Vacancies and Structural Unemployment

An analysis of unemployment and vacancies in Germany

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29 - 07 - 2024

Introduction

In Germany we have a lot discussions about labour shortage and unemployed people how allegedly do not want to work. But how is it really? I will give you here some instructions and R code to analys the relationship between unemployment and job vacancies between. The data on job vacancies come from the Institut für Arbeitsmarkt - und Berufsforschung (IAB), and the data on the number of unemployed people come from the official unemployment statistics of the Bundesagentur für Arbeit.

First, the necessary libraries are loaded and the data is prepared for further processing.

Theoretical assumptions and hypothesis

Do some theoretical thoughts, for example:

To keep it simple, I'm going to use the neoclassical labor market model as a guide. This is unrealistic and outdated (even if economists just don't want to give up on it), but depending on how the results turn out, we can still make a few statements.

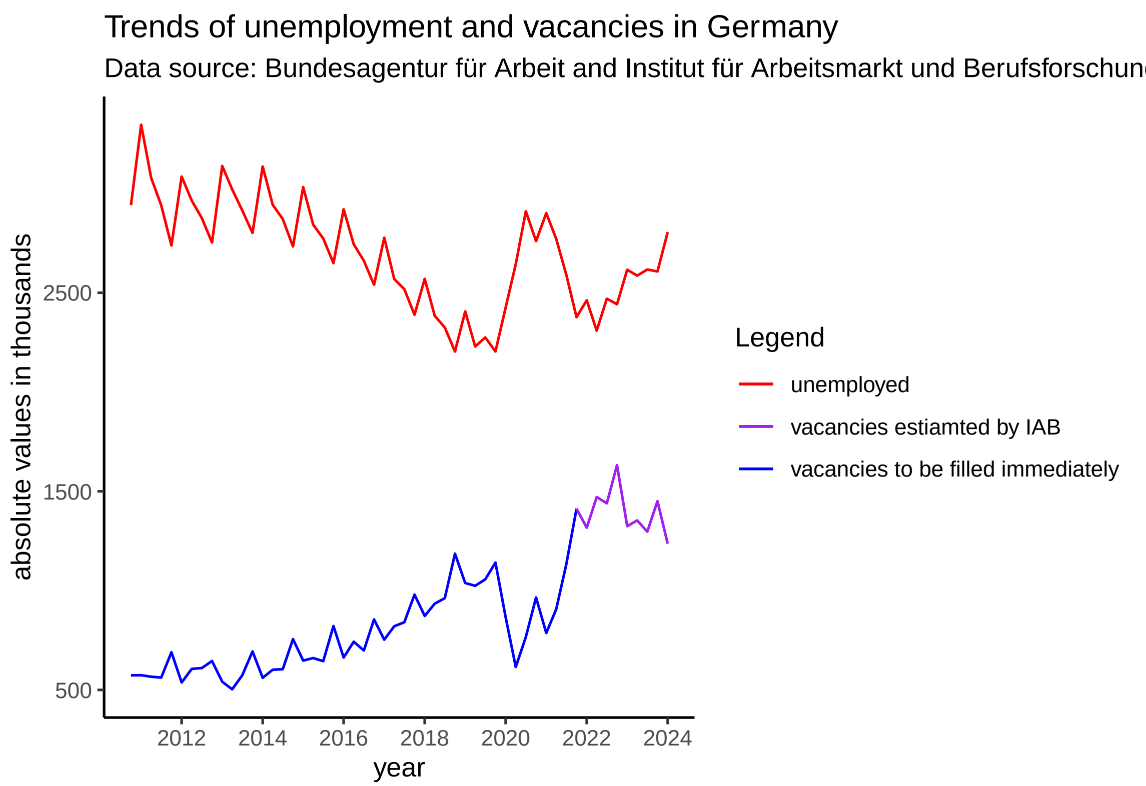
The assumptions of the neoclassical labor market model are as follows: 1. Anyone can do any job. 2. Everyone is geographically mobile. There are no barriers to employment, such as children or caring for relatives.

I'm going to reject a third assumption of the model right away. The neoclassical model claims that there is no structural unemployment. If I were to accept that, I could save myself the trouble of analyzing it. Rather, we want to try to falsify this assumption. To do so, I put forward the following hypothesis.

H1: There exist not enough jobs, which means that not all unemployed people can find work.

Evidence from the data

Now move on to the data analysis. Since we have time series data, it makes sense to first display the data in a linear plot.



As we can see the number of unemployed is much higher than the number of vacancies to be filled immediately at any time. The next step is to subtract the vacancies from the number of unemployed and thus calculate the missing jobs Δvacancies. But we choose only some dates to keep the table short. We will see the full table at the and in the appendix.

Following our results in the table on the next side our null hypothesis can be rejected and H1 is supported. Neoclassical economists might argue the reason is thst the minimum wage is too high and therefore labour is too expensive. Unfortunately, however, employees have to pay rent and food from their wages. This makes the assumption that wages are flexible downwards without limit untenable. If, as in Germany, minimum full-time wages have to be topped up by the state with social benefits, the minimum wage is actually too low. Think about it!

Calculation of missing jobs			
date	total[1]	vacancies[1]	Δ Vacancies[1,2]
2010-10-01	2941	573.3	2367.7
2011-01-01	3346	574.1	2771.9
2017-01-01	2777	752.9	2024.1
2017-04-01	2569	820.5	1748.5
2022-10-01	2442	1631.7	810.3
2023-01-01	2616	1324.5	1291.5
2023-04-01	2586	1353.7	1232.3
2023-07-01	2617	1296.9	1320.1
2023-10-01	2607	1450.6	1156.4

[1] Values in thousands

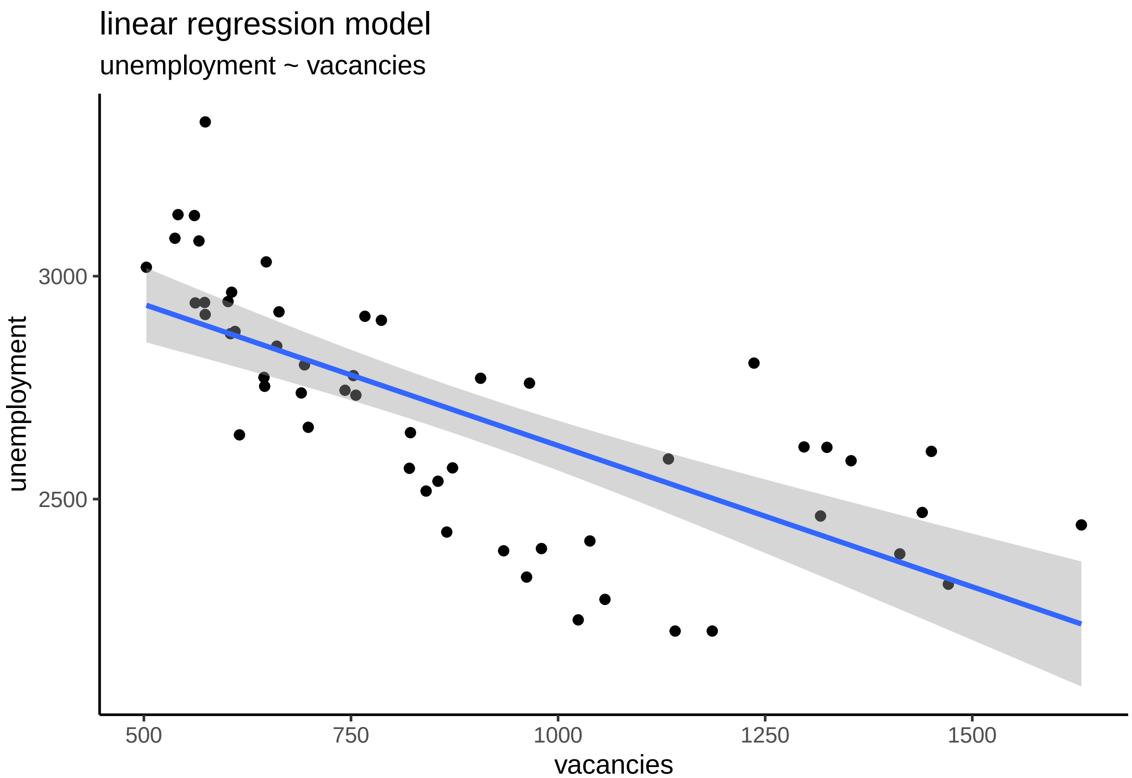
[2] From 2020 onwards, the calculation is based on estimates from the IAB

Since the first hypothesis is supported by the data, the question arises as to whether unemployment is actually caused by too few available jobs. Let us calculate a linear model to ckeck it out.

Table 2: Regression Results

	Dependent variable:
	total
Constant	3,253.375***
	(80.272)
vacancies	−0.633***
	(0.086)
Observations	54
R^2	0.509
Adjusted R^2	0.499
Residual Std. Error	190.236 (df = 52)
F Statistic	53.813*** (df = 1; 52) (p = 0.000)
Note:	*p<0.1; **p<0.05; ***p<0.01

The regression model shows that the number of vacancies has a statistically significant negative impact on the total number. On average, each additional vacancy reduces the total number of unemployed by about 0.6334 units. Around 50% of the variability in unemployment can be explained by job vacancies. However, there is still a substantial amount of unexplained variability, suggesting that other factors may also influence the total. This could be due to qualification or regional mismatches. Commitments such as childcare could also be a factor. The regression results will be visualized in the next step to provide a more intuitive understanding of the relationship between vacancies. I also add the confidence intervals.



Were at the end now

Conclusion

Next a little conclusion. For example: As we have seen, the idea that every unemployed person goes to work is unrealistic over the entire observation period, even if we assume that everyone is qualified for every job and is not subject to spatial restrictions. There is a huge gap between public discourse and reality.

Instead of focusing on individuals, it would be better to push for an effective economic policy that creates new jobs - a policy that focuses on full employment. The effect would be, this much can be said at this point, that the unemployment rate would fall considerably as a result. Of course, the number of jobs is not the only problem. But it is one that could be addressed.

Appendix

Here is the full table with all Δvacancies.

Calculation of missing jobs			
date	total[1]	vacancies[1]	Δ Vacancies[1,2]
2010-10-01	2941	573.3	2367.7
2011-01-01	3346	574.1	2771.9
2011-04-01	3079	566.5	2512.5
2011-07-01	2940	562.0	2378.0
2011-10-01	2738	690.0	2048.0
2012-01-01	3085	537.5	2547.5
2012-04-01	2964	605.9	2358.1
2012-07-01	2876	610.0	2266.0
2012-10-01	2753	645.8	2107.2
2013-01-01	3138	541.2	2596.8
2013-04-01	3020	503.0	2517.0
2013-07-01	2914	574.0	2340.0
2013-10-01	2801	693.9	2107.1
2014-01-01	3136	561.0	2575.0
2014-04-01	2943	601.6	2341.4
2014-07-01	2871	604.5	2266.5
2014-10-01	2733	755.9	1977.1

2015-01-01	3032	647.7	2384.3
2015-04-01	2843	660.4	2182.6
2015-07-01	2773	645.0	2128.0
2015-10-01	2649	821.8	1827.2
2016-01-01	2920	663.1	2256.9
2016-04-01	2744	742.8	2001.2
2016-07-01	2661	698.4	1962.6
2016-10-01	2540	855.0	1685.0
2017-01-01	2777	752.9	2024.1
2017-04-01	2569	820.5	1748.5
2017-07-01	2518	840.7	1677.3
2017-10-01	2389	979.9	1409.1
2018-01-01	2570	872.6	1697.4
2018-04-01	2384	934.3	1449.7
2018-07-01	2325	962.0	1363.0
2018-10-01	2204	1186.1	1017.9
2019-01-01	2406	1038.4	1367.6
2019-04-01	2229	1024.3	1204.7
2019-07-01	2275	1056.6	1218.4
2019-10-01	2204	1141.3	1062.7
2020-01-01	2426	865.6	1560.4
2020-04-01	2644	615.4	2028.6
2020-07-01	2910	766.8	2143.2
2020-10-01	2760	965.5	1794.5
2021-01-01	2901	786.7	2114.3
2021-04-01	2771	906.5	1864.5
2021-07-01	2590	1133.2	1456.8
2021-10-01	2377	1412.5	964.5
2022-01-01	2462	1316.8	1145.2

2022-04-01	2309	1471.1	837.9
2022-07-01	2470	1439.6	1030.4
2022-10-01	2442	1631.7	810.3
2023-01-01	2616	1324.5	1291.5
2023-04-01	2586	1353.7	1232.3
2023-07-01	2617	1296.9	1320.1
2023-10-01	2607	1450.6	1156.4
2024-01-01	2805	1236.5	1568.5

[1] Values in thousands

[2] From 2020 onwards, the calculation is based on estimates from the IAB