

Abstract

The increase in life satisfaction during retirement from unemployment has been widely accepted as a result of identity change. This paper, however, suggests that individual's financial situation is underestimated. Using German Socio-Economic Panel data, this paper combines entropy balancing matching and difference-in-differences estimation, and the machine learning algorithm LASSO is used for variable selection in the matching process. The heterogeneity analysis demonstrates that the life satisfaction increase is mostly concentrated on those whose financial status is better.

Introduction

The literature finds that unemployed individuals' life satisfaction (LS) increases after they retire. Since the transition is not accompanied by substantial changes in financial resources or leisure time, a widely accepted explanation is social identity, naming retirement restores compliance with social work norms (Hetschko, Knabe, and Schöb 2014; 2019; Ponomarenko, Leist, and Chauvel 2019).

This explanation belongs to nonmaterial explanations for why unemployment reduces happiness. Since unemployment reduces happiness after actual income is controlled for, most studies explain this finding via nonmaterial-based theories.

However, some scholars suggest that material deprivation is the root cause. For example, Luo (2020) finds that the unemployed have insufficient income to support their living, i.e., household income < minimum required income (MIQ). Those who do not suffer from material deprivation may not experience a LS decrease and may even experience a LS increase.

This paper suggests that the role of personal finance is underestimated. Using German Socio-Economic Panel (GSOEP) data, this paper finds that the increase in LS is mainly concentrated on those with income > MIQ. Using entropy balancing (EB) matching and LASSO variable selection to reweight the control group yields similar results.

Data

This paper uses German SOEP (1984-2018), one of the most utilized datasets in happiness economics.

This paper focuses on the transition to retirement from employment or unemployment. The sample contains 1,456 transitions from unemployment (i.e., the treatment group) and 3,478 from employment (control). The final sample contains up to 5 years before and after the transition, with 41,920 observations.

Key variables include:

Life satisfaction (LS): dependent variable - How satisfied are you with your life?

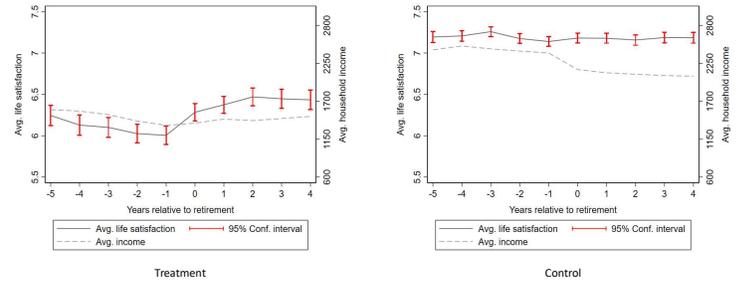
Household income is the monthly equivalent net household income.

Minimum required income (MIQ): What would you personally consider the minimum net household monthly income that your household would need in your current living situation?

Summary Statistics

Summary statistics and graphs show that during the transition to retirement, the LS of the treatment group **increased**, while their income remained **similar**. In contrast, the LS of the control group remained **similar**, while their income **decreased**. The results indicate that personal finance may play an important role in the changes in LS.

Group Subgroup	Treat		Control	
	Unemploy (1)	Retire (2)	Employ (3)	Retire (4)
Life satisfaction (0-10)	6.09 (2.1)	6.39 (1.96)	7.19 (1.67)	7.18 (1.74)
Household income	1471 (995)	1430 (825)	2445 (2091)	2104 (1311)
Observations	6181	6194	14381	15164



Empirical strategy

This paper uses a DiD approach to remove the "pure retirement" effect.

The Individual fixed effects (FE) is used to eliminate the bias caused by selection of time-invariant **unobservables**, such as personality traits.

Entropy balancing (EB) matching is utilized to remove the bias caused by selection of **observables**. During the matching process, two procedures are used to select the control variables: manual selection and automatic selection by the machine learning algorithm LASSO. This process is doubly-robust.

The specification is

$$LS_{it} = \alpha_i + \beta RETIRE + \gamma T + \delta (RETIRE \times T) + \theta X_{it} + \varepsilon_{it}$$

where α_i is the individual FEs, $RETIRE$ is the retirement indicator, T is the treatment indicator (omitted due to FE specification).

Results

The replication shows that retiring from unemployment increases LS.

Dependent Variable: Life Satisfaction

	(1) No matching	(2) EB manual	(3) EB Lasso
Retire	0.111*** (0.0268)	-0.235* (0.125)	0.0691 (0.0467)
Treat × retire	0.207*** (0.0397)	0.391*** (0.134)	0.152*** (0.0512)
Log income	0.369*** (0.0371)		
Observations	38,760	38,413	35,888
R-square	0.019	0.141	0.108

The heterogeneity analysis divides $Retire \times T$ according to if income > MIQ, and finds that the increase in LS is mainly concentrated on people with income > MIQ.

	(1) No matching	(2) EB manual	(3) EB Lasso
Retire	0.110*** (0.0268)	-0.235* (0.125)	0.0674 (0.0468)
Treat × retire	0.0993 (0.0752)	0.269* (0.146)	0.0355 (0.0851)
(Income ≤ MRI)	0.223*** (0.0603)	0.460*** (0.144)	0.171** (0.0714)
(Income > MRI)	0.368*** (0.0371)		
Log income	0.368*** (0.0371)		
Observations	38,760	38,413	35,888
R-square	0.019	0.141	0.108

*** p<0.01, ** p<0.05, * p<0.1

Conclusion

Using SOEP data, this paper combines DiD and entropy balancing matching (the machine learning algorithm LASSO is used for variable selection in the matching process), and shows that during the transition from unemployment to retirement, the increase in LS is mainly concentrated on people with better financial conditions.

References

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