What Explains the Variation in Unemployment Rates Across the United States?

William Yu
Economist
UCLA Anderson Forecast
September 2022

Summary

- There is a variation in unemployment rates across the country. We identify a couple of socioeconomic and industrial variables to explain the difference. Human capital is among the most important. A county with a highly educated workforce is associated with a lower unemployment rate and a higher employment-to-population ratio.
- Unlike the past three recession and recovery cycles, in this recovery cycle, the manufacturing sector might play a role in revitalizing local economies.

Since the peak of the Covid-19 pandemic in April 2020, U.S. unemployment rates have been declining to the level of so-called "full employment" (Figure 1). In August 2022, the U.S. unemployment rate is 3.7%, which is one of the lowest since the 1970s. Meanwhile, we have seen the fastest decline of unemployment over the past two years since the peak of 14.7% in April 2020. While Americans are pleased with the tight labor market for negotiating a higher wage and getting a better position, we notice there is a variation of unemployment rates across the country.

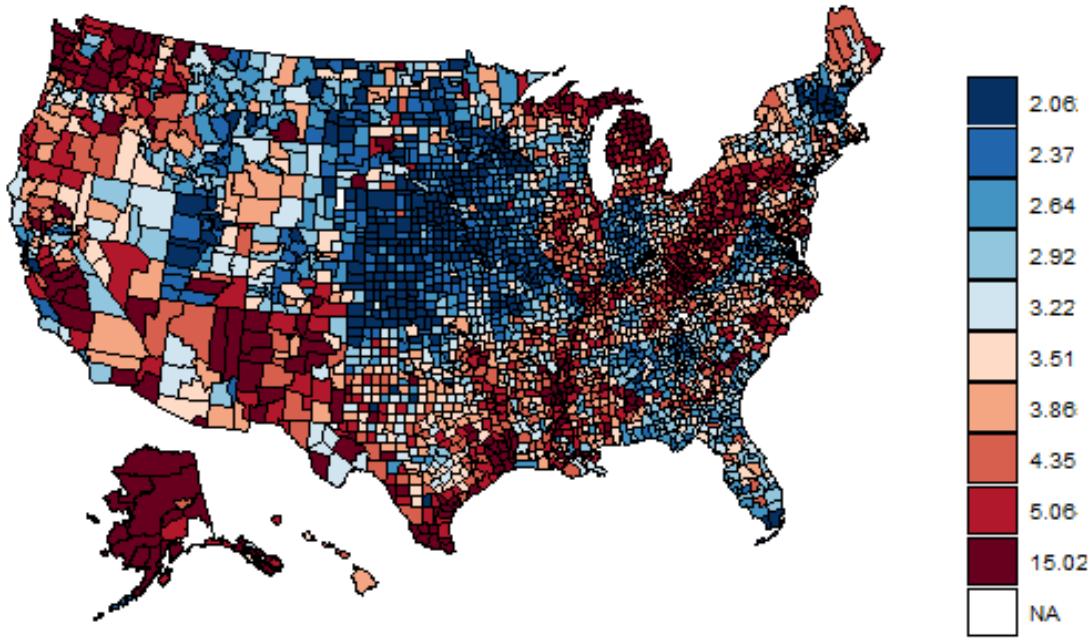
Figure 2 shows the variation of county unemployment rates across the country in June 2022, in which blue colors indicate low unemployment rates while red colors indicate high unemployment. Figure 3 shows the distribution of unemployment rates in June 2022. While its level and variation of unemployment rates are much lower and smaller in June 2022 than in April 2020 (Figure 4), the contributing factors to these uneven unemployment rates across the U.S. remain puzzling. For example, in California, why is it that Los Angeles County's unemployment rate was 4.9% in June 2022, higher than Riverside County's 3.6%, Orange County's 2.6%, and San Francisco's 2%?

To answer this question, we conduct a few multivariate linear regression models, in which the dependent variable is county unemployment rates in June 2022. It is worth noting that unemployment rates could be a subjective measurement from the household survey because its denominator is whether people consider themselves as part of the labor force; that is, whether

people who are not employed are currently looking for a job. To conduct a robustness check and to avoid a potential subjective bias, we also use another more straightforward labor market measurement: each county's employment-to-population ratio in June 2022.

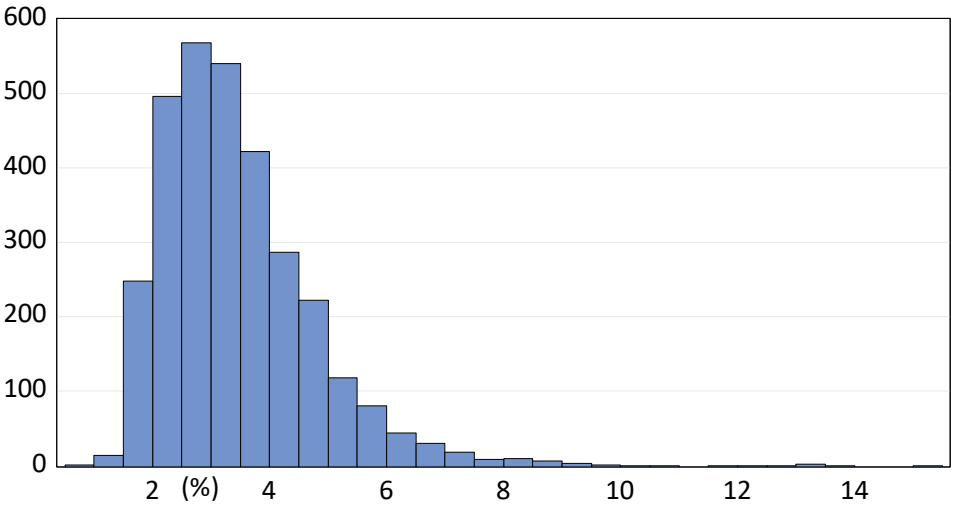
Figure 1. U.S. Unemployment Rates

Figure 2. Unemployment Rates by County in June 2022



Source: Bureau of Labor Statistics

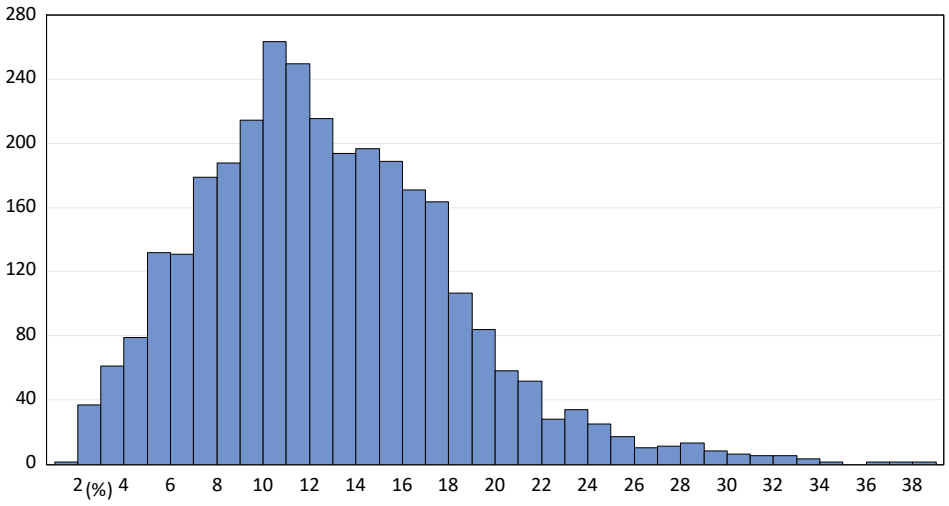
Figure 3. Distribution of Unemployment Rates by County in June 2022



Series: UR22	
Sample 1 3142	
Observations 3138	
Mean	3.459855
Median	3.228461
Maximum	15.02305
Minimum	0.753314
Std. Dev.	1.360454
Skewness	1.917739
Kurtosis	10.96393
Jarque-Bera	10216.17
Probability	0.000000

Source: Bureau of Labor Statistics

Figure 4. Distribution of Unemployment Rates by County in April 2020



Series: UR20	
Sample 1 3142	
Observations 3138	
Mean	12.74937
Median	12.18953
Maximum	38.30917
Minimum	1.883726
Std. Dev.	5.460133
Skewness	0.694822
Kurtosis	3.848389
Jarque-Bera	346.6014
Probability	0.000000

Source: Bureau of Labor Statistics

For potential explanatory predictors to unemployment rates, we consider two major groups of variables: one is the age and socioeconomic variables by county in 2019 from the U.S. Census' American Community Survey. The other is the sector (NAICS 2-digit code) job share from the Quarterly Census of Employment and Wages (QCEW) in 2019. The reason we use the data sample in 2019 rather than the later years is twofold: (1) We want to enhance the exogeneity of these explanatory variables, meaning they caused the difference of unemployment rates and not the other way around. (2) To avoid the complex and abnormal economic changes in 2020 and 2021 due to the pandemic. See the appendix for more details.

Factors to Explain Variation in Unemployment Rates

As shown in the appendix, we use Models 1, 3, and 5 to explain the variation in unemployment rates by county in June 2022. The statistically significant predictors[1] are as follows.

- *Population share for age above 75 (Negative)*: When a county has a higher elderly population, the county's unemployment rate is lower.
- *Population density (Positive)*: A more urbanized county is associated with a higher unemployment rate perhaps because more people are looking for a job in a city than in rural areas.
- *Population (Positive):* A county with larger population is associated with a higher

[1] We use the significance level with t-statistics bigger than 3 or less than -3.

unemployment rate perhaps because more percentage of people are looking for a job in a bigger city.

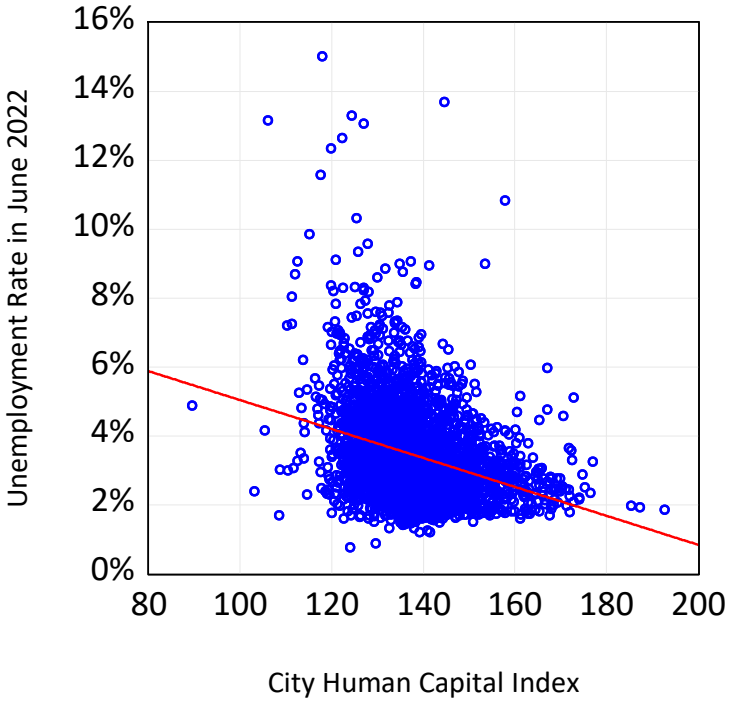
- *City Human Capital Index (Negative)*: A county with higher human capital is associated with a lower unemployment rate partly because a more educated workforce is easier to employ and is more competitive for jobs in this "knowledge" economy. Figure 5 shows the simple inverse correlation between human capital and the unemployment rate. There were a number of studies that present the theory and evidence of positive correlation between human capital and favorable labor market performances, e.g. Lucas (1988)[2], Acemoglu (1996)[3], Simon (1998)[4], and Shapiro (2006)[5].
- *Labor force participation (Negative)*: This is somewhat surprising for its inverse correlation with the unemployment rate. We thought that if more people were looking for a job (higher labor force participation) but cannot get one, we would see a higher unemployment rate. The result suggests the opposite. The reason could be that after controlling other variables, a region with higher labor force participation means it has more economic opportunity and dynamism and eventually results in a lower unemployment rate.
- *Covid-19 cumulative mortality rate as of June 2022 (Positive)*: A region that got hit hard by Covid-19 will be facing more household and economic loss and disruption and results in higher unemployment in the region.
- *Job share in the manufacturing sector (Negative):* It is interesting to see that a county with higher share of jobs in the manufacturing sector is associated with a lower unemployment rate. This is very different from the past three recessions which happened in 1991, 2001, and 2008, all of which had suffered significant and permanent job loss during and after the recession partially due to outsourcing. Our colleague Ed Leamer has identified in the previous Anderson Forecast reports that the weak job recovery (e.g. "L" shaped instead of "V" shaped) in the manufacturing sector was the main reason for the overall sluggish job recovery in the aftermaths of the past three recessions (Figure 6).

  Why is this time different? There might be two reasons. First, the Covid pandemic recession indeed was a very different recession compared to the previous three. Second, facing the problems and challenges brought by globalization and the pandemic, we are considering more localized supply chains and therefore creating an American manufacturing renaissance, in particular in durable goods manufacturing. Figure 7 shows the simple inverse correlation between job share in the manufacturing sector and the unemployment rate.
- *Job share in the health care and social service sector (Positive):* It is not clear why the job share in this sector is positively associated with a high unemployment rate. One possible reason

[2] Robert Lucas, "On the Mechanics of Economic Development, " *Journal of Monetary Economics,* 22 (1988), 3-42.
[3] Daron Acemoglu, "A Microfoundation for Social Increasing Returns in Human Capital Accumulation," *Quarterly Journal of Economics*, 111:3 (1996), 779-804.
[4] Curtis Simon, "Human Capital and Metropolitan Employment Growth," *Journal of Urban Economics*, 43, (1998), 223-243.
[5] Jesse Shapiro, "Smart Cities: Quality o Life, Productivity, and the Growth Effects of Human Capital," *Review of Economic and Statistics*, 88:2, (2006), 324-335.

is the majority of the workforce in this sector are low-skilled social service workers, e.g. home-help workers. Due to their low wages, they might need to be actively looking for another job, which drives up the unemployment rate.

Figure 5. Correlation Between City Human Capital Index and Unemployment Rate (2022/6)



Sources: Bureau of Labor Statistics, American Community Survey and Anderson Forecast

Figure 6. Payroll Jobs in the Manufacturing Sector

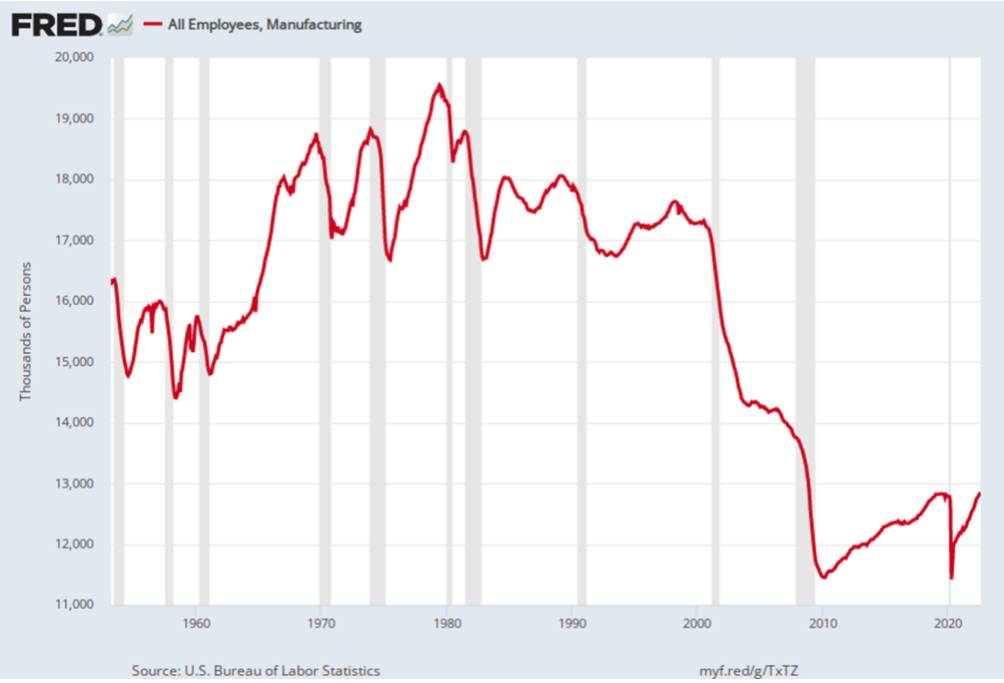
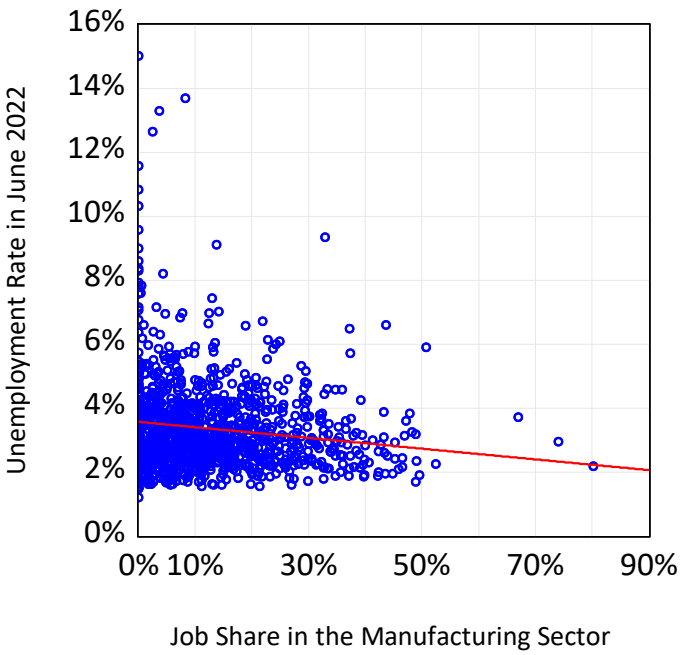


Figure 7. Correlation Between Job Share in the Manufacturing Sector and Unemployment Rate (2022/6)



Sources: Bureau of Labor Statistics, American Community Survey and Anderson Forecast

Now let's use Model 1 to make an in-sample prediction based on all the input variables for San Francisco County, Orange County, Riverside County, and L.A. County. The prediction follows a similar order for unemployment rates in these four counties even though the model predictions are persistently higher than the actual ones in June 2022:

- San Francisco County: prediction is 3.2% and the actual rate is 2%.
- Orange County: prediction is 3.9% and the actual rate is 2.6%.
- Riverside County: prediction is 4.2% and the actual rate is 3.6%.
- L.A. County: prediction is 6.6% and the actual rate is 4.9%.

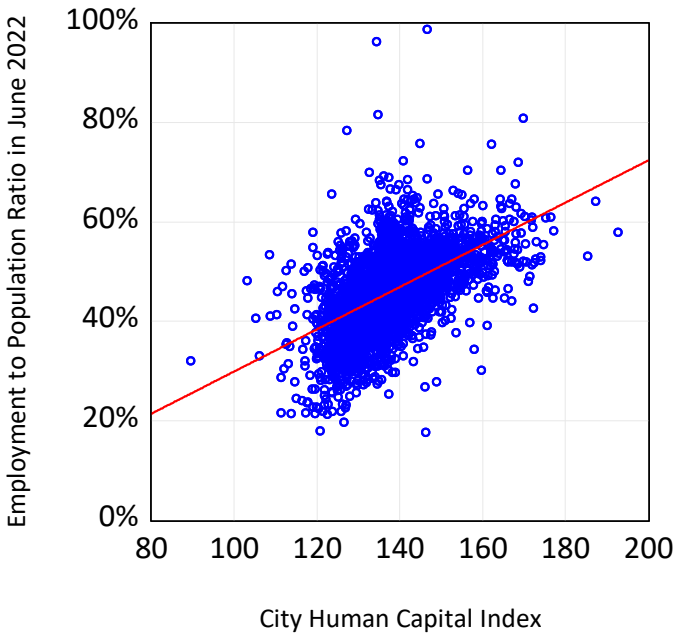
Factors to Explain Variation in Employment-to-Population Ratios

As shown in the appendix, we use Models 2, 4, and 6 to explain the variation in employment-to-population ratio by county in June 2022. The statistically significant predictors[6] are as follows:

- *Population share for age between 65 and 74 (Negative)*: When a county has more senior elders, the county's employment-to-population ratio is lower.
- *Population share for age between 20 and 34 (Negative)*: When a county has more young residents, the county's employment-to-population ratio is lower partially because some of these young adults might still be in college or graduate school.
- *City Human Capital Index (Positive)*: A county with higher human capital is associated with a higher employment-to-population ratio partly because a more educated workforce more easily employed. Figure 8 shows the simple positive correlation between human capital and employment-to-population ratio.
- *Population share with disability insurance (Negative)*: A county with higher use of disability insurance is associated with lower employment.
- *Employment share with work from home (Positive)*: A county with a higher share of employees working from home is associated with higher employment.
- *Covid-19 cumulative mortality rate as of June 2022 (Negative)*: A county with higher COVID mortality is associated with lower employment.
- *Job share in the manufacturing, agriculture, construction, and transportation and warehousing sectors (Positive):* For the same reason we explained in the previous section, a county with a higher job share in the manufacturing sector is associated with higher employment. In addition, we know the construction sector has been doing well in the recent housing boom markets. The transportation and warehousing industry have been expanding due to the rise of e-commerce, boosted of the pandemic.
- *UCLA/GoDaddy's Microbusiness Activity Index, MAI (Positive):* The MAI is an index to measure digital infrastructure, online microbusiness formation and growth, and microbusiness engagement on the Internet. When a county has a higher MAI, it is positively correlated with a higher employment-to-population ratio (Figure 9). For more details about the MAI, see Yu and Bengali (2021)[7] and Bengali and Yu (2021)[8] and the Microbusiness Activity Index Update.

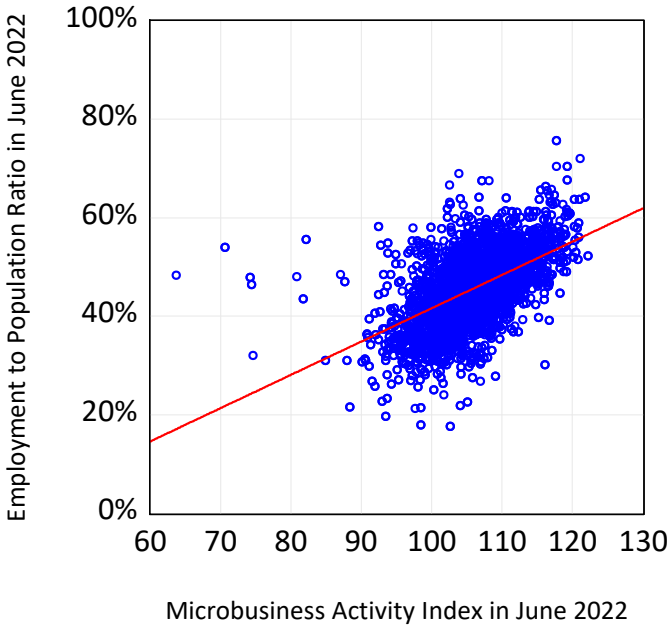
[6] We use the significance level with t-statistics bigger than 3 or less than -3.
[7] "Digital Infrastructure, the Economy and Online Microbusiness." https://www.anderson.ucla.edu/about/centers/ucla-anderson-forecast/projects-and-partnerships/godaddy
[8] "What Drives Microbusiness Formation and Growth?" https://www.anderson.ucla.edu/about/centers/ucla-anderson-forecast/projects-and-partnerships/godaddy

Figure 8. Correlation Between City Human Capital Index and Employment to Population Ratio (2022/6)



Sources: Bureau of Labor Statistics, American Community Survey and Anderson Forecast

Figure 9. Correlation Between Microbusiness Activity Index and Employment to Population Ratio (2022/6)



Sources: Bureau of Labor Statistics, American Community Survey, and Anderson Forecast

Conclusions

The take-aways of the report are as follows:

There are variations of unemployment rates and employment-to-population ratios across the U.S. despite the nation as a whole being at the full employment level currently. Using a multivariate regression model, we find a couple of significant factors that are correlated with county labor markets and economy. We suggest that human capital is among the most significant. A region with a highly educated workforce is associated with a lower unemployment rate and a higher employment-to-population ratio. The Microbusiness Activity Index indicates digital infrastructure is positively associated with local employment. Unlike the past three recession and recovery cycles, in this recovery cycle, the manufacturing sector might play a role in revitalizing local economies, perhaps in response to the rising concerns and risks related to globalization and the pandemic.

Appendix

Explanatory Variable Description

Variable Name	Description
a75a	Population share for age above 75
a6574	Population share for age 65 to 74
a5564	Population share for age 55 to 64
a2034	Population share for age 20 to 34
pdensity	Population density (population/land mass)
pop	Population
chci	City Human Capital Index (weighted education attainment)
lcp	Labor forec participation rate
disable	Population share with disable insurance
wfh	Employment share with work from home
mhomeprice	Median home price
deathp	COVID-cumulative mortality rate as of June 2022
np11	Job share in Agriculture, forestry, fishing and hunting
np21	Job share in Mining, quarrying, and oil and gas extraction
np22	Job share in Utilities
np23	Job share in Construction
np3133	Job share in Manufacturing
np42	Job share in Wholesale trade
np4445	Job share in Retail trade
np4849	Job share in Transportation and warehousing
np51	Job share in Information
np52	Job share in Finance and insurance
np53	Job share in Real estate and rental and leasing
np54	Job share in Professional and technical services
np55	Job share in Management of companies and enterprises
np56	Job share in Administrative and waste services
np61	Job share in Educational services
np62	Job share in Health care and social assistance
np71	Job share in Arts, entertainment, and recreation
np72	Job share in Accommodation and food services
np81	Job share in Other services, except public administration
wgtIndex_even	GoDaddy Microbusiness Activity Index (MAI)

Model 1

Dependent variable: unemployment rate

Variable	*Estimate*	*Std error*	*t statistic*	*p Value*
(Intercept)	9.7388	0.7599	12.815	0.000
a75a	-0.1098	0.0181	-6.072	0.000
a6574	0.0423	0.0212	1.992	0.046
a5564	0.0532	0.0201	2.652	0.008
a2034	0.0065	0.0103	0.631	0.528
pdensity	0.0001	0.0000	4.095	0.000
pop	0.0000	0.0000	4.852	0.000
chci	-0.0249	0.0041	-6.023	0.000
lcp	-0.0544	0.0050	-10.970	0.000
disable	0.0050	0.0082	0.607	0.544
wfh	-0.0254	0.0100	-2.550	0.011
mhomeprice	0.0000	0.0000	-0.723	0.470
deathp	0.0001	0.0000	4.414	0.000
np11	1.0216	0.6423	1.591	0.112
np21	0.2928	0.5634	0.520	0.603
np22	11.4639	2.6123	4.388	0.000
np23	-0.9530	0.6119	-1.557	0.120
np3133	-0.8780	0.2349	-3.738	0.000
np42	-2.4158	0.9207	-2.624	0.009
np4445	-2.3244	0.7026	-3.308	0.001
np4849	0.2611	0.6022	0.434	0.665
np51	-1.7406	3.0179	-0.577	0.564
np52	-1.6888	1.3062	-1.293	0.196
np53	7.9004	3.3604	2.351	0.019
np54	-0.2944	1.0379	-0.284	0.777
np55	4.3220	2.4070	1.796	0.073
np56	-0.1657	0.8509	-0.195	0.846
np61	3.7581	1.9912	1.887	0.059
np62	1.4658	0.3152	4.651	0.000
np71	-1.1676	1.5481	-0.754	0.451
np72	2.5765	0.5529	4.660	0.000
np81	5.7413	1.7924	3.203	0.001
wgtIndex_even	-0.0044	0.0054	-0.813	0.416
Observations = 2625			Adj. R-squared = 0.31	

Note: Shaded rows represent the variables are statistically significant at 0.5% level.

Model 2

Dependent variable: employment to population ratio

Variable	*Estimate*	*Std error*	*t statistic*	*p Value*
(Intercept)	14.7122	3.4942	4.210	0.000
a75a	0.0044	0.0870	0.051	0.959
a6574	-0.6489	0.0947	-6.851	0.000
a5564	0.2819	0.0956	2.949	0.003
a2034	-0.4058	0.0473	-8.578	0.000
pdensity	0.0000	0.0001	0.084	0.933
pop	0.0000	0.0000	-1.851	0.064
chci	0.2617	0.0191	13.678	0.000
disable	-0.4970	0.0367	-13.554	0.000
wfh	0.2017	0.0476	4.238	0.000
mhomeprice	0.0000	0.0000	0.843	0.399
deathp	-0.0005	0.0001	-5.739	0.000
np11	10.9444	3.0604	3.576	0.000
np21	2.3156	2.7148	0.853	0.394
np22	-65.8319	12.5701	-5.237	0.000
np23	15.4476	2.9480	5.240	0.000
np3133	10.4285	1.0982	9.496	0.000
np42	22.8596	4.3659	5.236	0.000
np4445	-2.9123	3.3868	-0.860	0.390
np4849	10.0214	2.8916	3.466	0.001
np51	25.5565	14.5335	1.758	0.079
np52	12.6800	6.2805	2.019	0.044
np53	-26.7407	16.1964	-1.651	0.099
np54	-7.3619	4.9947	-1.474	0.141
np55	-23.7558	11.6092	-2.046	0.041
np56	-1.2442	4.0987	-0.304	0.761
np61	-28.0780	9.5961	-2.926	0.003
np62	-0.3867	1.5170	-0.255	0.799
np71	21.4467	7.4264	2.888	0.004
np72	-0.5510	2.6630	-0.207	0.836
np81	-2.8737	8.6305	-0.333	0.739
wgtIndex_even	0.1049	0.0258	4.075	0.000
Observations = 2626			Adj. R-squared = 0.57	

Note: Shaded rows represent the variables are statistically significant at 0.5% level.

Model 3

Dependent variable: unemployment rate

Variable	*Estimate*	*Std error*	*t statistic*	*p Value*
(Intercept)	8.3258	0.5488	15.171	0.000
a75a	-0.1662	0.0140	-11.835	0.000
a6574	0.0777	0.0164	4.733	0.000
a5564	0.0458	0.0157	2.911	0.004
a2034	0.0169	0.0093	1.813	0.070
pdensity	0.0001	0.0000	3.893	0.000
pop	0.0000	0.0000	5.522	0.000
chci	-0.0184	0.0033	-5.533	0.000
lcp	-0.0582	0.0043	-13.514	0.000
disable	0.0200	0.0073	2.756	0.006
wfh	-0.0260	0.0073	-3.554	0.000
mhomeprice	0.0000	0.0000	1.944	0.052
deathp	0.0001	0.0000	4.013	0.000
Observations = 3130			Adj. R-squared = 0.29	

Model 4

Dependent variable: employment to population ratio

Variable	*Estimate*	*Std error*	*t statistic*	*p Value*
(Intercept)	29.7347	3.0275	9.822	0.000
a75a	0.3477	0.0880	3.953	0.000
a6574	-1.0451	0.0936	-11.160	0.000
a5564	0.6782	0.0983	6.902	0.000
a2034	-0.4569	0.0548	-8.338	0.000
pdensity	0.0000	0.0001	-0.497	0.619
pop	0.0000	0.0000	-1.509	0.132
chci	0.2442	0.0195	12.555	0.000
disable	-0.5830	0.0411	-14.187	0.000
wfh	0.2189	0.0457	4.795	0.000
mhomeprice	0.0000	0.0000	0.914	0.361
deathp	-0.0007	0.0001	-7.518	0.000
Observations = 3130			Adj. R-squared = 0.52	

Note: Shaded rows represent the variables are statistically significant at 0.5% level.

Model 5

Dependent variable: unemployment rate

Variable	*Estimate*	*Std error*	*t statistic*	*p Value*
(Intercept)	10.347	0.504	20.534	0.000
np11	0.705	0.683	1.033	0.302
np21	0.283	0.613	0.462	0.644
np22	17.281	2.880	6.000	0.000
np23	-2.434	0.651	-3.736	0.000
np3133	-1.353	0.240	-5.645	0.000
np42	-7.517	0.935	-8.040	0.000
np4445	-1.236	0.750	-1.649	0.099
np4849	-0.369	0.654	-0.564	0.573
np51	-4.651	3.109	-1.496	0.135
np52	-4.533	1.401	-3.235	0.001
np53	12.226	3.586	3.410	0.001
np54	-2.450	1.076	-2.276	0.023
np55	1.648	2.607	0.632	0.527
np56	1.590	0.913	1.743	0.081
np61	0.161	2.119	0.076	0.940
np62	1.370	0.345	3.974	0.000
np71	-3.335	1.647	-2.026	0.043
np72	1.752	0.596	2.939	0.003
np81	3.888	1.940	2.004	0.045
wgtIndex_even	-0.062	0.005	-12.468	0.000
Observations = 2626			Adj. R-squared = 0.15	

Note: Shaded rows represent the variables are statistically significant at 0.5% level.

Model 6

Dependent variable: employment to population ratio

Variable	*Estimate*	*Std error*	*t statistic*	*p Value*
(Intercept)	-13.5978	2.6389	-5.153	0.000
np11	9.6054	3.5449	2.710	0.007
np21	0.1457	3.2083	0.045	0.964
np22	-96.2345	15.0731	-6.385	0.000
np23	29.1992	3.4086	8.566	0.000
np3133	9.7921	1.2549	7.803	0.000
np42	50.2379	4.8919	10.270	0.000
np4445	-18.8930	3.9233	-4.816	0.000
np4849	12.8892	3.4245	3.764	0.000
np51	45.5608	16.2705	2.800	0.005
np52	22.6042	7.3320	3.083	0.002
np53	-30.5419	18.7701	-1.627	0.104
np54	21.1036	5.6339	3.746	0.000
np55	6.6932	13.6461	0.490	0.624
np56	-9.6105	4.7758	-2.012	0.044
np61	22.2072	11.0913	2.002	0.045
np62	-2.9503	1.8040	-1.635	0.102
np71	52.8479	8.5758	6.162	0.000
np72	2.2300	3.1172	0.715	0.474
np81	9.8029	10.1485	0.966	0.334
wgtIndex_even	0.5235	0.0261	20.039	0.000
Observations = 2627			Adj. R-squared = 0.37	

Note: Shaded rows represent the variables are statistically significant at 0.5% level.