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Wage Cyclicality and Labor Market Sorting: Comment

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Abstract

Figueiredo (2022) examines wage cyclicality across the skill mismatch distribution finding large differences. Some key results include finding that wages are acyclical in good labor market matches but procyclical in poor matches. Using the public replication material provided by the authors, we were able to exactly duplicate the results of the study. Further, using several further robustness checks, such as subtracting (potentially correlated) covariates in the regressions, using different standard errors (rather than clustered ones), or different time periods of the data left the key results largely unchanged with some minor caveats.

1. Introduction

Figueiredo (2022) examines wage cyclicality in the U.S. across the skill mismatch distribution finding large differences, including finding that wages are acyclical in good labor market matches but procyclical in poor matches. Such results are important since wage rigidity is theorized in macroeconomics to account for a substantial amount of the fluctuations in unemployment (Bewley (2002), Shimer (2005) and Hall (2005)).

Using the public replication material provided by the authors, we were able to exactly duplicate the results of the study. Further, using several further robustness checks, such as adding or subtracting variables in the regressions or using different standard errors left all the key results largely unchanged.

Figueiredo (2022) constructs a skill mismatch index using worker-level panel data from the 1979 National Longitudinal Survey of Youth (NLSY79) together with O*NET data with data covering the period of 1979 to 2016. Such skill mismatch measures are popular in the labor literature (see Baley, Figueiredo, and Ulbricht 2020, Guvenen et al. 2020)).

Some key results include findings that skill mismatch is negatively associated with job duration, and that wages are acyclical in good labor market matches but procyclical in poor matches.

In the present paper, we investigate whether their analytical results are reproducible and replicable and further test their robustness to several specification checks: 1. Removing covariates in the wage regressions, 2. running the regressions with non-clustered standard errors, and 3. replicating the results using data from different time periods: 1979-1997 and 1998-2016.

In terms of reproducibility, we would like to acknowledge that Figueiredo (2022) was successfully reproduced by the data editor's team at *American Economic Review: Insights*. We also successfully reproduced all the main tables and figures in Figueiredo (2022) using their codes. We uncovered no coding errors.

We would like to thank the original authors for making available the raw data.

2. Reproducibility

We also successfully reproduced all the main tables and figures in Figueiredo (2022) using their codes together with data from the NLSY79 and O*NET. We detected no coding errors in their replication materials.

However, we did have some small challenges with the output of some of the replication files. For instance, the replication files produce tables as .tex files ("table1.tex" and "table2.tex"). Upon opening these .tex files and compiling them, a LaTex error is received saying "! LaTex Error: Missing \begin{document}. To correct for this, we needed to add "\documentclass{article}", "\begin{document}?" at the beginning of the replication package Table1.tex output file and "\end{document}" at the end of the Table1.tex replication package output file. Once making this adjust, Table 1 was able to be produced (see below).

However, the Table2.tex output file similarly gave an error but was too difficult to debug so we rewrote the .tex file which produced paper Table 2 (see below).

Moving to the figures, the replication files produced the paper figures as suitable pdf files which we will discuss the robustness of further below in our Replication section. The reproduced original paper figures (all panels from Figure 2a through Figure 3c) are denoted "All Figueiredo (2022) variables" in the table figures below.

3. Robustness Checks

We now turn our attention to our sensitivity analysis. We test the robustness of the results by performing a robustness replication by changing how some of the regressions are run. We chose this approach given that the results could potentially be sensitive to collinearity among covariates or the fact that standard errors are being clustered. Hence, we run some of the same regressions removing one covariate at a time. We also run the same regressions without clustering standard errors.

3.1 Multicollinearity and Removing Covariates From The Regression Model

Due to the possibility of multicollinearity in the wage regression, we felt it was important to test the robustness of the results to removing various covariates.

We removed each covariate one by one systematically and analyzed the sensitivity of the output of the replication files.

Table 2a and Table 2b of this paper show some of the robustness results for Table 2 Column 1 in Figueiredo (2022), namely regression coefficients, standard errors, t-statistics and p-values. Removing coefficients like age and education leaves the coefficients relatively unchanged and the t-statistics/p-values still statistically significant at the 1% level.

We also use the 'speccheck' package of Brodeur, Cook and Heyes (2020) which demonstrates that the results (coefficients and t-stats) are relatively unaffected by randomly adding or removing covariates (see Figure 1).

Looking to heterogeneity which is depicted in the series of figures 2a-3c in Figueiredo (2022), we can further examine sensitivity of the paper's results.

For example, removing the age-squared regression changes some results including slightly moving wage-elasticity estimates slightly upward but by only a small magnitude. Analyzing wage semi-elasticity among job stayers, in Figueiredo (2022) Figure 2a (Left panel), some of the wage semi-elasticities among the lowest mismatch percentiles go from negative to positive after removing age-squared from the regressions (see Figure 2a). In Figueiredo (2022) Figure 3c (Left panel) some of the wage semi-elasticities among lower underqualification percentiles are now statistically significant after removing age-squared from the regressions (see Figure 3c). Nonetheless, wage semi-elasticities are still clearly increasing with mismatch and underqualification.

Removing education as a covariate does seem to push the upper mismatch percentiles of semielasticities up somewhat considerably, among new hires from unemployment. For example, in Figure 2a, the wage semi-elasticity in the top mismatch percentile goes from 4 to 5 (see Figure 2a below "All Figueiredo (2022) variables" versus "No Education").

3.2 Non-Clustered Standard Errors

Figueiredo (2022) uses clustered standard errors in its analysis. Clustered standard errors are often useful when treatment is assigned at the level of a cluster instead of at the individual level. Since the number of clusters in the sample is a fairly negligible fraction of the number of clusters in the population, regular non-clustered standard errors are not necessarily inflated (Abadie, Athey, Imbens and Wooldridge (2023)). Re-running Figueiredo (2022) without clustering standard errors demonstrates this. Largely the standard errors are unchanged and any statistical inference made about various mismatch percentiles is unchanged. For example, looking at the Figueiredo (2022) Figure 2a Middle Panel with clustered versus and non-clustered standard errors (see Figure 2a) demonstrates that they essentially yield the conclusions about inference, that is at which mismatch percentiles are wage semi-elasticities statistically significant.

3.3 Different Time Periods

We broke up the replication file output data ("data_analysis.dta") which regressions are performed using data from 1979-2016 on into two equal time periods to perform further robustness checks: 1979-1997 and 1998-2016.

The earlier time period 1979-1997 marks a labor market where labor productivity was still relatively high compared to 1998-2016. In addition, the 1979-1997 time period is marked by more traditional monetary policy induced recessions whereas the recessions in the 1998-2016 period were namely induced by asset bubbles including the early 2000s tech bubble and the 2008-2009 Great Recession which followed a housing bubble.

Table 2a and Table 2b of this paper show some of the robustness results for Table 2 Column 1 in Figueiredo (2022), namely regression coefficients, standard errors, t-statistics and p-values. when splitting the data into the two equal time periods: 1979-1997 and 1998-2016.

While the results are somewhat unchanged particularly for the 1979-1997 period. However, it is worth nothing that when isolating the 1998-2016 period data, unemployment (U_t) is no longer statistically significant (t-state = -1.63 and p = 0.104) potentially contradicting wage cyclicality findings across the skill mismatch distribution. That being said, U_t * N_{ti,t} remains statistically significant at the 1% level although the coefficient changes from approximately -5 to -3.

Moving to the figures, the first thing to notice in Figures 2a through 3c is that the standard errors in the 1979-1997 and 1998-2016 samples are much larger due to the reduced sample size in each case. Generally speaking the results across the 1979-1997 and 1998-2016 samples look very similar to the results of Figueiredo (2022) which uses the full sample from 1979-2016. Some exceptions include in Figure 3c middle panel and Figure 3c right panel wage semi-elasticities are instead declining with underqualification percentiles for new hires from unemployment and rising with underqualification percentiles for job switchers when looking at 1979-1997 a reversal versus the trends observed in the full samples.

4. Conclusion

Figueiredo (2022) examines wage cyclicality across the skill mismatch distribution finding large differences. Some key results include finding that wages are acyclical in good matches but procyclical in poor matches. Using the public replication material provided by the authors, we were able to exactly duplicate the results of the study. Further, across many robustness checks, such as adding or subtracting variables in the regressions or using different standard errors left or analyzing different time periods of the data, all the key results generally are largely unchanged.

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Table 1. Figueiredo (2022) Table 1 Reproduced After Amending LaTex code to add "\documentclass{article}", "\begin{document}" at the beginning of the replication package "table1.tex" output file and "\end{document}" at the end of the "table1.tex" replication package output file

	Mean	Standard Deviation
Panel A: Sample characteristics		
Age (years)	35.85	9.75
Non-white	0.17	0.37
College graduate	0.37	0.48
Panel B: Labor Market Outcomes		
Job tenure (months)	54.56	65.04
Labor market experience (years)	15.88	9.23
Hourly wage (log)	7.37	0.71
Total $\#$ transitions (EE+UE)	9.66	6.27
Total $\#$ EE transitions	4.98	3.95
Panel C: Mismatch		
Skill Mismatch	27.22	14.53
Overqualification	16.27	16.32
Underqualification	10.95	13.31

Table 2a. Figueiredo (2022) Table 2 Column 1 Coefficients and Standard Errors AfterAdding and Removing Covariates

	All	No	No age	1979-	1998-
		education		1997	2016
Ut	-0.712	-0.621	-0.711	-0.809	-0.392
	(0.210)	(0.212)	(0.210)	(0.348)	(0.241)
Ut * Ni,t	-1.584	-2.218	-1.584	-1.346	-1.693
	(0.320)	(0.324)	(0.319)	(0.336)	(0.553)
F	50.90	49.35	53.19	47.57	7.15
Ν	384,094	384,094	384,094	195,203	188,890

 Table 2b. Figueiredo (2022) Table 2 Column 1 T-stats and P-Values After Adding and

 Removing Covariates

	All	No education	No age	1979- 1997	1998- 2016
U _t T-Stat/ p-value	-3.39 0.001	-2.93 0.003	-3.390 0.001	-2.32 0.020	-1.63 0.104
Ut * Ni,t T-Stat/ p-value	-4.96 0.000	-6.84 0.000	-4.96 0.000	-4.01 0.000	-3.06 0.002
F	50.90	49.35	53.19	47.57	7.15
	0.000	0.000	0.000	0.000	0.000
Ν	384,094	384,094	384,094	195,203	188,890



Figure 1. Results from running Table 2 Column 1 regression in 'speccheck' package of Brodeur, Cook and Heyes (2020)



Figure 2a. Figueiredo (2022) Figure 2a Left Panel Robustness Checks

Figure 2a. Figueiredo (2022) Figure 2a Middle Panel Robustness Checks





Figure 2a. Figueiredo (2022) Figure 2a Right Panel Robustness Checks

Figure 2b. Figueiredo (2022) Figure 2b Left Panel Robustness Checks





Figure 2b. Figueiredo (2022) Figure 2b Middle Panel Robustness Checks

Figure 2b. Figueiredo (2022) Figure 2b Right Panel Robustness Checks





Figure 2c. Figueiredo (2022) Figure 2c Left Panel Robustness Checks

Figure 2c. Figueiredo (2022) Figure 2c Middle Panel Robustness Checks





Figure 2c. Figueiredo (2022) Figure 2c Right Panel Robustness Checks

Figure 3a. Figueiredo (2022) Figure 3a Left Panel Robustness Checks





Figure 3a. Figueiredo (2022) Figure 3a Middle Panel Robustness Checks

Figure 3a. Figueiredo (2022) Figure 3a Right Panel Robustness Checks





Figure 3b. Figueiredo (2022) Figure 3b Left Panel Robustness Checks







Figure 3b. Figueiredo (2022) Figure 3b Right Panel Robustness Checks

Figure 3c. Figueiredo (2022) Figure 3c Left Panel Robustness Checks





Figure 3c. Figueiredo (2022) Figure 3c Middle Panel Robustness Checks

Figure 3c. Figueiredo (2022) Figure 3c Right Panel Robustness Checks

