Topics

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Overeducation, Overskilling and Mental Well-being

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Abstract: This paper estimates the effects of overeducation and overskilling on mental well-being in Australia. Using fixed-effects (FE) panel estimations, our analysis shows that overeducation does not significantly affect people's mental well-being. However, overskilling has strong detrimental consequences for mental well-being. Using a panel data quantile regression model with FE, we show that the negative effects of overskilling are highly heterogeneous, with larger impact at the lower end of the distribution of mental well-being. Furthermore, our dynamic analysis shows that the damaging effects of overskilling are transitory, and we find evidence of complete mental well-being adaptation one year after becoming overskilled.

Keywords: overeducation, overskilling, mental well-being, panel quantile regression
JEL Classification: I21, I31, J24

1 Introduction

The labor market outcomes of education–occupation mismatches have been extensively studied during the last three decades. Overeducation, in which case workers have received more years of education than is required for their job, is prevalent and widespread in many countries, such as Australia (Carroll and Tani 2013), Canada (Vahey 2000), Germany (Daly, Buchel, and Duncan 2000), Portugal (Kiker, Santos, and de Oliveira 1997; Alba-Ramirez 1993), Sweden (Korpi and Tahlin 2009), the United Kingdom (Sloane, Battu, and Seaman 1999; Dolton and Silles 2008) and the United States (Rumberger 1987; Tsai 2010). These studies generally find that

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overeducation has adverse consequences for labor market outcomes. Overeducated workers are found to have lower earnings compared to those matched ones with the same educational attainment. They also report lower job satisfaction and have higher propensity to quit voluntarily from their position.[1]

A few recent studies notice that overskilling is a type of worker–job mismatch that is different from overeducation. As discussed in McGuinness and Sloane (2011), overeducation relies on the comparison between educational attainments with the entry skill requirements of the job. However, overskilling provides a comparison between workers' accumulated skills with the actual skill requirement of the job. Consequently, overskilling can be considered as a more direct measure of skill mismatch. Similar to overeducation, overskilling has also been found to exert negative influences on labor market outcomes such as wages and job satisfaction (Allen and van der Velden 2001; McGuinness and Sloane 2011; Mavromaras et al. 2013).

Job mismatches can also affect workers' mental well-being. Such an impact can exist for several reasons. For example, compared to well-matched workers, overeducated/overskilled workers may have unmet aspirations or expectations about their job, which are likely to generate a psychological well-being loss (Artes, Salinas-Jimenez, and Salinas-Jimenez 2014). Furthermore, overeducated/overskilled people may compare themselves with people having the same educational attainments/skills but with a matched job, who have been found in existing studies to have better labor market outcomes such as higher wages (Hartog 2000; McGuinness 2006; Leuven and Oosterbeek 2011). Such relative concerns have been proved to be an important channel to damage people's subjective well-being (Clark et al. 2008b; Dolan, Peasgood, and White 2008). If overeducation or overskilling exerts detrimental impact on people's mental well-being, then existing studies focusing primarily on their labor market outcomes may have understated the negative consequences of educational and skill mismatches for the society.

Some studies have investigated the relationship between educational mismatch and subjective well-being. For example, using data from the first wave of the Household, Income and Labour Dynamics in Australia (HILDA), Fleming and Kler (2008) shows that across all six measures of job satisfaction, overeducated workers are relatively less satisfied when compared with their non-overeducated counterparts.[2] Artes, Salinas-Jimenez and Salinas-Jimenez (2014)

1 Summaries of existing studies can be found in Hartog (2000), McGuinness (2006) and Leuven and Oosterbeek (2011).

2 It is unclear how overeducation is defined in Fleming and Kler (2008).

uses the indirect self-assessment method to measure educational mismatch.[3] This study finds a sizable significant negative impact of educational mismatch on life satisfaction for overeducated individuals, using data from two rounds of the European Social Survey (ESS). In addition, using data from Round 3 of the ESS, Bracke, Pattyn and von dem Knesebeck (2013) construct two objective indicators of overeducation using the realized matches (RM) method and the job analyst (JA) method.[4] This study finds that overeducated people report higher levels of depressive symptoms. Using the same data, Bracke, van de Straat and Missinne (2014) construct an indicator of overeducation using the realized matches (RM) method and find that the mental health benefits produced by education attainment are limited or even completely eliminated by educational mismatch.

A few studies have used fixed effects (FE) panel estimation to account for unobserved individual heterogeneity. Kleibrink and Haisken-DeNew (2012) find a negative impact of overeducation on life satisfaction when using the longitudinal data from the German Socio-Economic Panel. Moreover, using the SONAR data about school–work transition in the Flemish Region of Belgium, Verhaest and Omey (2009) show that overeducation, which is measured on the basis of an objective JA measure, exerts a large negative impact on job satisfaction. This negative consequence is also found to diminish with the years of work experience. In addition, Mavromaras et al. (2013) use the first seven wave of the HILDA and analyze the impact of overskilling and overeducation on overall job satisfaction among university graduates. Their overskilling measure is self-reported and the overeducation variable is generated objectively using the RM method. Mavromaras et al. (2013) find that being overeducated does not have an impact on job satisfaction, while being overskilled confers significant negative influence. Being both overeducated and overskilled have the largest negative impact on job satisfaction. Finally, the analysis of Piper (2015) using the British Household Panel Survey (BHPS) finds that overeducation, measured using the RM method, leads to low levels of life satisfaction, with more recently overeducated individuals less dissatisfied with life.

This paper contributes to the important literature in two ways. First, using data from the longitudinal HILDA survey, we examine the mental

3 The method is based on workers' self-assessment of the match between their actual education and the educational requirements of their job.

4 The RM method is based on the comparison between the years of education an individual received and the modal/mean years of education observed within the corresponding occupational group, while the job analyst (JA) method is based on systematic expert evaluations of the level of education attainments needed to perform a specific job.

well-being effects of both overeducation and overskilling. The overskilling variable we use is subjectively measured. Our objective overeducation variable is constructed using the RM method. Namely, overeducation is defined as existing if the years of education an individual received is greater than the modal years of education observed within each two-digit level occupation defined by the Australian and New Zealand Standard Classification of Occupations (ANZSCO). Using FE panel estimation and the recently developed panel data quantile regression model with fixed effects (QR–FE) by Canay (2011), we examine both the mean and distributional mental well-being effects of overeducation and overskilling, controlling for individual FE.[5] Second, we contribute to the literature on dynamic (anticipation and adaptation) effects of life events on subjective well-being. The dynamic effects of many life events such as marriage, divorce, widowhood, child birth, layoff and disability on people's subjective well-being have already been investigated (Clark et al. 2008a; Oswald and Powdthavee 2008; Clark and Georgellis 2013; Qari 2014).We contribute to this strand of literature by estimating the dynamic effects on mental well-being of two new labor market events that have not been examined before: overeducation and overskilling.

Using FE panel estimation, we find no evidence of an impact of overeducation on the mental well-being of workers. In contrast, overskilling has strong detrimental consequences for mental well-being. Our analysis using panel data QR–FE has uncovered strong heterogeneity in the links between overskilling and mental well-being. Accounting for the distributional heterogeneity in the mental well-being effects illustrates larger depressing impact of overskilling on people at the lower end than at other parts of the well-being distribution. However, we find little evidence that overeducation affects the distribution of mental well-being. Furthermore, exploiting the longitudinal and dynamic nature of our data, we show that the negative mental well-being effects of overskilling found are not likely to be driven by reverse causality. We show that the adverse effects of overskilling on well-being are intense but transitory. We find evidence of complete adaptation one year after becoming overskilled.

The remaining paper is organized as follows. Section 2 describes the data and presents summary statistics. Section 3 discusses the empirical approach. Section 4 presents the estimation results and Section 5 concludes.

5 Using conditional quantile regression for cross sectional data, McGuinness and Bennett (2007) investigate the impact of overeducation on wages. This study shows that the wage penalty of overeducation is the largest at the lower end of wage distribution.

2 Data

2.1 Data and Variables

HILDA is a large-scale, nationally representative household panel survey in Australia. Starting from 2001, HILDA annually collects rich information on people's demographics, life events, health and mental well-being. We restrict our attention to employees aged 20–60 in full-time employment. There are 60,887 observations satisfying this requirement in the HILDA data. After dropping observations with incomplete information on variables of interest, our final sample consists of 52,975 observations for 12,051 individuals between 2001 and 2013.

HILDA does not have questions on overeducation. We follow the existing studies and use the RM method to construct a measure of overeducation, which is based on the education and occupation information in HILDA.[6] For each two-digit level occupation defined by the ANZSCO, overeducation is defined as existing if the years of education an individual received is greater than the modal years of education (the most frequent level of education) observed within the corresponding occupational group (Tsai 2010; Mavromaras et al. 2013). Some studies alternatively calculate the mean education level within each occupation and classify a worker as overeducated if his/her education is one standard deviation above the average education in the occupational group (Hartog 2000). We use this alternative definition of overeducation to check the robustness of our findings in Section 4.3.2.

The measure of overskilling is derived from the data. In HILDA, respondents were asked to rate their agreement to the statement "I use many of my skills and abilities in my current job". Their responses were scored on a 7-point scale with a response of 1 corresponding to strongly disagree up to 7 strongly agree. We follow Mavromaras and McGuinness (2012) and classify individuals selecting 1–5 on the scale as overskilled, and those selecting 6–7 as skill matched. In the sensitivity analysis in Section 4.3.2, we consider respondents selecting 1–4 as overskilled and use those selecting 5–7 as the reference category of skill matched.[7]

6 The HILDA data do not have sufficient information for us to construct the overeducation measure using the indirect self-assessment method or the JA method.

7 HILDA does not have information about underskilling. Mavromaras et al. (2013) note that when this information is available in the UK Workplace Employment Relations Study (WERS), underskilled people only account for less than 5 % of the WERS sample and they do not suffer a wage penalty.

The main mental well-being measure we use is based on the 36-item Short Form Health Survey (SF-36). Butterworth and Crosier (2004) show that the SF-36 data in HILDA are psychometrically sound, with high consistency, validity and reliability. HILDA respondents were asked all SF-36 questions about their physical health and mental well-being in each wave. Fourteen out of the 36 questions fall in the category of mental well-being, which can be categorized into four scales that measure different components of mental well-being: (i) social functioning (SF) (measuring social limitations), (ii) role-emotional (RE) (measuring limitation in work or activities due to emotional health), (iii) vitality (VT) (measuring fatigue and energy) and (iv) mental health (MH) (measuring feelings of anxiety and depression). These four components are standardized to range from 0 to 100 in HILDA, with higher scores representing better mental well-being. We generate our overall measure of mental well-being for each observation by calculating an average of the four scales. This overall measure has been used as index of mental well-being in recent health studies (Cornaglia, Feldman, and Leigh 2014; Frijters, Johnston, and Shields 2014; Mahuteau and Zhu 2015). It is a strong predictor of doctor-diagnosed depression or anxiety (Frijters, Johnston, and Shields 2014), which is likely to be experienced by overeducated or overskilled workers having unmet aspirations or expectations about their job (Artes, Salinas-Jimenez, and Salinas-Jimenez 2014).[8] It should be noted that both overskilling and mental well-being are subjectively measured. The correlation between two subjective variables is likely to be higher than between a subjective variable and an objective one (Coburn 1975). In this sense, the (negative) association between overskilling and mental well-being may be overstated when using the two subjective measures.

Descriptive statistics by overeducation and overskilling status are reported in Table 1. Among the 53,021 observations, 21.22 % of them are overeducated for their jobs, 38.20 % are overskilled and 7.12 % are both overeducated and overskilled. The proportion of overeducated workers in Australia (28.24 % = 21.22 % + 7.12 %) is higher than the 18.84 % in Germany (Kleibrink and Haisken–DeNew 2012), the 24.4 % in the United Kingdom (Dolton and Silles 2008) and the 22 % in the United States (Tsai 2010). However, it is smaller than the 34.76 % in Europe (as a whole) (Artes, Salinas-Jimenez, and Salinas-Jimenez 2014). Furthermore, 45.32 % (= 38.20 % + 7.12 %) of the observations are overskilled, much higher than the 14 % in the United Kingdom (McGuinness and Sloane 2011).

8 This mental health measure has been used in existing studies to examine its relationship with labor market outcomes such as perceived job insecurity (Adam and Flatau 2006), retirement timing (Gill et al. 2006) and employment outcome (Frijters, Johnston, and Shields 2014).

The differences in the mean SF-36 mental well-being measure and its components appear to be negligible between overeducated employees and non-overeducated employees. However, the two-sample *t*-test still weakly rejects the null hypothesis that the mean well-being is equal for the two groups at the 10 % level ($p = 0.056$). Furthermore, overskilled workers report lower levels of mental well-being than their well-matched counterparts, and this observation is strongly supported by the two-sample *t*-test ($p = 0.000$). A rough comparison of mean well-being suggests that the adverse well-being effect (if any) may be larger for overskilling than for overeducation.

2.2 Raw Distributional Differences in Mental Well-being between Mismatched and Matched Employees

Table 1 shows that overeducated employees share similar level of mean mental well-being as non-overeducated persons, while overskilled employees are less mentally well than their matched counterparts. It is natural to ponder upon whether there are any differences between mismatched and matched individuals along the whole distribution of well-being. Figure 1 presents the kernel density estimates of our main mental well-being measure for each group defined by overeducation and overskilling status. The distributions of mental well-being are very similar for overeducated people and non-overeducated people. Figure 2, which depicts the mental well-being gap between the two groups of people at various percentiles of the well-being distribution, suggests that there are barely discernable distributional differences.

The distributions of mental well-being for overskilled people and non-overskilled people are significantly different. The two-sample Kolmogorov–Smirnov test strongly rejects the null hypothesis that the mental well-being for the two groups comes from the same distribution (p-value = 0.000). Figure 2 shows that discernable gaps exist between the two groups at various percentiles of the well-being distribution, with varying amplitude along the distribution. This gives *prima facie* evidence that the adverse effects of overskilling may be more strongly felt by people at the lower parts of the mental well-being distribution than at the top end. The distributional patterns presented in Figures 1 and 2 suggest that the effects of overskilling may be heterogeneous on different parts of the distribution of mental well-being. However, the simple unconditional differences in well-being can misstate the true well-being effects of overeducation and overskilling. The next section discusses the empirical regression methods utilized in this study that can control for the confounding effects of important observed factors and unobserved individual heterogeneity.

Table 1: Summary statistics.

	Full sample		Overeducation				Overskilling			
			Yes		No		Yes		No	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Mental well-being measures										
SF – 36 mental well-being	78.61	15.99	78.87	15.94	78.54	16.00	77.05	16.05	79.58	15.87
(1) SF	87.28	19.18	88.05	18.69	87.07	19.31	86.01	19.46	88.06	18.96
(2) RE	89.06	26.27	88.75	26.76	89.15	26.14	88.06	27.20	89.68	25.67
(3) VT	62.33	18.06	62.76	18.02	62.21	18.07	60.54	17.67	63.44	18.21
(4) MH	75.77	15.42	75.90	14.80	75.73	15.59	73.58	15.66	77.12	15.12
Socioeconomic characteristics										
Age (years)	38.69	11.02	40.39	10.13	38.24	11.20	37.61	10.90	39.37	11.04
Male	0.61	0.49	0.55	0.50	0.62	0.48	0.63	0.48	0.59	0.49
Married	0.71	0.46	0.75	0.43	0.69	0.46	0.67	0.47	0.72	0.45
Schooling (years)	12.80	2.14	15.86	0.89	11.97	1.54	12.54	2.05	12.96	2.18
Individual income (in 000s, 2013$)	73.04	47.00	95.11	61.42	67.09	40.26	67.05	42.67	76.74	49.12
Family size	2.88	1.37	2.86	1.31	2.89	1.39	2.86	1.38	2.90	1.37
Live in a major city	0.67	0.47	0.79	0.41	0.64	0.48	0.69	0.46	0.66	0.47
Union member	0.32	0.46	0.37	0.48	0.30	0.46	0.28	0.45	0.34	0.47
Tenure with current occupation	9.14	9.29	9.04	9.06	9.16	9.35	8.06	8.60	9.80	9.63
Tenure with current employer	6.98	7.91	7.40	8.11	6.87	7.85	6.47	7.49	7.30	8.14
Public sector	0.29	0.45	0.44	0.50	0.25	0.43	0.23	0.42	0.32	0.47
Observations	53,021		11,250		41,771		20,255		32,766	

Data source: HILDA 2001–2013. SF, social functioning; RE, role-emotional; VT, vitality; MH, mental health.

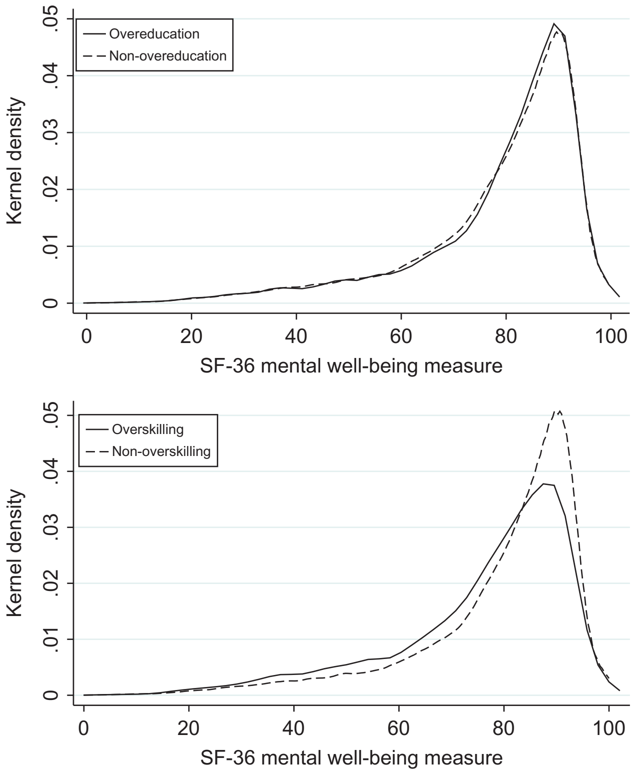

Figure 1: Kernel density estimates of SF-36 mental well-being.

3 Empirical Approach

We consider the following mental well-being equation:

$$MWB_{it} = Overedu_{it}\beta_1 + Overskill_{it}\beta_2 + X'_{it}\gamma + u_i + \epsilon_{it} \tag{1}$$

where MWB_{it} denotes the mental well-being measure. $Overedu_{it}$ is a binary variable equal to one if an individual is overeducated and zero otherwise. $Overskill_{it}$ is a dummy variable similarly defined to indicate whether one is overskilled or not. X_{it} is a vector of control variables including age, age squared, a married dummy, years of schooling, individual income, number of family members, a dummy variable indicating whether living in a major city, union membership dummy, tenure with current occupation, tenure with current employer, whether working in public sector, state of residence dummies and wave dummies. Time-invariant unobserved heterogeneity is controlled for by the

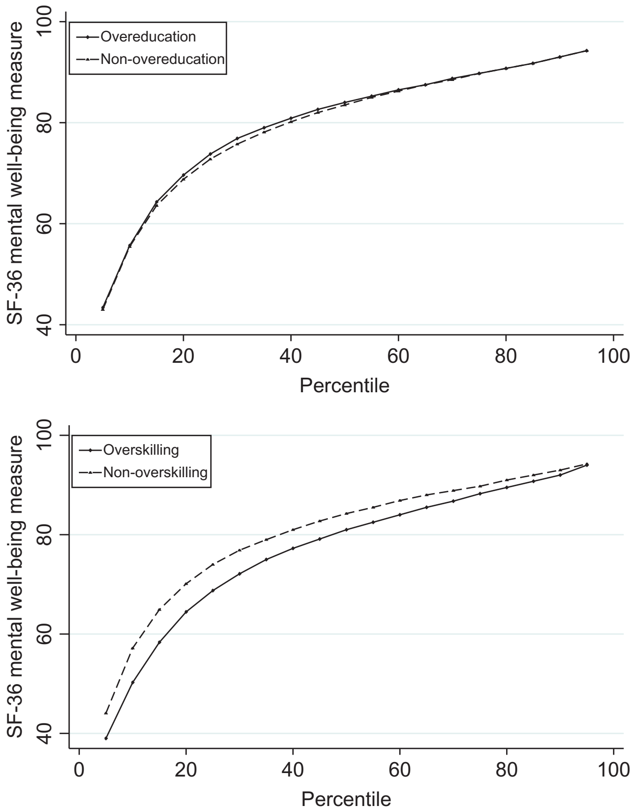

Figure 2: SF-36 mental well-being by percentile.

individual FE, u_i, and ϵ_{it} is the idiosyncratic error term. β_1 and β_2 separately measure the mean effects of overeducation and overskilling on individual mental well-being. We estimate eq. (1) with FE panel estimation, which can remove the bias in β_1 and β_2 due to the unobserved individual heterogeneity u_i.

To investigate the heterogeneous effects of overeducation and overskilling on the full distribution of mental well-being, we utilize the panel data QR–FE developed by Canay (2011). Modeling FE as location shift variables, Canay (2011) shows that the QR–FE approach can be carried out using the following two-stage estimations.

First, estimate eq. (1) with FE panel regression to obtain consistent estimates of coefficients $(\widehat{\beta}_1, \widehat{\beta}_2, \widehat{\gamma})$, and then calculate the unobserved FE for each individual as

$$\widehat{u}_i = \frac{1}{T}\sum_{t=1}^{T}\left(MWB_{it} - Overedu_{it}\widehat{\beta}_1 - Overskill_{it}\widehat{\beta}_2 - X_{it}'\widehat{\gamma}\right) \tag{2}$$

Second, estimate the conditional quantile regression model of Koenker and Bassett (1978), using ($\widehat{MWB}_{it} = MWB_{it} - \widehat{u}_i$) as the dependent variable. In other words, we solve the following minimization problem

$$\left(\widehat{\beta}_{1\tau}, \widehat{\beta}_{2\tau}, \widehat{\gamma}_\tau\right) = arg \min_{(\beta_{1\tau}, \beta_{2\tau}, \gamma_\tau)} \frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T} \left[\rho_\tau\left(\widehat{MWB}_{it} - Overedu_{it}\beta_{1\tau} - Overskill_{it}\beta_{2\tau} - X_{it}'\gamma_\tau\right)\right] \tag{3}$$

where $\rho_\tau(u) = u[\tau - I(u<0)]$ and I is an indicator function. The estimated coefficients, $\widehat{\beta}_{1\tau}$ and $\widehat{\beta}_{2\tau}$, measure separately the effects of overeducation and overskilling on the τ-*th* percentile of the distribution of mental well-being.

4 Results

4.1 Overeducation, Overskilling and Mental Well-being

Table 2 reports the pooled ordinary least squares (OLS) and FE panel estimates of β_1 and β_2 in eq. (1).[9] Standard errors reported are corrected for clustering at the individual level. The OLS estimates reveal that there is no significant relationship between overeducation and mental well-being. In contrast, overskilling is significantly associated with lower levels of mental well-being for both genders. And the adverse mental well-being effect of overskilling seems to be larger for males than for females.

FE estimates also indicate that overeducation does not significantly affect people's mental well-being. However, the significant relationship between overskilling and mental well-being is still highly significant but in much smaller magnitude than OLS estimates, indicating that ignoring unobserved

9 Sample attrition is a common problem for analyses using longitudinal data. Using an approach similar to the one used in Cai and Waddoups (2011), we check whether attrition should be considered as a problem in the context of our study. We run a FE panel regression of attrition at time t on overeducation and overskilling at $t-1$, controlling for the same explanatory variables used in the mental well-being model. We find that neither overeducated people nor overskilled people are more likely to attrite from the survey than their matched counterparts. Consequently, attrition bias is probably not of a big concern in our analysis.

Table 2: Mean effects of overeducation and overskilling on mental well-being.

	OLS estimates			FE estimates		
	All	Male	Female	All	Male	Female
Overeducation	0.015	0.201	−0.403	−0.157	−0.197	−0.087
	(0.433)	(0.591)	(0.637)	(0.372)	(0.475)	(0.597)
Overskilling	−2.190***	−2.653***	−1.674***	−0.914***	−1.090***	−0.609**
	(0.206)	(0.253)	(0.346)	(0.146)	(0.177)	(0.254)

Note: Control variables include age, age squared, a married dummy, years of schooling, individual income, number of family members, a dummy variable indicating whether living in a major city, union membership dummy, tenure with current occupation, tenure with current employer, working in public sector, state of residence dummies and year dummies. Standard errors clustered at the individual level are reported in parenthesis.
*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

heterogeneity overstates the adverse impact of being overskilled. Similar to OLS estimates, FE estimates also indicate that the average negative impact of overskilling on mental well-being is still stronger for men than for women.[10]

Table 3 displays the QR–FE results at the tenth, twenty-fifth, fiftieth, seventy-fifth and ninetieth percentiles of the distribution of the SF-36 mental well-being measure. As opposed to the average case, overskilling has over double the negative impact at the tenth percentile of the well-being distribution than at the ninetieth percentile. Namely, we see larger impact of overskilling at the lower end of the distribution of mental well-being than at the top end. Psychological studies such as Tugade and Fredrickson (2004) and Cohn et al. (2009) argue that resilient individuals can use positive emotions to bounce back from negative emotional experiences. Individuals who are mentally well-off seem to cope with skill mismatch in a much more positive and resilient way than individuals scoring relatively low on mental well-being by avoiding stress and restructuring attitudes in a positive way. Furthermore, the adverse impact of overskilling is larger for men than women noticeably at the middle and bottom part of the well-being distribution. The larger adverse consequence

10 To better understand the magnitude of those influences, we compare the estimated effects of overskilling with those of two other negative life events reported by HILDA respondents, namely (1) being fired or made redundant in the last 12 months and (2) being a victim of property crimes (such as theft and house breaking) in the last 12 months. We find that the adverse effect of overskilling on mental well-being is around half of the impact of being fired or made redundant by employers. Furthermore, the mean well-being effect of overskilling is close to that of being a victim of property crimes.

Table 3: Heterogeneous effects on mental well-being.

	Q10	Q25	Q50	Q75	Q90
All					
Overeducation	0.175	0.046	−0.178**	−0.412**	0.220
	(0.568)	(0.180)	(0.065)	(0.191)	(0.375)
Overskilling	−1.536***	−1.215***	−0.816***	−0.567***	−0.673***
	(0.295)	(0.100)	(0.038)	(0.093)	(0.166)
Male					
Overeducation	0.111	−0.014	−0.160*	−0.177	0.021
	(0.666)	(0.225)	(0.090)	(0.257)	(0.449)
Overskilling	−2.170***	−1.423***	−0.852***	−0.517***	−0.515**
	(0.402)	(0.126)	(0.051)	(0.112)	(0.205)
Female					
Overeducation	−0.316	0.127	−0.204**	−0.626**	0.454
	(0.679)	(0.263)	(0.103)	(0.303)	(0.561)
Overskilling	−0.578	−0.959***	−0.798***	−0.576***	−0.882***
	(0.463)	(0.177)	(0.062)	(0.159)	(0.300)

Note: Control variables include age, age squared, a married dummy, years of schooling, individual income, number of family members, a dummy variable indicating whether living in a major city, union membership dummy, tenure with current occupation, tenure with current employer, working in public sector, state of residence dummies and year dummies. Standard errors clustered at the individual level are reported in parenthesis.
*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

for men may be related to their traditional identity as the breadwinner in the family (Akerlof and Kranton 2000), for whom a matched job plays a relatively more important role in overall mental well-being than for women. The larger impact at the lower end shows that this problem aggravates for men scoring relatively low on the distribution of mental wellbeing, who are also associated with lower earned income. It is quite clear that focusing on the average effects will obscure substantial heterogeneity in the effects of overskilling over the mental well-being distribution. In addition, the impact of overeducation is only negative and significant at the fiftieth and seventy-fifth percentiles of the mental well-being distribution. A small proportion of people may still be affected negatively by overeducation. Unlike the influence of overskilling, the adverse impact of overeducation is not strongly felt across the full mental well-being distribution.[11]

11 We have included both overeducation and overskilling in our estimations. There is a possibility that the effects of overeducation on mental well-being may run indirectly through its impact on overskilling. However, we find that dropping the overskilling variable from the

As reported in Section 2.2, there are 11,250 overeducated observations and 20,255 overskilled observations in our final sample. Among these mismatched ones, 3,780 observations are both overeducated and overskilled, accounting, respectively, for 33.6 % and 18.7 % of the overeducated and the overskilled observations. One natural question to ask is that: is there any interaction effect of overeducation and overskilling on mental well-being? Put it in another way, do overskilled people become even less mentally well if they are overeducated for their occupation at the same time? Table 4 reports the results when including overeducation, overskilling and their interaction term in the FE and QR–FE estimations.

Table 4 shows that being *overeducated only* does not significantly affect the mental well-being throughout its distribution, while the effects of being *overskilled only* are still significantly negative and decreasing in magnitude when moving up to higher percentiles. Although having a negative sign, the coefficient estimates of the interaction term between overeducation and overskilling are not statistically significant at the mean, which suggest that the damaging impact of being overskilled on people's mental well-being is not aggravated if they are also overeducated for their position at the same time. In addition, we note that the interaction term is negative and statistically significant at the fiftieth and seventy-fifth percentiles of the mental well-being distribution, however, being *overeducated only* is not. Consequently, the significant negative effects of overeducation reported in Table 3 for the same percentiles are driven by the small group of overeducated people who are also overskilled. These results further highlight the important detrimental consequences of overskilling for mental well-being. Overeducation, however, plays a trivial role in influencing workers' mental well-being. As we do not find much evidence of the existence of interaction effects between overeducation and overskilling, we will examine the effects of the two distinct types of job mismatches without interacting them in our following analysis.

It should be noted that the estimated relative importance of overskilling as opposed to overeducation for mental well-being can be misleading if the mismatch variables are not measured satisfactorily. In addition, both overskilling and mental well-being are subjectively measured. Coburn (1975) argues that the correlation between two subjective variables is likely to be higher than between a subjective variable and an objective one. Consequently, we may have overstated the negative impact of overskilling on mental well-being.

regressions gives similar coefficient estimates of overeducation. Mavromaras et al. (2013) show that overeducation and overskilling are distinct empirical phenomena with different labor market outcomes. They show that the correlation between overeducation and overskilling is relatively low at 0.197. In our analysis, we find the correlation coefficient between the two variables is also low and of a similar magnitude to theirs.

Table 4: Interacting overeducation and overskilling.

	Mean	**Q10**	**Q25**	**Q50**	**Q75**	**Q90**
All						
Overeducation	−0.004	0.525	0.196	−0.095	−0.257	0.327
	(0.401)	(0.600)	(0.194)	(0.074)	(0.216)	(0.460)
Overskilling	−0.837***	−1.444***	−1.150***	−0.769***	−0.491***	−0.629***
	(0.160)	(0.294)	(0.110)	(0.042)	(0.103)	(0.185)
Overeducation × Overskilling	−0.387	−0.970	−0.376	−0.209**	−0.418**	−0.207
	(0.353)	(0.789)	(0.254)	(0.099)	(0.225)	(0.440)
Male						
Overeducation	−0.068	0.319	0.192	−0.083	0.041	0.232
	(0.513)	(0.720)	(0.239)	(0.103)	(0.286)	(0.546)
Overskilling	−1.032***	−2.083***	−1.338***	−0.820***	−0.401**	−0.464**
	(0.194)	(0.391)	(0.140)	(0.057)	(0.122)	(0.222)
Overeducation × Overskilling	−0.313	−0.664	−0.449	−0.164	−0.604**	−0.289
	(0.436)	(1.063)	(0.324)	(0.133)	(0.286)	(0.598)
Female						
Overeducation	0.149	0.174	0.268	−0.099	−0.539*	0.505
	(0.639)	(0.670)	(0.297)	(0.114)	(0.328)	(0.632)
Overskilling	−0.464*	−0.297	−0.877***	−0.738***	−0.535***	−0.950***
	(0.281)	(0.483)	(0.193)	(0.068)	(0.174)	(0.353)
Overeducation × Overskilling	−0.643	−1.320	−0.383	−0.244	−0.277	−0.116
	(0.595)	(1.021)	(0.409)	(0.158)	(0.394)	(0.712)

Note: Control variables include age, age squared, a married dummy, years of schooling, individual income, number of family members, a dummy variable indicating whether living in a major city, union membership dummy, tenure with current occupation, tenure with current employer, working in public sector, state of residence dummies and year dummies. Standard errors clustered at the individual level are reported in parenthesis.
**p* < 0.1; ***p* < 0.05; ****p* < 0.01.

4.2 Effects of Overeducation and Overskilling on Constituents of Mental Well-being

While Tables 2 and 3 report significant and heterogeneous effects of mismatch between employees and jobs on the overall measure of mental well-being, it is worth going further and investigating each component which make up this multifaceted indicator. Indeed, these heterogeneous effects may be stronger for some aspects of mental well-being and weaker for others. We estimate separately the effects of overeducation and overskilling on each constituent of SF-36 mental well-being following the same methodology as we did with the overall SF-36 and report the results in Table 5.

Consistent with the results reported in Table 2, on average, overeducation does not reduce each component of the mental well-being measure. In terms of the distribution of each SF-36 component, a significant impact can be found at the median of the distribution of SF, RE and MH, which is driven by a small group of overeducated people who are also overskilled.

Overskilling has been found to have a significant adverse impact on the mean of each component of well-being. The average effects on SF and VT are similar to each other. Among the four constituents of mental well-being, on average, RE and MH are more negatively affected by overskilling. Table 5 also shows that being overskilled for one's job does not have a uniform damaging impact on the four components of the SF-36 mental well-being measure. The adverse influences are heterogeneous, generally with greater amplitude at the lower end of the well-being distribution than at the upper part.

Looking at the mean gender results, we find that overskilling has a significant negative impact on SF, RE and VT for males but not for females. In contrast, overskilling has a similar impact on MH for both genders. In terms of distributional patterns, males are more adversely affected by overskilling than females only at the lower part of the distribution of each well-being component. At the median and above, the effects of overskilling on each of the four components of mental well-being are very similar for the two genders.

4.3 Robustness Checks

4.3.1 Life Satisfaction as a Measure of Overall Subjective Well-being

In this section, we use life satisfaction as an alternative overall measure of subjective well-being in our analysis. This well-being measure has been used in many studies such as Clark et al. (2008a) and Qari (2014). In each wave of

Table 5: Effects of overeducation and overskilling on constituents of mental well-being.

	Overeducation				Overskilling			
	Mean	**Q25**	**Q50**	**Q75**	**Mean**	**Q25**	**Q50**	**Q75**
SF								
All	−0.559	−0.179	−0.572***	−0.414	−0.728***	−1.921***	−0.554***	−0.219
	(0.444)	(0.332)	(0.079)	(0.295)	(0.188)	(0.256)	(0.041)	(0.144)
Male	−0.425	−0.382	−0.548***	−0.143	−−0.937***	−2.080***	−0.545***	−0.179
	(0.554)	(0.269)	(0.114)	(0.395)	(0.229)	(0.321)	(0.058)	(0.179)
Female	−0.738	−0.077	−0.609***	−0.703	−0.382	−1.272***	−0.575***	−0.253
	(0.743)	(0.684)	(0.122)	(0.468)	(0.327)	(0.352)	(0.067)	(0.264)
RE								
All	0.122	−0.136**	−0.089**	0.549	−1.027***	−1.608***	−0.583***	−0.137
	(0.725)	(0.047)	(0.041)	(0.626)	(0.287)	(0.026)	(0.041)	(0.256)
Male	−0.406	−0.153**	−0.118**	0.810	−1.167***	−1.607***	−0.573***	−0.186
	(0.897)	(0.064)	(0.059)	(0.731)	(0.348)	(0.032)	(0.031)	(0.270)
Female	0.968	0.099	−0.053	0.283	−0.770	−0.594***	−0.600***	−0.095
	(1.205)	(0.074)	(0.060)	(1.218)	(0.502)	(0.042)	(0.034)	(0.383)
VT								
All	0.023	0.149	−0.007	0.039	−0.863***	−0.904***	−0.865***	−0.929***
	(0.400)	(0.189)	(0.078)	(0.191)	(0.155)	(0.123)	(0.048)	(0.112)
Male	0.321	0.258	−0.039	0.015	−1.155***	−1.226***	−0.900***	−0.962***
	(0.514)	(0.267)	(0.125)	(0.267)	(0.192)	(0.158)	(0.072)	(0.143)
Female	−0.466	−0.034	−0.023	0.035	−0.367	−0.315	−0.834***	−0.791***
	(0.639)	(0.301)	(0.133)	(0.303)	(0.261)	(0.210)	(0.085)	(0.195)

(*continued*)

Table 5: (*continued*)

	Overeducation				Overskilling			
	Mean	**Q25**	**Q50**	**Q75**	**Mean**	**Q25**	**Q50**	**Q75**
MH								
All	−0.212	−0.167	−0.251***	−0.349**	−1.038***	−1.467***	−0.980***	−0.690***
	(0.350)	(0.174)	(0.068)	(0.166)	(0.137)	(0.110)	(0.040)	(0.101)
Male	−0.281	−0.125	−0.227**	−0.190	−1.099***	−1.560***	−1.022***	−0.702***
	(0.453)	(0.248)	(0.109)	(0.225)	(0.170)	(0.138)	(0.060)	(0.128)
Female	−0.112	−0.328	−0.271**	−0.424	−0.916***	−1.308**	−0.950***	−0.663**
	(0.551)	(0.246)	(0.109)	(0.274)	(0.232)	(0.180)	(0.068)	(0.164)

Note: Control variables include age, age squared, a married dummy, years of schooling, individual income, number of family members, a dummy variable indicating whether living in a major city, union membership dummy, tenure with current occupation, tenure with current employer, working in public sector, state of residence dummies and year dummies. Standard errors clustered at the individual level are reported in parenthesis. SF, social functioning; RE, role-emotional; VT, vitality; MH, mental health.

*p < 0.1; **p < 0.05; ***p < 0.01.

HILDA, respondents were asked to rate their overall life satisfaction on a Likert scale of 0 (very dissatisfied) to 10 (very satisfied). In addition, respondents were asked to rate their satisfaction with job. Job mismatches may also affect workers' subjective evaluation of their job. We use both life satisfaction and job satisfaction as alternative measures of subjective well-being to check the robustness of our findings.

Table 6 reports the distributions of the two subjective well-being measures by mismatch status. On average, overeducated workers and their non-overeducated counterparts share similar distributions of life satisfaction and job satisfaction. Overskilled workers have higher propensity to report low levels of subjective well-being than non-overskilled workers, and they are less likely to report high levels of subjective well-being. In general, Table 6 shows similar patterns of subjective well-being distributions to those revealed in Figures 1 and 2.

Table 6: Subjective well-being distribution by mismatch status (%).

	Satisfaction with life				Satisfaction with job			
	Overeducation		Overskilling		Overeducation		Overskilling	
	Yes	No	Yes	No	Yes	No	Yes	No
0	0.02	0.05	0.03	0.05	0.19	0.34	0.39	0.25
1	0.04	0.07	0.06	0.06	0.38	0.45	0.57	0.36
2	0.14	0.20	0.23	0.16	0.90	0.78	1.11	0.62
3	0.40	0.40	0.53	0.33	1.38	1.45	2.01	1.07
4	0.81	0.85	1.14	0.66	2.02	1.99	2.81	1.50
5	2.68	3.46	4.22	2.73	4.80	5.83	7.71	4.32
6	5.95	6.37	8.14	5.13	9.29	7.94	11.06	6.48
7	24.69	22.85	27.33	20.71	24.08	20.86	25.49	19.10
8	38.49	37.25	36.72	38.01	32.92	31.39	29.90	32.83
9	22.14	20.03	16.22	23.11	19.58	19.89	14.10	23.37
10	4.64	8.46	5.38	9.06	4.46	9.06	4.83	10.10
Total	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Mean	7.80	7.83	7.61	7.96	7.46	7.57	7.18	7.79
Observations	11,250	41,771	20,255	32,766	11,250	41,771	20,255	32,766

Data source: HILDA 2001–2013.

We use life satisfaction and job satisfaction variables as dependent variables in our FE and QR–FE estimations. The two dependent variables are categorical variables on an 11-point Likert scale (0–10). They can be considered as approximately continuous and used in quantile regressions (Binder and Coad 2011, 2015).

Table 7 reports the FE and QR–FE estimates. We find similar results to those reported in Tables 3 and 4.[12] On average, overeducation does not reduce people's satisfaction with life and job. In contrast, overskilling has damaging effects on subjective well-being, and the effect becomes smaller in magnitude when moving up the distributions of life satisfaction and job satisfaction.

Overall subjective well-being is a global conception of well-being that aggregates the happiness with different domains of life (van Praag, Frijters, and Carbonell 2003), and satisfaction with job, one of the many domains of life, may be a channel through which job mismatches have an impact on subjective well-being. To assess the degree to which the negative well-being effects of job mismatches can be explained by the associated declines in satisfaction with job, we include job satisfaction as an additional control in the FE and QR–FE regressions. The results are reported in Table 8. Comparing with results shown in Tables 2 and 7, we find around half of the average negative well-being effect of overskilling can be attributed to its negative impact on job satisfaction. In addition, controlling for job satisfaction reduces the negative well-being effect of overskilling at the twenty-fifth percentile to a larger extent than that at the seventy-fifth percentile, suggesting that reduced job satisfaction, as a consequence of overskilling, is a more important channel responsible for reduced mental well-being for people who are less mentally well.

4.3.2 Alternative Definitions of Overeducation and Overskilling

In this section, we use alternative definitions of overeducation and overskilling to test the robustness of our findings. Instead of defining overeducation as

12 In waves 7, 9, 11 and 13 of HILDA, there is information about the Kessler Psychological Distress Scale (K10) score, which is a global measure of distress based on ten questions about anxiety and depressive symptoms that each individual has experienced during the past 4 weeks (Andrews and Slade 2001; Kessler et al. 2002). Each respondent was asked to rate their level of psychological distress regarding each of the following 10-item scale: (1) tired out for no good reasons, (2) nervous, (3) so nervous that nothing could calm you down, (4) hopeless, (5) restless or fidgety, (6) so restless that you could not sit still, (7) depressed, (8) everything was an effort, (9) so sad that nothing could cheer you up and (10) worthless. Each scale used a 5-point response option: (1) all of the time, (2) most of the time, (3) some of the time, (4) a little of the time and (5) none of the time. These responses were scored from 1 to 5 and have been aggregated in HILDA to an overall measure of anxiety and depression: K10 score. The K10 score ranges from 10 to 50, with higher values indicating less psychological distress and better mental well-being. We use the K10 score as an alternative measure of mental well-being, employing the same FE and QR-FE regression analyses. Similar results are obtained.

Table 7: Effects of overeducation and overskilling on subjective well-being.

	Satisfaction with life				Satisfaction with job			
	Mean	**Q25**	**Q50**	**Q75**	**Mean**	**Q25**	**Q50**	**Q75**
All								
Overeducation	−0.018	−0.031*	−0.018***	−0.005	0.021	0.027	0.006	0.030
	(0.026)	(0.075)	(0.005)	(0.067)	(0.040)	(0.020)	(0.008)	(0.020)
Overskilling	−0.099***	−0.113***	−0.096***	−0.087***	−0.312***	−0.332***	−0.293***	−0.257***
	(0.011)	(0.010)	(0.003)	(0.010)	(0.018)	(0.013)	(0.005)	(0.012)
Male								
Overeducation	−0.034	−0.044**	−0.018**	0.001	−0.002	0.008	−0.003	0.048
	(0.034)	(0.022)	(0.008)	(0.022)	(0.051)	(0.027)	(0.086)	(0.036)
Overskilling	−0.095***	−0.113***	−0.093***	−0.090***	−0.310***	−0.327***	−0.281***	−0.250***
	(0.014)	(0.013)	(0.005)	(0.012)	(0.022)	(0.017)	(0.008)	(0.015)
Female								
Overeducation	0.009	−0.003	−0.018**	−0.017	0.095	0.045	0.011	0.007
	(0.042)	(0.024)	(0.008)	(0.026)	(0.065)	(0.030)	(0.013)	(0.032)
Overskilling	−0.108***	−0.112***	−0.098***	−0.081***	−0.318**	−0.336***	−0.306***	−0.259***
	(0.019)	(0.015)	(0.005)	(0.016)	(0.030)	(0.020)	(0.009)	(0.020)

Note: Control variables include age, age squared, a married dummy, years of schooling, individual income, number of family members, a dummy variable indicating whether living in a major city, union membership dummy, tenure with current occupation, tenure with current employer, working in public sector, state of residence dummies and year dummies. Standard errors clustered at the individual level are reported in parenthesis.
*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Table 8: Well-being effects of overeducation and overskilling (after controlling for job satisfaction).

	SF-36 mental well-being				Satisfaction with life			
	Mean	**Q25**	**Q50**	**Q75**	**Mean**	**Q25**	**Q50**	**Q75**
All								
Overeducation	−0.168	0.036	−0.169**	−0.333*	−0.022	−0.024*	−0.022***	0.000
	(0.368)	(0.186)	(0.072)	(0.067)	(0.025)	(0.013)	(0.006)	(0.015)
Overskilling	−0.472***	−0.564***	−0.468***	−0.531***	−0.045***	−0.049***	−0.045***	−0.053***
	(0.144)	(0.103)	(0.042)	(0.091)	(0.011)	(0.009)	(0.004)	(0.009)
Male								
Overeducation	−0.173	0.028	−0.129	−0.086	−0.030	−0.038**	−0.022**	−0.002
	(0.470)	(0.021)	(0.101)	(0.225)	(0.032)	(0.019)	(0.009)	(0.019)
Overskilling	−0.664***	−0.733***	−0.515***	−0.478***	−0.039***	−0.048***	−0.045***	−0.059***
	(0.176)	(0.122)	(0.056)	(0.106)	(0.014)	(0.011)	(0.005)	(0.011)
Female								
Overeducation	−0.197	0.060	−0.240**	−0.773**	−0.006	−0.013	−0.021**	−0.002
	(0.589)	(0.311)	(0.106)	(0.333)	(0.041)	(0.019)	(0.009)	(0.023)
Overskilling	−0.147	−0.223	−0.394***	−0.552***	−0.056***	−0.040***	−0.045***	−0.047***
	(0.251)	(0.184)	(0.066)	(0.176)	(0.019)	(0.014)	(0.006)	(0.015)

Note: Control variables include age, age squared, a married dummy, years of schooling, individual income, number of family members, a dummy variable indicating whether living in a major city, union membership dummy, tenure with current occupation, tenure with current employer, working in public sector, state of residence dummies and year dummies. Standard errors clustered at the individual level are reported in parenthesis.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

having received more years of education than the modal years observed in the corresponding occupation, we define an individual to be overeducated if the years of education he/she received is one standard deviation above the mean education years in his/her occupation. Regarding the definition of overskilling, we alternatively classify those selecting 1–4 on the 7-point scale response to the statement of "I use many of my skills and abilities in my current job" as overskilled, while those reporting 5–7 as well-matched overeducation and overskilling. We separately use the alternative definitions of overeducation and overskilling, and the FE and QR–FE estimation results are reported in Table 9. The mean and distributional effects on the measure of SF-36 mental well-being turn out to be similar to those reported in Tables 2, 3 and 7.[13]

4.3.3 Are Our Findings Driven by Reverse Causality?

The FE and QR–FE methods we use can address the endogeneity bias resulting from unobserved individual heterogeneity. However, they cannot deal with the bias from the possible reversal relationship between job mismatches and mental well-being. Individuals who have experienced a negative shock to mental well-being can be more likely to become overskilled for their jobs. If this is the case, we may have overestimated the adverse consequences of overskilling for mental well-being. In this section, we exploit the longitudinal nature of HILDA and test whether there were significant declines in mental well-being prior to the incidence of overeducation/overskilling.

13 Non-overeducated workers, as the reference group, may consist of people whose education correctly matched to their jobs and those who are undereducated for their jobs. If undereducation has a significant impact on mental well-being, then using non-overeducated people as the reference group (rather than using the matched ones only) may bias our estimates for overeducation. To check whether this practice seriously affects our results, we construct a measure of undereducation defined by having less education than the mode years of education in the corresponding occupational group and further include this measure in our estimations. We find that being undereducated does not affect people's mental well-being. The coefficient estimates of overeducation barely change after controlling for undereducation, and the estimated effects of overskilling remain virtually identical. Using an alternative definition of undereducation, which indicates whether each individual's education is one standard deviation below the mean in each occupation or not, gives very similar results.

Table 9: Alternative definitions of overeducation and overskilling.

	Alternative definition of overeducation				Alternative definition of overskilling			
	Mean	**Q25**	**Q50**	**Q75**	**Mean**	**Q25**	**Q50**	**Q75**
All								
Overeducation	−0.006	0.130	−0.045	−0.174	−0.144	0.153	−0.167**	−0.289
	(0.365)	(0.168)	(0.065)	(0.187)	(0.372)	(0.170)	(0.065)	(0.195)
Overskilling	−0.915***	−1.226***	−0.815***	−0.584***	−0.974***	−1.444***	−0.886***	−0.448***
	(0.146)	(0.100)	(0.038)	(0.093)	(0.195)	(0.137)	(0.049)	(0.119)
Male								
Overeducation	−0.054	0.031	−0.052	−0.189	−0.190	0.115	−0.161*	−0.171
	(0.462)	(0.204)	(0.090)	(0.237)	(0.474)	(0.233)	(0.093)	(0.247)
Overskilling	−1.090***	−1.434**	−0.852***	−0.514***	−1.261***	−1.598***	−0.884***	−0.365**
	(0.177)	(0.127)	(0.051)	(0.112)	(0.239)	(0.171)	(0.068)	(0.152)
Female								
Overeducation	0.050	0.232	−0.055	−0.590*	−0.081	0.088	−0.187*	−0.621**
	(0.390)	(0.251)	(0.166)	(0.306)	(0.599)	(0.264)	(0.101)	(0.291)
Overskilling	−0.610**	−0.949***	−0.799***	−0.564***	−0.469*	−1.134***	−0.892***	−0.574***
	(0.254)	(0.173)	(0.063)	(0.158)	(0.283)	(0.210)	(0.075)	(0.210)

Note: Control variables include age, age squared, a married dummy, years of schooling, individual income, number of family members, a dummy variable indicating whether living in a major city, union membership dummy, tenure with current occupation, tenure with current employer, working in public sector, state of residence dummies and year dummies. Standard errors clustered at the individual level are reported in parenthesis.
$^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

To this purpose, we run FE panel regressions of mental well-being measures on a set of year dummy variables, which indicate, respectively, one, two, three and more years before and after the year when each worker became overeducated/overskilled. The approach we use is similar to that used in Cornaglia, Feldman, and Leigh (2014) and Mahuteau and Zhu (2015). If there is a drop in mental well-being before overeducation/overskilling started, the mental well-being effect of the dummy indicating two years prior to overeducation/overskilling ($t-2$) should be statistically different from the mental well-being effect of the dummy representing one year before becoming overeducated/overskilled (t–1). We select the dummy indicating one year before overeducation/overskilling happened (t–1) as the reference category, so we only need to test whether the estimated coefficients β_{1t-2} and β_{2t-2} in eq. (4) have a positive sign and whether they are statistically significant. Namely, we estimate the following equation with FE panel regression:

$$\begin{aligned} MWB_{it} = {} & Overedu_{it-(3+)}\beta_{1t-(3+)} + Overedu_{it-2}\beta_{1t-2} + Overedu_{it}\beta_{1t} + \\ & Overedu_{it+1}\beta_{1t+1} + Overedu_{it+2}\beta_{1t+2} + Overedu_{it+(3+)}\beta_{1t+(3+)} + \\ & Overskill_{it-(3+)}\beta_{2t-(3+)} + Overskill_{it-2}\beta_{2t-2} + Overskill_{it}\beta_{2t} + \\ & Overskill_{it+1}\beta_{2t+1} + Overskill_{it+2}\beta_{2t+2} + Overskill_{it+(3+)}\beta_{2t+(3+)} \\ & + X'_{it}\gamma + u_i + \varepsilon_{it} \end{aligned} \tag{4}$$

Table 10 reports the results of these tests. We find that the estimated coefficients, β_{1t-2} and β_{2t-2}, are both statistically not significant. Thus, we find no evidence that people's mental well-being becomes significantly lower prior to the incidence of overeducation and overskilling. In addition, Table 10 shows that the coefficient estimates of the year dummy indicating three or more years before overeducation and overskilling happened are also not statistically significant. This suggests that the well-being of individuals three or more years before becoming overeducated/overskilled is not statistically different to the well-being one year before the incidence of overeducation/overskilling. Using life satisfaction as the dependent variable yields similar results. Thus, we find no evidence of a significant decline in mental well-being right before overeducation/overskilling started, and the results reported in previous sections are unlikely to be driven by reverse causality.

Consistent with our expectation, Table 10 shows that there is a significant difference in mental well-being between the year prior to overskilling and the year in which workers became overskilled. The dynamic results provided in Table 10 indicate the negative impact of overskilling on mental well-being is transitory. Individuals experience a significant decline in mental well-being

Table 10: Dynamic well-being effects of overeducation and overskilling.

	SF-36 mental well-being					Satisfaction with life
	Overall	**VT**	**SF**	**RE**	**MH**	
Overeducation						
Three or more years before ($t-(3+)$)	0.218	0.845	−0.362	−0.293	0.680	−0.075
	(1.013)	(1.452)	(1.818)	(1.099)	(0.878)	(0.077)
Two years before ($t-2$)	−0.455	0.318	−1.861	−0.387	0.108	−0.031
	(0.708)	(0.972)	(1.307)	(0.727)	(0.590)	(0.050)
One year before (reference) ($t-1$)	–	–	–	–	–	–
Year becoming overeducated (t)	−0.199	−0.186	−1.013	0.103	0.302	−0.047
	(0.564)	(0.690)	(1.162)	(0.628)	(0.554)	(0.042)
One year after ($t+1$)	0.834	0.654	1.596	0.723	0.363	0.008
	(0.551)	(0.732)	(1.037)	(0.599)	(0.500)	(0.039)
Two years after ($t+2$)	0.053	0.286	0.416	−0.455	−0.033	0.003
	(0.556)	(0.699)	(1.151)	(0.565)	(0.515)	(0.040)
Three or more years after ($t+(3+)$)	0.772	−0.702	3.834	0.128	−0.172	−0.010
	(1.150)	(1.575)	(2.338)	(1.225)	(1.148)	(0.098)
Overskilling						
Three or more years before ($t-(3+)$)	−0.222	−0.680	−0.505	0.0833	0.213	0.018
	(0.541)	(0.687)	(0.994)	(0.540)	(0.504)	(0.039)
Two years before ($t-2$)	−0.333	−0.346	−0.774*	−0.173	−0.0378	0.0134
	(0.240)	(0.325)	(0.467)	(0.254)	(0.230)	(0.018)
One year before (reference) ($t-1$)	–	–	–	–	–	–

Year becoming overskilled (t)	−0.939***	−0.752**	−1.115**	−0.836***	−1.05***	−0.088***
	(0.250)	(0.318)	(0.493)	(0.257)	(0.236)	(0.019)
One year after (t + 1)	−0.243	−0.194	−0.144	−0.398	−0.236	−0.024
	(0.246)	(0.319)	(0.472)	(0.248)	(0.234)	(0.019)
Two years after (t + 2)	−0.335	−0.672**	−0.055	−0.323	−0.289	−0.019
	(0.238)	(0.313)	(0.464)	(0.246)	(0.225)	(0.019)
Three or more years after (t + (3 +))	−0.057	−1.097	0.342	0.354	0.173	0.064
	(0.547)	(0.724)	(1.001)	(0.563)	(0.511)	(0.041)

Note: Control variables include age, age squared, a married dummy, years of schooling, individual income, number of family members, a dummy variable indicating whether living in a major city, union membership dummy, tenure with current occupation, tenure with current employer, working in public sector, state of residence dummies and year dummies. Standard errors clustered at the individual level are reported in parenthesis. SF, social functioning; RE, role-emotional; VT, vitality; MH, mental health.

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

right after becoming overskilled. Their mental well-being then will restore to pre-overskilling level 1 year after the event. Thus, the well-being adaptation to overskilling is rapid and complete.[14]

5 Conclusion

Using data from the longitudinal HILDA survey, this paper estimates the effects of overeducation and overskilling on mental well-being. Our FE panel estimation results show that on average, overeducation does not significantly affect the SF-36 mental well-being measure. This result is similar to the finding of Mavromaras et al. (2013) which shows that overeducation does not reduce overall job satisfaction but differs from previous studies that find a negative impact on job satisfaction (Fleming and Kler 2008; Verhaest and Omey 2009), life satisfaction (Kleibrink and Haisken-DeNew 2012; Artes, Salinas-Jimenez, and Salinas-Jimenez 2014; Piper 2015) and mental health (Bracke, Pattyn, and von dem Knesebeck 2013; Bracke, van de Straat, and Missinne 2014). We show that it is overskilling that has strong detrimental consequences for mental well-being. In a related literature, McGuinness and Wooden (2009) show that overskilled workers are much more likely to quit their current job voluntarily and Mavromaras et al. (2013) find the overskilling leads to lower levels of job satisfaction.

Using the panel data QR–FE by Canay (2011), we find strong evidence of heterogeneous links between overskilling and mental well-being. The depressing effects of overskilling are larger for workers at the lower end than at other parts of the well-being distribution. A possible explanation is that individuals who are mentally well-off seem to cope with skill mismatch in a much more positive and resilient way than individuals scoring relatively low on mental well-being by avoiding stress and restructuring attitudes in a positive way (Tugade and Fredrickson 2004; Cohn et al. 2009). In addition, we show that being overskilled for one's job does not have a uniform damaging impact on the four components of the SF-36 mental well-being measure. The average effects of overskilling are similar for SF and VT, which, respectively, measure social limitations and

14 Using data from the German Socio-Economic Panel and the British Household Panel Survey, Clark et al. (2008a) and Clark and Georgellis (2013) find evidence of complete adaptation to (positive and negative) life events such as marriage, divorce, widowhood, child birth and layoff within a few years, but not so for unemployment. In addition, Qari (2014) shows that that marriage is associated with a permanent spike in life satisfaction, which runs counter to the findings of Clark et al. (2008a) and Clark and Georgellis (2013) showing that individuals quickly return to the baseline level after a short honeymoon period of marriage.

fatigue and energy. RE and MH are most negatively affected by overskilling. Overskilling generates feelings of anxiety and depression and limitations in work or activities possibly through unmet aspirations or expectations experienced by overskilled workers.

Exploiting the longitudinal and dynamic nature of our data, we show that the negative well-being effects of overskilling are not driven by reverse causality. Furthermore, the documented negative effects of overskilling on mental well-being are transitory, and we find evidence of full adaptation one year after becoming overskilled. This rapid and complete adaptation does not mean that the adverse effects of overskilling on mental well-being are not likely to snowball into further negative outcomes, which may have further adverse consequences for individuals' well-being. For example, using the same HILDA data, Frijters, Johnston and Shields (2014) show that a one-standard deviation decrease in the measure of mental well-being leads to a 30-percentage point decrease in employment. Our analysis show that overskilling decreases mental well-being by around 0.06 (= −0.914/16) standard deviation, which suggests that the indirect adverse effect of overskilling on employment through the channel of reduced mental well-being may be 1.8 percentage points.

The results presented in this paper call for policy attention to the detrimental impact of overskilling on people's mental well-being, in addition to its widely documented wage penalties. Our analyses show that the existing studies mostly focusing on labor market outcomes of overskilling have understated the negative consequences of skill mismatch for the society. This adverse impact of overskilling is particularly worrisome as it has been found to be difficult for overskilled workers to move to skill matched jobs (McGuinness and Wooden 2009; Mavromaras and McGuinness 2012). Since workers' productivity can be adversely affected by overskilling directly through the inefficient skill–job allocation (Allen and van der Velden 2001; McGuinness and Sloane 2011) and indirectly through reduced mental well-being (Chatterji et al. 2007; Cseh 2008), the eradication of the incidence of overskilling in working places can benefit both employers' interests and employees' welfare. Policies in promoting the match between skills and jobs could include (but are not limited to) the following: (1) employers allocate workers with new skills to positions matching their expertise, (2) apprenticeship programs can be used as an important mechanism to match workers and jobs in meeting the changing needs of improving productivity and (3) attendance in higher education institutions should be considered jointly with future skill needs.

A few caveats apply to our results. We use the empirical method to measure overeducation. It would be preferable to measure overeducation using the worker self-assessment method and the JA method to check the robustness of our results. If overeducation is not measured satisfactorily, the estimated relative importance of overskilling as opposed to overeducation for mental well-being can be biased. Since overeducation and overskilling are related, the coefficient of overskilling may reflect part of the effect actually attributed to overeducation. Moreover, both overskilling and the outcome variables are subjectively measured. The correlation between two subjective variables is likely to be higher than between a subjective variable and an objective one (Coburn 1975). Consequently, we may have overstated the negative impact of overskilling on mental well-being and understated the impact of overeducation. These issues cannot be addressed due to the data limitation. We leave these aspects for future research.

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