	(0.517)
Minority	-0.343+	-0.485	-0.147	-0.347+	-0.499	-0.144
	(0.193)	(0.333)	(0.453)	(0.196)	(0.366)	(0.455)
Northeast	0.087	0.380	0.930+	0.016	0.212	1.120+
	(0.205)	(0.349)	(0.539)	(0.209)	(0.426)	(0.590)
Midwest	0.334+	-0.177	0.259	0.309+	-0.056	0.200
	(0.173)	(0.359)	(0.406)	(0.174)	(0.374)	(0.413)
West	0.016	0.579	0.567	-0.004	0.578	0.378
	(0.197)	(0.366)	(0.468)	(0.200)	(0.417)	(0.494)
Autumn	0.207	0.157	0.133	0.253	0.180	0.221
	(0.153)	(0.292)	(0.337)	(0.154)	(0.317)	(0.341)
Winter	0.276	0.386	-1.006	0.288	0.471	-1.045

	Observable factors			Observable factors and personality		
	Without disability	Non-work-limited disability	Work-limited disability	Without disability	Non-work-limited disability	Work-limited disability
	(0.184)	(0.347)	(0.653)	(0.188)	(0.409)	(0.777)
Non-homeowner	-0.138	-0.182	0.204	-0.157	-0.047	0.054
	(0.238)	(0.408)	(0.400)	(0.240)	(0.469)	(0.490)
Dependent child	-0.168	-0.335	0.187	-0.183	-0.100	0.182
	(0.223)	(0.446)	(0.648)	(0.203)	(0.499)	(0.695)
Openness	-	-	-	0.006	0.208	0.095
				(0.128)	(0.226)	(0.270)
Conscientiousness	-	-	-	0.390**	1.095**	0.206
				(0.149)	(0.289)	(0.360)
Extraversion	-	-	-	-0.300**	0.046	0.205
				(0.108)	(0.197)	(0.223)
Agreeableness	-	-	-	0.045	-0.590*	-0.081
				(0.135)	(0.261)	(0.314)
Neuroticism	-	-	-	0.038	0.136	-0.306
				(0.105)	(0.206)	(0.273)
Constant	0.097	0.091	-0.959+	-0.669	-2.869*	-1.245
	(0.253)	(0.466)	(0.529)	(0.831)	(1.384)	(1.791)
N	522	177	146	522	177	146

Note. Robust standard errors are reported in parentheses. ***p* < .01. **p* < .05. +*p* < .10.

Table 3

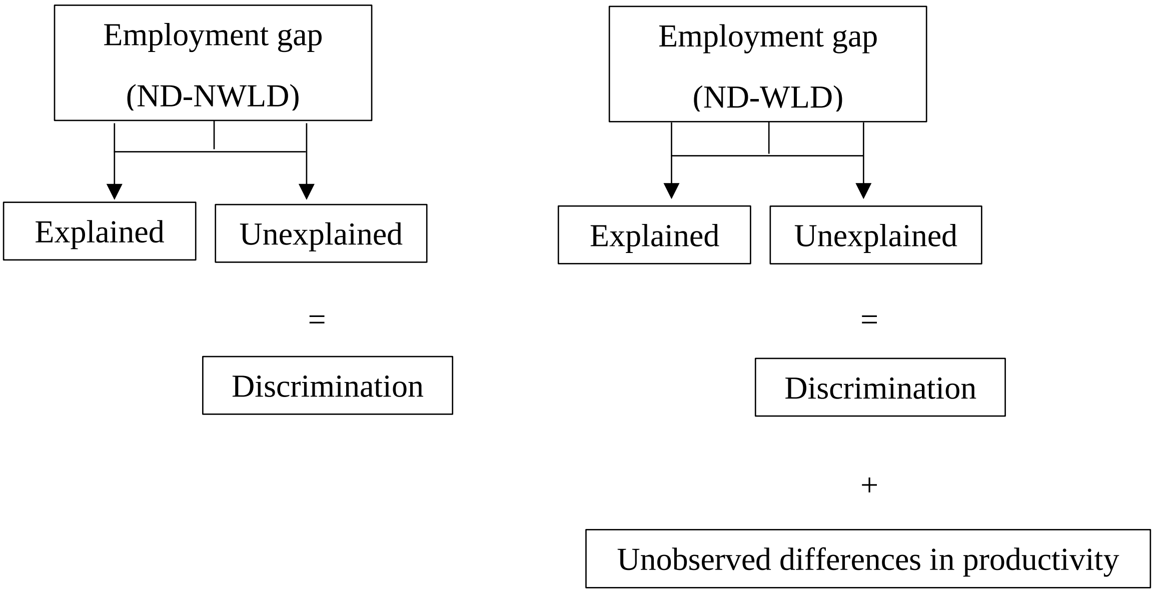
Decomposition Results (Age up to 65 Years)

	Observable factors	Observable factors and personality
Without disability versus non-work-limited disability		
Predicted employment difference, *E* + *U*	0.025 (NS)	0.025 (NS)
Explained, *E*	0.031 (124.00%)	0.051 (204.00%)
Unexplained, *U* = *D*	-0.006 (-24.00%)	-0.026 (-104.00%)
Discrimination, *D*	-0.006 (-24.00%)	-0.026 (-104.00%)
Without disability versus work-limited disability		
Predicted employment difference, *E* + *U*	0.309**	0.265**
Explained, *E*	0.069 (22.33%)	0.113 (42.64%)
Unexplained, *U* = *D* + *P*	0.240 (77.67%)	0.152 (57.36%)
Discrimination, *D*	-0.006 (-1.94%)	-0.026 (-9.81%)
Unobserved differences in productivity, *P*	0.246 (79.61%)	0.178 (67.17%)

Note. NS, not significant. $^{**}p < .01$. $^{*}p < .05$. $^{+}p < .10$.

Figure 1

Employment Gap Decomposition



Note. ND, without disabilities; NWLD, non-work-limited disabled; WLD, work-limited disabled. Employment gap is defined as the difference in predicted employment probabilities between two respective groups.

Supplemental Material

Table S1

Big Five Personality Traits

Question	Personality trait	λ_f	λ_d
Please tell me whether each of these describes you. You are someone who…			
… has a forgiving nature.	Agreeableness	0.662	0.645
… is sometimes rude to others. (R) [E]	Agreeableness	0.266	-
… is considerate and kind to almost everyone.	Agreeableness	0.755	0.699
… tends to be lazy. (R)	Conscientiousness	0.317	0.299
… does a thorough job.	Conscientiousness	0.750	0.755
… does things efficiently.	Conscientiousness	0.832	0.820
… is talkative.	Extraversion	0.695	0.729
… is reserved. (R) [E]	Extraversion	-0.012	-
… is outgoing, sociable.	Extraversion	0.906	0.930
… worries a lot.	Neuroticism	0.588	0.647
… gets nervous easily.	Neuroticism	0.615	0.685
… is relaxed, handles stress well. (R)	Neuroticism	0.791	0.729
… has an active imagination.	Openness to experience	0.662	0.656
… values artistic experiences.	Openness to experience	0.679	0.651
… is original, comes up with new ideas.	Openness to experience	0.719	0.702

Note. (R) indicates the items with reversed scale. [E] indicates the items that were dropped due to low factor loadings. All factor loadings (λ) were estimated with fixed factor scaling. λ_f refers to the full model will all indicators, and λ_d refers to the model with dropped items.

Table S2

Decomposition Results (Age up to 70 Years)

	Observable factors	Observable factors and personality
Without disability versus non-work-limited disability		
Predicted employment difference, $E + U$	0.027+	0.026+
Explained, E	0.049 (181.48%)	0.067 (257.69%)
Unexplained, $U = D$	-0.022 (-81.48%)	-0.041 (-157.69%)
Discrimination, D	-0.022 (-81.48%)	-0.041 (-157.69%)
Without disability versus work-limited disability		
Predicted employment difference, $E + U$	0.293**	0.278**
Explained, E	0.091 (31.06%)	0.130 (46.76%)
Unexplained, $U = D + P$	0.202 (68.94%)	0.148 (53.24%)
Discrimination, D	-0.022 (-7.51%)	-0.041 (-14.75%)
Unobserved differences in productivity, P	0.224 (76.45%)	0.189 (67.99%)

Note. NS, not significant. $^{**}p < .01$. $^{*}p < .05$. $^{+}p < .10$.