The labour market effects of the financial crisis: the role of non-cognitive skills

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Abstract

In the last twenty years, most economies in the world had to deal with unprecedented global shocks; the Great Recession first, and now the Covid19-induced downturn. This paper looks at the role of non-cognitive skills in the impact of the Great Recession on employment and unemployment. We exploit variation in the severity of the recession across different industries in Britain. We find that people were indeed more likely to lose their jobs if they worked in an industry hit harder by the crisis, conditional on social background and educational attainment. Non-cognitive skills (overconfidence and self-esteem) seem to have protective power against economic shocks: overconfident people and those with higher self-esteem were more likely to stay employed and less likely to lose their jobs due to the crisis.

Keywords: non-cognitive skills, financial crisis, overconfidence

JEL-codes: J24, J01,

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Introduction

Economic recessions have well-studied negative effects on labour market outcomes, overall and for sub-groups (Del Bono & Morando, 2021, Yagan, 2019). Although the role of non-cognitive skills has been broadly investigated in a series of labour market outcomes (Almlund et al. 2011), we know very little about the mediating role these skills play during an economic bust. During challenging times, the role of socio-emotional skills might become even more pronounced. This could explain why the literature on human

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capital found socio-emotional skills to be so important in determining several outcomes, ranging from the labour market to health and wellbeing.

This paper looks at whether certain non-cognitive skills (overconfidence and self-esteem) played a role in keeping employment during the financial crisis in the Great Britain. We use a rich cohort study, the 1970 British Cohort Study (BCS70), that follows a cohort born in 1970 up until age 46. The data cover information on parental background, educational attainment (test scores and degrees) and employment history before, during and after the financial crisis. To identify the causal effects of the crisis on employment, we exploit the fact that the financial crisis affected economic sectors to a different extent. Certain sectors and industries were hit disproportionally (Lallement 2011). We exploit this phenomenon by grouping individuals based on their pre-crisis employment (industry) status to two groups: those working in industries hit more vs. less by the crisis. We use the Labour Force Survey (LFS) to identify which industries were hit more vs less by comparing the rise in unemployment rates across industries between Q2 2009 and Q2 2007. Then, we set up a difference in differences (DiD) identification strategy to look at the effects of the crisis on employment and unemployment. We study the mediating role of non-cognitive skills by looking at the heterogeneity of these effects along the distribution of overconfidence and self-esteem. Our identification strategy relies on the assumption that socio-emotional skills are orthogonal to the intensity of the shock experienced by each industry during the Great Recession.

Overconfidence is a more and more studied personality trait that has been linked to labour market and educational performance, as well as to the gender gap in expected wages (Briel et al. 2021; Reuben, Sapienza, and Zingales 2015) and the probability of working in a top job (Adamecz-Völgyi and Shure 2022). Despite the acknowledgement in the psychological literature that "the significance of overconfidence to the conduct of human affairs can hardly be overstated" (Griffin and Tversky 1992: 432) and an "individual's choice, persistence, and performance can be explained by their beliefs about how well they will do on the activity and the extent to which they value the activity" (Eccles et al. 1983: 68), no previous studies have explored the role of overconfidence in labor market resilience to economic shocks.

Psychologists typically differentiate between three types of overconfidence: overplacement of one's skills compared to others, overestimation of own abilities compared to objective measures, and overestimation of the precision of certain beliefs (overprecision) (Moore and Healy 2008). We use the second definition and measure overconfidence by looking at whether one's self-assessed cognitive skills (how well individuals think they do in mathematics and how clever they are) are higher than their performance on a series of tests. Overconfidence is thus different from confidence since overconfidence implies individuals have an inflated sense of self relative to their actual ability (Adamecz-Völgyi and Shure 2022).

Using the BCS70, we find that individuals were indeed more likely to become unemployed and less likely to stay employed if they worked in an industry hit harder by the crisis (as identified from the LFS). Interacting the DiD-treatment variable with overconfidence scores and self-esteem reveals that individuals with higher overconfidence and self-esteem were more likely to keep their jobs and were less likely to become unemployed than those with lower levels of these two skills. Thus, non-cognitive skills could help to increase labour market resilience during economic crisis.

This paper contributes to better understanding the overall and heterogenous effects of a severe economic shock. As socio-emotional skills are malleable, even in adult life (Barrera-Osorio, Kugler, and Silliman 2020), we raise the possibility of targeted interventions to help workers in hardship to boost their socio-emotional skills. This might be particularly important nowadays, when most countries face an economic recession following the pandemic and the implications of the Russian invasion of Ukraine on the global economy, and there is a huge demand for re-skilling workers (Pissarides 2020).

We contribute to two strands of the literature. First, the literature on the impact of economic downturns. Several studies have found a negative effect of economic recessions on labour market outcomes, overall and for sub-groups (e.g. Yagan 2019; Del Bono and Morando 2021). We contribute to this by investigating the role of skills as mediators, which could potentially explain some of this heterogeneity.

Second, we also contribute to the literature on soft skills and labour market success (e.g. Prevoo and ter Weel 2015). More importantly, very little work has been done to study their mediator role in “bad” situations. Some exceptions are Blázquez Cuesta and Budría (2018) that looks at the role of non-cognitive skills in decreasing the negative impact of income deprivation on one’s mental health, and Johnston, Kung, and Shields (2021) showing that higher locus of control decreases the negative effect of the earnings shock due to Covid19.

The rest of the paper is structured as follows. Section 2 presents the data while section 3 shows descriptive statistics on industries and specifies high and low-hit industries. Section 4 details our identification ad empirical strategy, section 5 presents our results. Section 6 concludes with a discussion.

Data

As mentioned above, this paper uses two data sources: the Labour Force Survey (LFS) and the 1970 British Cohort Study (BCS70).

The Labour Force Survey

We use the UK LFS to identify industries hit more vs. less by the crisis. The LFS data were collected with a stratified single stage systematic probability sampling procedure. The survey covers every person who is living in the selected private households. The resident population comprises persons who regard the sample address as their main address or have lived more than six months in that household. The interviews were carried out in each (calendar) quarter via in-person (face-to-face) interviewers (Computer-Assisted Personal Interviewing, CAPI).

The LFS defines a person employed if they are over 16 years old and worked more than an hours per week, or if they have a job, but they were temporary away from it due to paid leave (e.g. holiday, sick leave, etc). The LFS defines a person unemployed if they have no job currently, sought work in the last four weeks and would be available to start working within two weeks.

We use the LFS data from two sources. First, we use the individual-level quarterly LFS files (Ref to UKDS) to look at employment and unemployment rates among those aged 35-45 (to make the sample comparable to the sample of the BCS70) in the Great Britain between 2005 and 2011. We use these data to plot aggregate employment and unemployment rates for this particular subsample of the LFS to compare them to the same information in the BCS70 to show that they follow a similar trend (Figure 1). Second, we use unemployment rates by previous job industry as published by the Office of National Statistics (ONS), because information on previous industry is not available in the individual-level files. We use these data to investigate how the unemployment rate by previous industry changed between 2005 and 2011, and we also use these data to identify which industries were hit more vs. less by the crisis. For this purpose, we compare unemployment rates by the industry of previous employment in the first quarter of 2009 and 2008. The first quarter of 2008 is the last quarter before the crisis hit in Q2 2008, so we use the last pre-crisis quarter as a base and look at how unemployment rates increased until the same period of the next year.

The BCS70

The BCS70 follows individuals born in a specific week in 1970 across the Great Britain. The cohort has since been followed up until age 46. The advantage of this dataset is the vast amount of longitudinal information about the cohort members and their parents. The database offers rich information on cognitive and non-cognitive skills, individual characteristics and long-term labour market history, employment and wages.

Labour market outcomes

The BCS70 measures self-assessed labour market status at the time of the data collection, and also retrospectively between waves. Cohort members are asked about whether they work, their occupation, the industry of their firm, wages and hours worked. We harmonized occupation and industry coding across waves and between the LFS and the BCS70 categories according to Appendix X.

Measuring overconfidence

As mentioned above, we construct a measure of overestimation to capture overconfidence by comparing individuals' subjective estimated abilities (what individuals think about how clever they are and how good they are in school) to an objective measure of their cognitive abilities. We measure objective cognitive abilities via tests taken at age 5, 10 and 16. The advantage of using longitudinal data is that we have many measures from several points in time, which we can combine to create a more robust measure of cognitive ability. As in previous studies exploring the importance of cognitive ability, we combine existing survey measures into an index (Bütikofer and Peri 2021; Lindqvist and Vestman 2011). We create a standardized index of the resulting continuous scores of these 18 tests using Confirmatory Factor Analysis (CFA) (Thompson and Daniel 1996). We also use a binary version of this measure capturing whether one's cognitive ability index is above or below the sample mean. We measure subjective estimated abilities via questions taken at age 10 and 16 and create an index of these categorical variables (measured using a Likert scale) using Item Response Theory (IRT) (Edelen and Reeve 2007).

Following Anderson et al. (2012), we construct an index of overconfidence by regressing each cohort member's percentile rank in the distribution of estimated ability on their percentile rank in the distribution of objective cognitive ability and predict the residuals (*residual score*). The residual score captures the variability in self-perceived rank after the variance predicted by actual rank has been removed and is one of the most used methods to capture overconfidence in the psychology literature (Belmi et al. 2019). Those with a positive overconfidence score are higher on the subjective estimated ability distribution than where they are based on their objective cognitive skills, while negative scores reflect underconfidence. Figure A2 in the Appendix shows the distribution of the standardized overconfidence score.

Measuring self-esteem

Self-esteem is measured at age 16. Figure A1 in the Appendix shows the distribution of self-esteem, standardized to mean 0 and SD 1.

Control variables

We exploit the rich nature of the longitudinal data to control for a range of characteristics. Taking into account prior literature (Dickson and Harmon 2011), we control for background characteristics that have been shown to be related to labor market success. This includes:

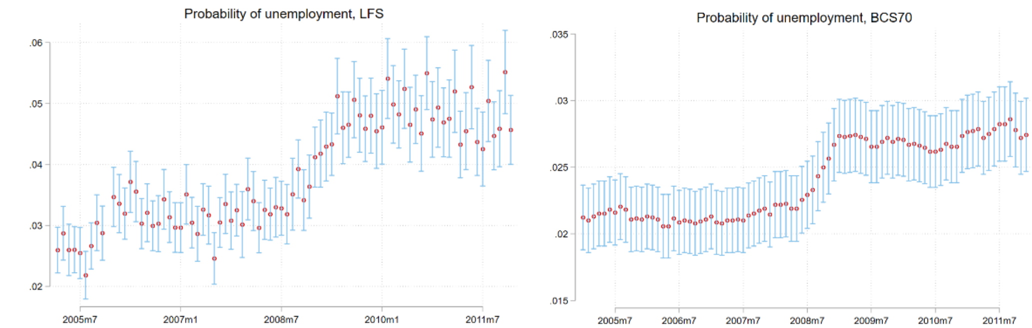
- Demographics and parental background
    - Region in the UK when born;
    - Parental SES based on NS-SEC categories when the cohort members were born. This is captured via a binary variable of low vs. high SES. *Low SES*: parental NS-SEC includes "Single parent or not working", "Other category", "V unskilled", "IV partly-skilled", "III manual". *High SES*: parental NS-SEC is "III non manual", "II managerial and technical" or "I professional".
    - Whether the cohort member's mother had a qualification when the cohort member was born;
    - Mother's year of birth
    - Ethnicity (English, Irish, Other European, West Indian, Indian, Pakistani, Bangladeshi, other).
- Educational attainment and outcomes:
    - University graduation
    - Math exam grades at age 16 (O-level or CSE examinations, seven categories);
    - Whether completed any A-level examinations (binary).t

Descriptive statistics and high vs. low-hit industries

Employment and unemployment in the LFS and the BCS70

Figure 1 shows employment and unemployment rates between 2005 and 2011 in the LFS and the BCS70. Trends in unemployment are similar, but in employment they are a bit different (note that the BCS70 is not weighted yet). Both data indicate a drop in employment as well as an increase in unemployment starting from the second quarter of 2008.

Figure 1: The probability unemployment in the LFS and the BCS70

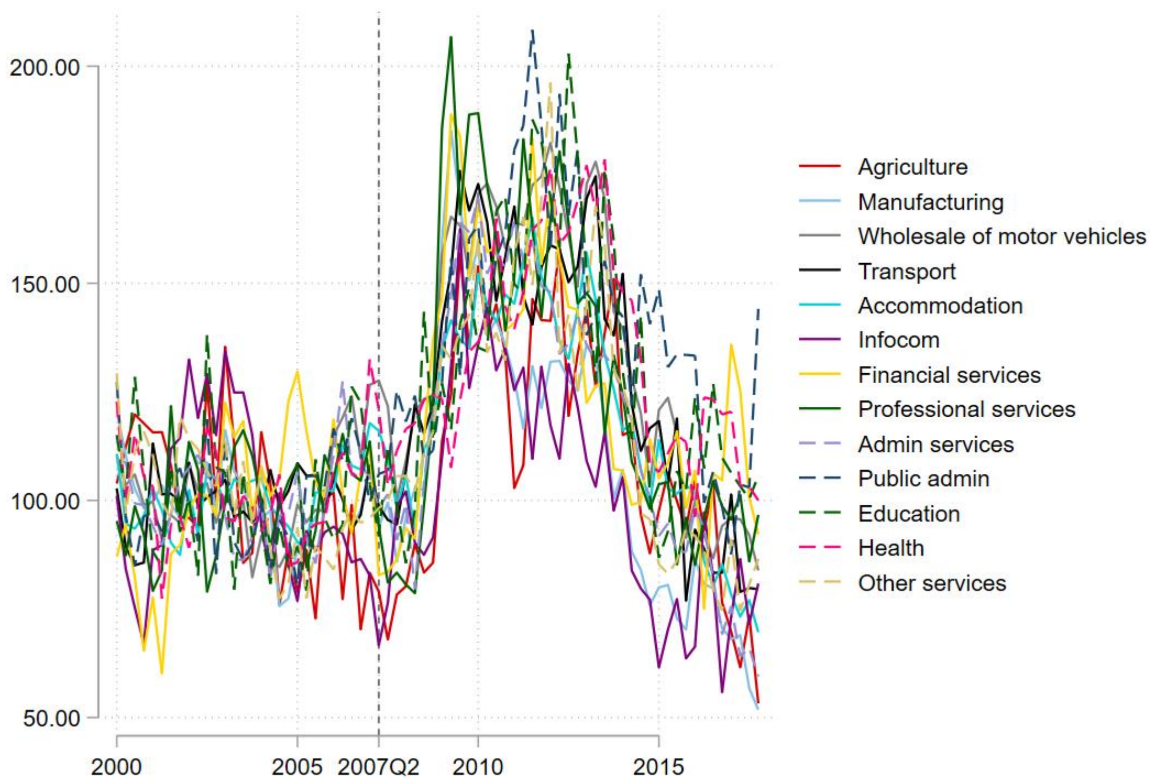


Source: individual LFS TBA. Great Britain only, those aged 35-45, weighted. BCS70: not weighted yet. source TBA.

Unemployment rate by previous industry in the LFS

Figure 2 show the change of unemployment rates by the industry of previous employment for aggregate LFS data (Source: ONS). There are clear difference across industries in terms of how hard the crisis hit them.

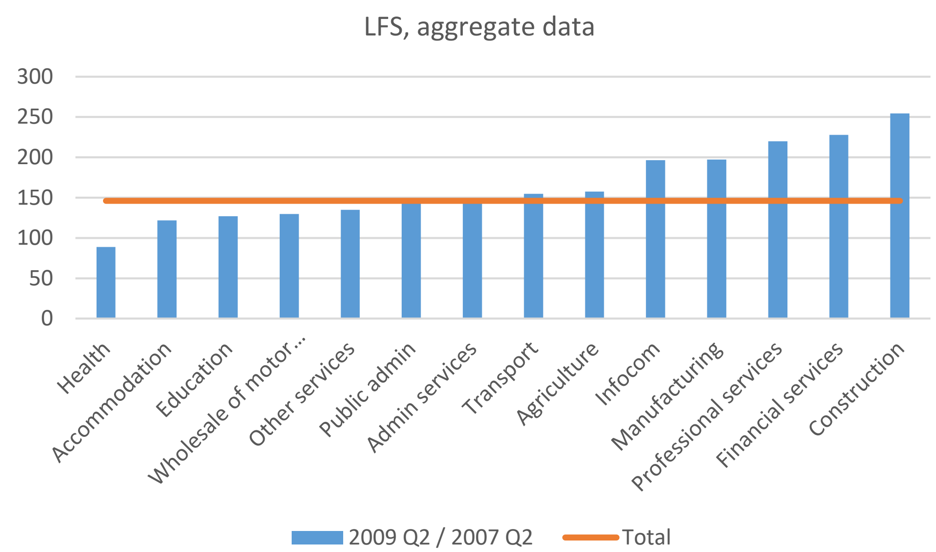
Figure 2: The change of unemployment rates by the industry of previous employment (LFS)



Source: aggregate LFS data from ONS.

Figure 3 shows the change of unemployment by previous industry between Q2 2009 and Q2 2007. The most hit industries are Professional services, Construction, Manufacturing, Financial services, Education, and Wholesale of motor vehicles. These industries will contribute to our treatment measure of indicating industries hit "more" by the crisis.

Figure 3: The change of unemployment rates by the industry of previous employment
The change in unemployment between 2007 Q2 and 2009 Q2



Source: ONS aggregate LFS data.

Table 1 shows the descriptive statistics of those working in high-hit (treated) and low-hit (control) industries before the crisis. The two groups have quite some statistically significant differences, although most statistically significant differences are not economically meaningful. Importantly, the differences in overconfidence and self-esteem are rather small.

Table 1: Descriptive statistics by the treated and control groups in the BCS70

variable	Obs.(n)	Control (mean)	Treated (mean)	beta	p
Date of observation	922992	581.50	581.50	0.00	1.00
Date of observation of pre-crisis industry	910812	573.17	573.17	0.00	0.97
Region at birth	790020	12.03	11.21	-0.82	0.00
High SES parents	759108	0.35	0.35	-0.01	0.00
Mother's year of birth	758016	1944.20	1944.02	-0.17	0.00
Age mother completed education	756672	15.72	15.78	0.06	0.00
Age father completed education	745668	16.03	16.03	0.00	0.78
Mother has a qualification	790020	0.55	0.55	0.00	0.26
Father has a qualification	790020	0.89	0.90	0.01	0.00
Female	790020	0.57	0.44	-0.13	0.00
Ethnicity	790020	10.09	10.51	0.42	0.00
Objective cognitive abilities, STD	790020	0.09	0.13	0.04	0.00
Academic self-concept score	790020	0.00	0.03	0.04	0.00

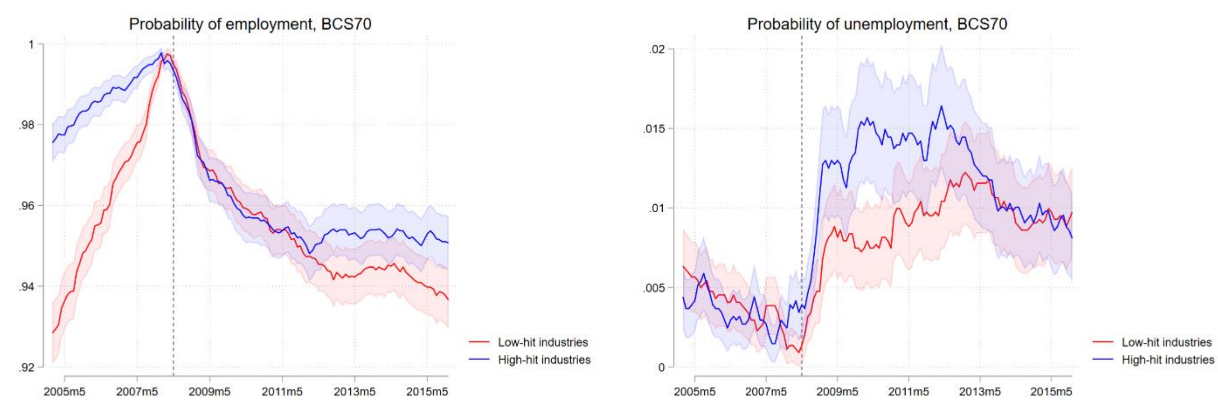
Math exam score, age 16	704760	32.03	34.30	2.28	0.00
A-level	790020	0.18	0.20	0.02	0.00
Graduate	818412	0.24	0.27	0.04	0.00
Overconfidence score, STD	790020	-0.02	0.00	0.02	0.00
Self-esteem, std	331800	-0.02	0.05	0.07	0.00

Source: BCS70 TBA.

Empirical strategy

We identify the effects of the financial crisis using a DiD strategy. First, we identify high-hit and low-hit industries from the LFS as detailed in the previous section. Then, we compare the differences in employment and unemployment rates between those working in high-hit and low-hit industries before the crisis to the same differences after the crisis. Our main identification assumption is that all observable and unobservable differences in employment and unemployment between the two groups would have been constant over time in the lack of the crisis. Figure 4 shows the employment and unemployment rates before and after the crisis in the two groups. Employment rates were higher and unemployment rates were lower among those who worked in high-hit industries before the crisis, and these differences seem to be relatively stable. While it is not possible to test whether unobserved differences are constant between the two groups, it seems that at least pre-crisis, the parallel trends assumption is not violated.

Figure 4: Probability of employment and unemployment among those working in high-hit (treated) and low-hit (control) industries before the crisis (BCS70)



Source: public BSC70 TBA.

Formally, we estimate the following DiD models:

$$y_{i.t} = \propto + \beta_1 * treated_i + \beta_2 * post\ crisis_t + \beta_3 * treated_i * post\ crisis_t + \delta * X_i + u_{i.t} \quad (1)^6$$

[6]+TBA: event study: same as eq (1) but with years instead of post crisis

where y_{it} is the outcome of individual i at time t (employment status between 2005 and 2011), $treated_i$ is a binary variable indicating whether individual worked in a high-hit industry before the crisis, $post\ crisis_t$ is a binary variable indicating whether the time of observation is after March 2008, and the interaction term of $treated$ and $post\ crisis$ identifies the DiD coefficient, β_3. X_i is a matrix of time-independent individual characteristics as the $ethnicity$, math exam score at age 16, $region,\ gender$, advanced level qualifications, socio-economic status, educational level, the mother's year of birth, the age of both the mother and father when they completed their education and the associated (level) of their qualifications.

Then, to look at the mediating role of non-cognitive skills (self-esteem and overconfidence) we introduce them into Equation 1: first on their own and then as an interaction term between each skill and the DiD variable.

Table 2: The effects of the crisis on the probability of employment

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5	(6) Model 6	(7) Model 7	(8) Model 8
Treated	0.008***	0.003***	0.003***	0.003***	0.003***	0.003***	0.001*	0.007***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Postcrisis	-0.005***	-0.002	-0.002	-0.002	-0.002	-0.002	-0.000	-0.003
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
DiD	-0.005***	-0.008***	-0.008***	-0.008***	-0.008***	-0.008***	-0.007***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Underconfidence					0.002***	0.003***		
					(0.000)	(0.000)		
DiD*Underconfidence						-0.003**		
						(0.001)		
Overconfidence					0.013***	0.012***		
					(0.001)	(0.001)		
DiD*Overconfidence						0.003***		
						(0.001)		
Overconfidence score, std			0.004***	0.003***				
			(0.000)	(0.000)				
DiD*Overconfidence_score				0.001**				
				(0.000)				
Self-esteem, std							0.009***	0.011***
							(0.000)	(0.000)
DiD*Self-esteem, std								0.002***
								(0.001)
Constant	0.923***	-4.744***	-4.710***	-4.711***	-4.740***	-4.741***	-5.701***	-2.938***
	(0.000)	(0.083)	(0.084)	(0.084)	(0.083)	(0.083)	(0.110)	(0.073)
Observations	912,004	590,462	590,462	590,462	590,462	590,462	284,441	324,447
R-squared	0.000	0.251	0.251	0.251	0.251	0.251	0.260	0.216
Controls	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Control variables: actual month, ethnicity, math exam score at age 16, region, gender, advanced level qualifications, socio-economic status, educational level, the mother's year of birth, the age of both the mother and father when they completed their education and the associated (level) of the qualification.

Results

Table 2 shows the effects of the crisis on the probability of employment. The first column (Model 1) indicates the effect without further control variables. The coefficient of the diff-in-diff (DiD) variable is significant and negative, which is consistent with our expectations. The crisis had about two times as large negative effect on the probability of employment among those who worked in a high-hit industry (-0 .005+ -0.005) as among those who did not (-0.005), over the course of 2008-2011. Controlling for background characteristics in Model 2 shows that conditional on these variables, the crisis mostly hit only those working in high-hit industries before the crisis. Overconfidence is positively correlated with the probability of employment (Model 3), as well as self-esteem (Model 6). The interaction terms of these two non-cognitive skills variables with the DiD variables are also significantly positive (Model 4 and 8). Thus, these skills not just help labour market success in general, but they provide additional protection during difficult times. Results are similar for unemployment as well (Table 3).

Table 3: The effects of the crisis on the probability of unemployment

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5
Treated	-0.000*	0.001***	0.001***	0.001***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Postcrisis	0.005***	0.002*	0.002*	0.002*	0.001
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
DiD	0.004***	0.005***	0.005***	0.004***	0.006***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
DiD*Underconfidence				0.003***	
				(0.001)	
Overconfidence				0.002***	
				(0.000)	
Overconfidence score, std			0.001***		
			(0.000)		
DiD*Overconfidence_score			0.002***		
			(0.000)		
Self-esteem, std					0.002***
					(0.000)
DiD*Self-esteem, std					0.005***
					(0.000)
Constant	0.004***	0.003	-0.008	-0.005	0.355***
	(0.000)	(0.035)	(0.035)	(0.035)	(0.055)
Observations	831,768	550,788	550,788	550,788	264,600
R-squared	0.002	0.004	0.004	0.004	0.006
Controls	No	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Control variables: actual month, ethnicity, math exam score at age 16, region, ,gender, advanced level qualifications, socio-economic status, educational level, the mother's year of birth, the age of both the mother and father when they completed their education and the associated (level) of the qualification.

Robustness checks

We are working on providing the following robustness checks. First, although the financial crisis started in the UK in the 3rd quarter of 2008, it already had started in the US in the previous year (Q3 2007). Thus, staring from this time, people and businesses in the UK might have already anticipated the coming of a crisis. To exclude any potential anticipation effects, we re-estimate our results by setting treated and control industries based on the change in unemployment between Q2 2009 and Q2 2007.

Second, we aim at decreasing the pre-crisis differences in employment by combining our DiD-strategy with semiparametric matching a la Abadie (2005) and Houngbedji (2016). Third, we provide two additional estimation strategy: two-way FE models and an event-study design. For the two-way FE models, we will substitute the discrete treatment with a continuous one, by using a continuous measure of unemployment rate. We will explore two ways of doing this: by using the change in unemployment between 2007 and 2009 as main regressor, such as in Stuart (2022), and by using the contemporaneous unemployment rate in a panel setting. When doing so, we will take into account the recent developments in the DiD literature, such as the estimator suggested by de Chaisemartin and D'Haultfoeuille (2022) and Borusyak, Jaravel, and Spiess (2021) to overcome the limitations of TWFE models. Lastly, the event-study design gives us a possibility to look at the effects of the crisis on the longer run, year by year (while also provides an opportunity to check the parallel trend assumption more rigorously).

Discussion

This paper looked at the role of non-cognitive skills in labour market resilience. We exploited the 2008-2009 financial crisis and the fact that it hit different industries to a different extent in Great Britain. Using the BCS70, we set up a DiD identification strategy to estimate the causal effects of the crisis on employment and unemployment. We then investigated the mediating role of two non-cognitive skills: overconfidence and self-esteem. We find that not just that these two skills are positively correlated with the probability of employment (and negatively with the probability of unemployment) but they also play a role in easing the negative effects of the crisis. As non-cognitive skills are malleable even in adulthood, these results might suggest that interventions aiming to develop these skills could increase labour market resilience in troubled times.

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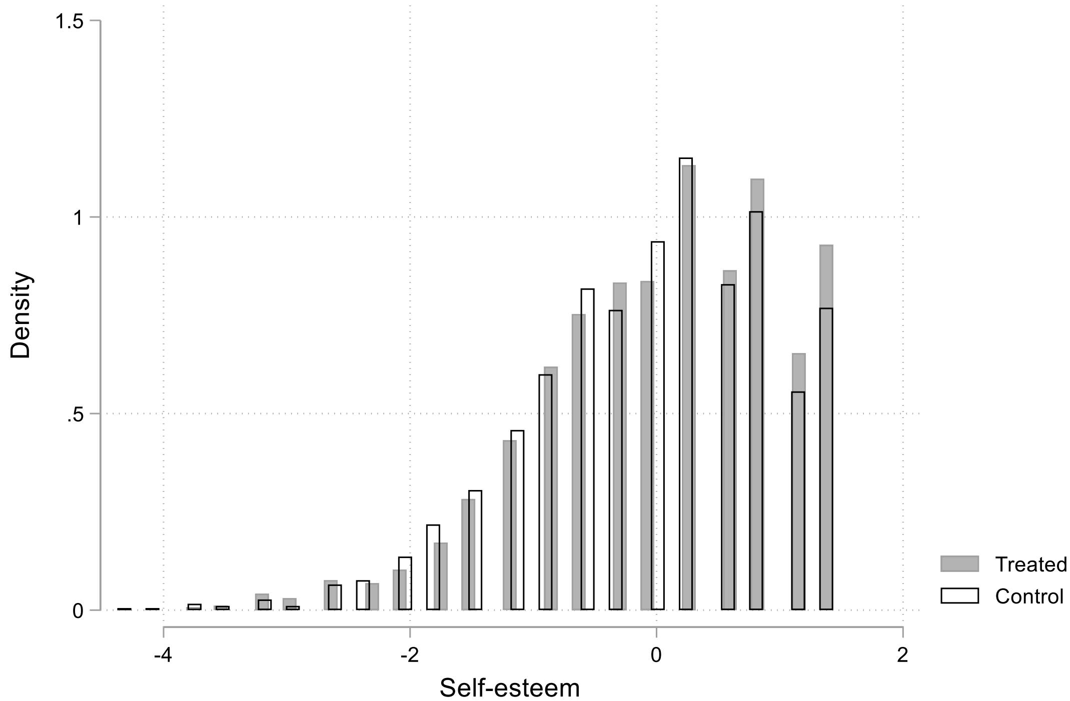
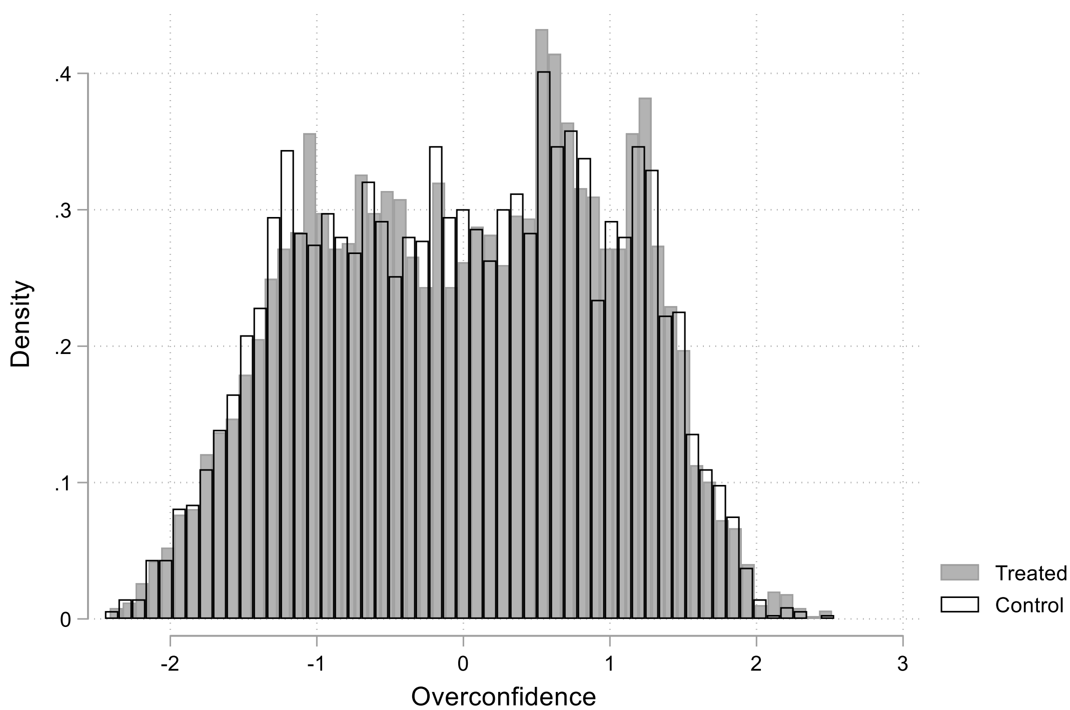
Appendix

Figure A1: The distribution of self-esteem by treatment status



Source: BCS70 TBA. No. of individuals: 5,038.

Figure A2: The distribution of overconfidence by treatment groups



Source: BCS70 TBA. No. of individuals: 12, 592.

Figure A3: The distribution of overconfidence by pre-crisis industry

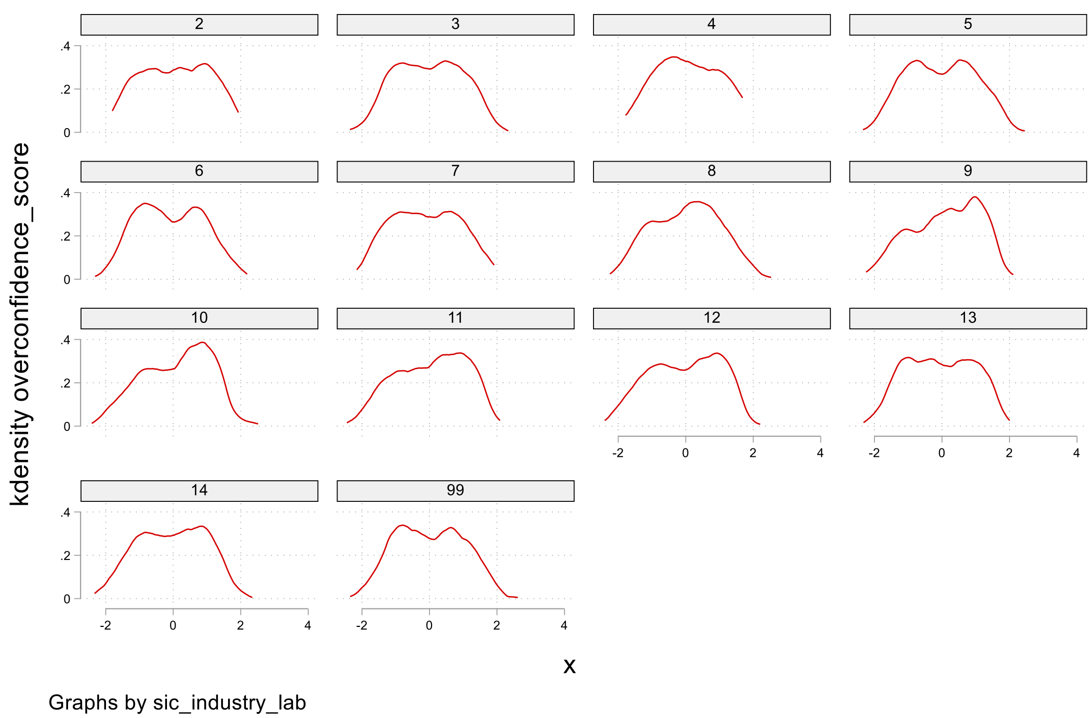


Figure A4: The distribution of self-esteem by by pre-crisis industry