u^* by Industry

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Abstract

This paper develops industry-level efficient unemployment rates using a sufficient statisitics approach. Industries vary in their proximity to efficient unemployment. In tight industries such as health/education services and finance, the actual unemployment rate is consistently close to or below the efficient unemployment rate. In slack industries such as construction and trade, the actual unemployment rate is above the efficient unemployment rate.

I thank Matthew DeHaven, Olivia Lattus, and Pascal Michaillat comments and conversations.
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1. Introduction

Research Question Do industries vary in their levels of efficient unemployment? If so, which industries are furthest from and which are closest to operating at efficiency?

To answer this question, I develop a measure of efficient unemployment by industry. I then estimate the unemployment gap by industry as the deviation of the actual unemployment rate from the efficient unemployment rate. The unemployment gap characterizes the degree of inefficiency in a labor market.

My approach is adapted from Michaillat and Saez (2021) which invents a sufficient statistics approach to estimate the efficient unemployment gap in the economy. The sufficient statistics method integrates reduced form and structural approaches to calculate otherwise unobservable estimates (Chetty (2009)).

Estimating unemployment gap by industry. In Michaillat and Saez (2021), elasticities between unemployment and vacancy are estimated by the Beveridge curve. This relationship is an input to calculating efficient unemployment rate. Other parameters include recruiting cost, social value of non-work time, unemployment rates, and vacancy rates. The approach identifies efficient unemployment by maximizing welfare considering relevant inputs.

Intuitively, my optimization balances industry level characteristics to identify efficient unemployment rates. For example, if recruiting cost is cheap, an industry should have higher efficient unemployment because it is easy to add employees. If recruiting costs are expensive, an industry should have lower efficient unemployment since it is harder to add employees.

Implementing this approach, I calculate elasticities and parameters at the industry level to estimate efficient unemployment rates. As in Ghayad and Dickens (2012), I estimate Beveridge curves by industry during the period from 2000-2022. I then algorithmically select two breaks in the Beveridge curve and consequently three elasticities are calculated. For most industries, breaks occur in during the Great Recession and at the onset of COVID-19. I also identify recruiting costs, unemployment rates, and vacancy rates by industry. The estimate of the social value of non-work time which is not industry specific is the parameter estimated in Mas and Pallais (2019) .

Industries too tight or too slack. I find industries such as trade and construction consistently operate with too much unemployment such that the actual unemployment rate is consistently above the efficient unemployment rate. Other industries such as health/education services operate closer to efficiency and are occasionally too tight such that the actual unemployment rate is below efficiency.

Variation by Industry. My finding aligns with evidence of industry variation across many labor market dimensions such as the existence of industry wage differentials where wages vary for given occupations across industries (Montgomery (1991)).

Characterizing industry heterogeneity of unemployment patterns could add a dimension to our understanding of the consequences of monetary policy. For example, a policy aimed at increasing slack in the labor market may bring a tight industry to efficiency but push an already slack industry further from efficiency. Fiscal policy could be designed to smooth differential effects across industries.

2. Beveridgean model of labor markets by industry

2.1. Measuring Vacancy Rate

Number of Vacancies I measure the number of vacancies using the Job Opening and Labor Turnover Survey (JOLTS) conducted by U.S. Bureau of Labor Statistics (2000-2022). Beginning in 2000, JOLTS monthly records the number of job openings in the United States labor market. A job opening is defined as a position for which a firm is actively recruiting for an existing position that could be filled within 30 days. For each 2017 North American Industry Classification System (NAICS) code, we observe the number of openings by industry.

Number of Employees The number of employees is measured monthly by the BLS[*]. The number of employees records the number of individuals engaged in full/part-time, salaried/hourly, on-paid leave, and permanent/temporary workers. For each NAICS code, we observed the number of employees by industry.

Number of Unemployed The number of unemployed per industry is estimated using the aggregate number of unemployed and the industry shares of the unemployed as measured in the Current Population Survey (CPS). In the CPS, experienced unemployed workers report the industry of their most recent jobs (Flood et al. (2022)). For each month, I estimate

[*]Table B-1. Employees on nonfarm payrolls by industry sector and selected industry detail, Seasonally adjusted (2022)

the share of total unemployment attributable to each industry, *i.e.* X% of unemployment comes from industry *i*.

The CPS and JOLTS use different industry codes. I use Soltas (2019) to maps between CPS industry shares of unemployment to the JOLTs NAICS industry codes. Using these shares, I calculate the number of unemployed by industry as each industry's share of total unemployment.

For inexperienced unemployed workers who are around 10% of the unemployed, I am unable to observe intended industry. Thus, the industry shares of experienced unemployed workers are used to estimate the unemployment share for both the experienced and inexperienced unemployed.

Calculate Vacancy Rate The vacancy rate is the ratio of the number of vacancies to the size of the labor force. For each industry, we can measure the vacancy rate for an industry by dividing an industry's number of vacancies by the size of that industry's the labor force.

$$\text{Vacancy Rate} = \frac{\text{Number of Vacancies}}{\text{Number of Employees} + \text{Number of Unemployed}} \tag{1}$$

2.2. Measuring Unemployment Rate

I use the unemployment rate by industry which are published in the Current Employment Statistics (CES) released by the BLS[**]. These unemployment rates are calculated using the CPS.

2.3. Constructing Beveridge curves

I calculate quarterly vacancy and unemployment rates by finding the average monthly rates within a quarterly period. Each series is seasonly adjusted.

Understanding elasticity of Beveridge curves. The Beveridge curve plots the relationship between vacancies and unemployment. In a tight labor market, there is low unemployment and a high number of vacancies. In a slack labor market, there is high unemployment and a low number of vacancies.

[**]Unemployed persons by industry and class of worker, Table A-14 (2022)

For a plot of log(vacancy rate) and log(unemployment rate), the (negated) slope is interpreted as an elasticity, ϵ. For a percent change in unemployment rate, we can identify the percent change in the vacancy rate.

$$\epsilon = -\frac{\partial \log(\text{vacancy rate})}{\partial \log(\text{unemployment rate})} \tag{2}$$

Identify breaks in the slope of the Beveridge curve. I test for breaks in the slope of the Beveridge curve using an algorithm developed in Bai and Perron (1998) and Bai and Perron (2003). The algorithm identifies the periods that are most similar by comparing all possible break positions and selecting the break position that minimizes the sum of squared residuals. By identifying breaks in the elasticity of the Beveridge curve, I distinguish periods of distinct labor market dynamics.

Select the number of breaks and length of isoelastic periods. I set the number of breaks to be two. The trim parameter is set to 10% such that an identified isoelastic period must represent at least 10% of the total period (22 years $\times$ 10% = 2.2 years). The suggested trim parameter is 15%. However, since the post-Covid period accounts for only $\sim$ 11% of the available observations, I chose to reduce the trim parameter to 10%.

Locations of algorithmically selected breaks. For most industries, the algorithm selects breaks at the onset of (1) the Great Recession and (2) the COVID-19 pandemic (December 2007 and March 2020, respectively). Since I chose to identify two breaks, there are three periods of isoelastic behavior for the fit Beveridge curve.

Industries vary by break size and location of break. I examine behavior of the Beveridge curve for Leisure and Hospitality and Finance. Leisure and Hospitality encompasses subindustries "Arts, Entertainment, Recreation and Accommodation" and "Food Services." Examples of occupations in the industry include: amusement and recreation attendants, fitness trainers, food servers, food preparation, cooks, waiters, and hotel staff. Finance includes subindustries related to financial service provision such as "Credit Intermediation and Related Activities" and "Funds, Trusts, and Other Financial Vehicles." Examples of occupations in the industry include: loan officers, bank tellers, financial examiners, financial advisors, bookkeepers, and auditors.

Leisure and Hospitality experienced a large break in Quarter 2, 2020 at the onset COVID-

19 pandemic (Figure 1C). Finance experienced a relatively small break in Quarter 4, 2020 during the COVID-19 pandemic (Figure 1D).

Figure 1 shows that Beveridge curve behavior varies by industry. Beveridge curves for each industry are presented in the appendix.

3. Efficient Unemployment by Industry

This section estimates efficient unemployment by industry using the sufficient statistics approach developed in Michaillat and Saez (2021).

3.1. Overview of the Method

Defining the Welfare Function Michaillat and Saez (2021) introduce a welfare function where work productivity of the employment and the non-work productivity positively contribute to the economy. Vacancies detract from welfare due to recruiting costs and a lack of productivity.

$$\mathcal{W}(n, u, v) = p(n + zu - cv)L \tag{3}$$

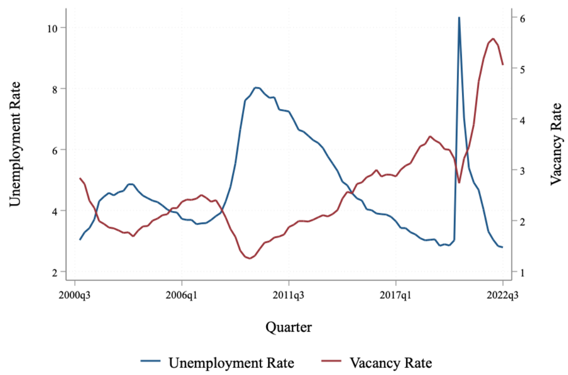
Let p be the productivity of workers, n be the employment rate, z be the value of non-work, u be unemployment rate, c be the cost of recruiting, v be the vacancy rate, and L is the population.

Welfare maximization and the Beveridge curve In an efficient market, the slope of the iso-welfare curve for $\hat{\mathcal{W}}(u, v) = W(1 - u, u, v)$ is equal to the slope of the Beveridge curve: $-\frac{\partial \hat{\mathcal{W}}}{\partial u} / \frac{\partial \hat{\mathcal{W}}}{\partial v} = v'(u)$. This efficiency condition can be expressed as $v'(u) = -\frac{1-\zeta}{\kappa}$, where κ is number of recruiters allocated to each vacancy and ζ is the marginal rate of substitution between unemployment and employment, defined by $\mathcal{W}$. Intuitively, the social cost of unemployment, $1 - \zeta$, is balanced by the value of the vacancies, $-\kappa v'(u)$ (since fewer recruiters need to be employed at smaller v).

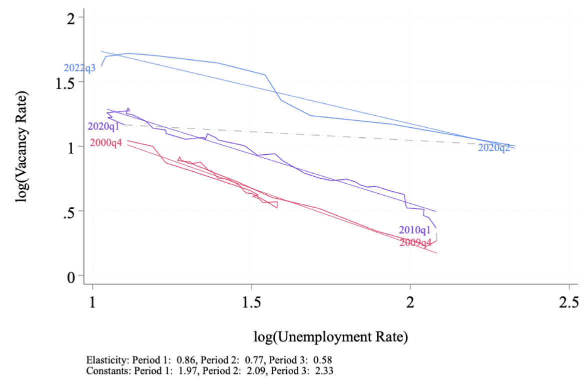
Under an assumption of isoelasticity of the Beveridge curve that $v(u) = \alpha u^{-\epsilon}$, the optimal tightness $\theta^* = \frac{1-\zeta}{\kappa\epsilon}$ and the optimal unemployment $u^* = \left[\frac{\kappa\epsilon}{1-\zeta} v u^{\epsilon}\right]^{\frac{1}{1+\epsilon}}$ can be identified from the Beveridge curve, κ and ζ.

Tradeoffs between unemployment and vacancies. With a high unemployment and low vacan-

Figure 1. Beveridge Curve in the United States, 2000-2022

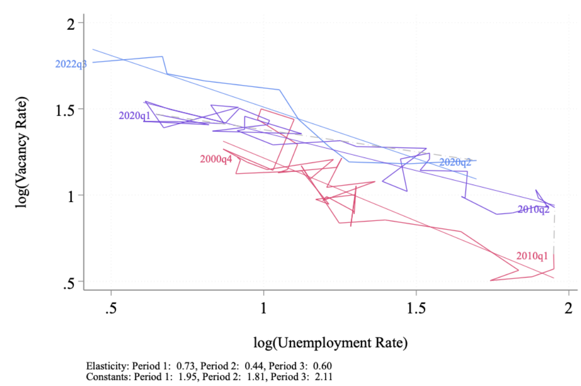


A. Unemployment Rate and Vacancy Rate



B. Beveridge Curve: All Nonfarm Industries

C. Beveridge Curve: Leisure and Hospitality



D. Beveridge Curve: Finance

Notes: Figure 1A presents the quarterly seasonally adjusted unemployment rate and vacancy rate for all nonfarm industries. Figure 1B presents the Beveridge curve for nonfarm industries. Figure 1A and **??** are constructed by aggregating all nonfarm industries. Figure 1C presents the Beveridge curve for the leisure and hospitality industry. Figure 1D presents the Beveridge curve for the finance industry. Figure 1B - Figure 1D present each algorithmically determined isoelastic period by color. Beginning and end dates of each period are labeled. Elasticity and constants are displayed for each period and industry.

cies, firms easily hire, but individuals struggle to find work. With low unemployment and high vacancies, individuals easily find work, but firms struggle to find employees.

The sufficient statistics approach allows Michaillat and Saez (2021) to develop a structural model of societal welfare, and estimate the model using empirically estimated parameters.

3.2. Parameters for Sufficient Statistics Estimation of Efficient Unemployment

Recruiting costs, κ Recruiting costs are estimated using the National Employer Survey (1997) conducted by the Census Bureau in 1997 (NES). The NES asked firms the percentage of labor within their firm devoted to recruiting.

Let κ_i be the number of recruiters per vacancy for industry i. Let ω_i be the percent of labor devoted to recruiting for industry i. We use the identity that percent of labor devoted to recruiting must equal the recruiters per vacancy $\times$ the vacancy rate.

$$\kappa v = \omega(1 - u) \tag{4}$$

$$\kappa = \frac{\omega}{v}(1 - u) \tag{5}$$

Table 1 reports recruiting cost by industry in the NES public file.

Value of Unemployment, ζ Following Michaillat and Saez (2021), I set the social value of nonwork to be $\zeta = 0.26$. They construct the parameter by aggregating estimates of the value of nonwork estimated in Mas and Pallais (2019) and Borgschulte and Martorell (2018). The social value of non-work estimates the relative value of non-work to employment.

Elasticity of Beveridge Curve, ϵ Elasticity of the Beveridge curve, ϵ_{it}, is measured for each industry i and period t where period is determined for each industry using the algorithmically identified breaks.

3.3. Sufficient Statistics Estimation of Efficient Unemployment

Efficient unemployment u^* can be estimated as

$$u^* = \left(\frac{\kappa\epsilon}{1 - \zeta} \cdot \frac{v}{u^{-\epsilon}}\right)^{\frac{1}{1+\epsilon}} \tag{6}$$

Table 1. Recruiting by Industry

	(1)	(2)	(3)
	Number of Firms	Recruiters per Vacancy, κ	% Labor Devoted to Recruiting
Trade	253	.84	2.56
Construction	173	.93	1.82
Leisure/Accom	114	1.03	4.11
Edu/Health	146	1.15	4.44
Finance	177	1.18	3.89
Trans/Utilities	218	1.31	3.34
Manufacturing	1827	1.33	2.83
Prof/Business	121	1.47	6.99

This table reports recruiting parameters by industry using the National Employers Survey. Column 1 reports the number of firms in each industry. Column 2 reports κ, the number of recruiters per vacancy within a industry. Column 3 reports the percent of labor firms within each industry devote to recruiting.

Estimates for industry-level recruiting costs, κ, are constant. The parameter for the social value of non-work, ζ, is constant across industries. Unemployment rate, u, and vacancy rates, v, are observed at the quarterly level. For each industry, we observe three elasticities, ϵ, for each intra-industry period.

3.4. Unemployment Gap, Actual versus Efficient Unemployment

The unemployment gap, $\tilde{u}$, is measured as the difference between the actual and the efficient unemployment rate.

$$\tilde{u} = u - u^* \tag{7}$$

Size of the Unemployment Gap. If $u = u^*$, an industry operates at efficiency. If $u > u^*$ or $u < u^*$, the industry is not operating efficiently. Figure 2 shows actual and efficient unemployment. Industries vary in their proximity to efficiency. Construction and Trade[†] operate the farthest from efficiency (Figures 2A and 2B). Finance and Education/Health Services operate the closest to efficiency (Figures 2G and 2H).

For all industries, the actual unemployment rate is more volatile than the efficient unemployment rate. Efficient unemployment responds to economic crisis, but not to the degree observed in actual unemployment.

Tight Industries Prior to the Great Recession, tighter industries such as Professional and Business Services, Finance, and Education/Health Services experienced lower unemployment rates than efficient. During the Great Recession, actual unemployment became higher than efficient. Following the Great Recession, these industries slowly return to be tight with actual unemployment rates near or at efficiency. This return suggests a recovery to the pre-crisis state.

Again following a brief increase in unemployment during COVID-19, these industries returned to actual unemployment rates below the efficient unemployment rate. This suggests that these industries quickly recovered from COVID-19 and have again become tight.

Slack Industries Industries such as Construction, Trade, and Manufacturing consistently experience actual unemployment rates higher than their efficient unemployment rates. In

[†]Trade includes wholesale and retail trade. Wholesale trade is selling goods to retailers. Retail trade is selling goods to consumers.

good economic times, the unemployment gap shrinks and firms operate closer to efficiency. In bad economic times, the unemployment gap grows and firms operate farther from efficiency.

4. Conclusion

Summary. I estimate the efficient unemployment gap by industry using Michaillat and Saez (2021)'s sufficient statistics approach. Industries vary in slack and tightness of labor markets. I find that some consistently operate too tight or near efficiency while others are consistently too slack.

Implications. Heterogeneity by industry suggests policy should be designed with an understanding of the differences in labor market conditions. Unemployment insurance generosity could be more generous for those in slack industries and less generous for those in tight industries.

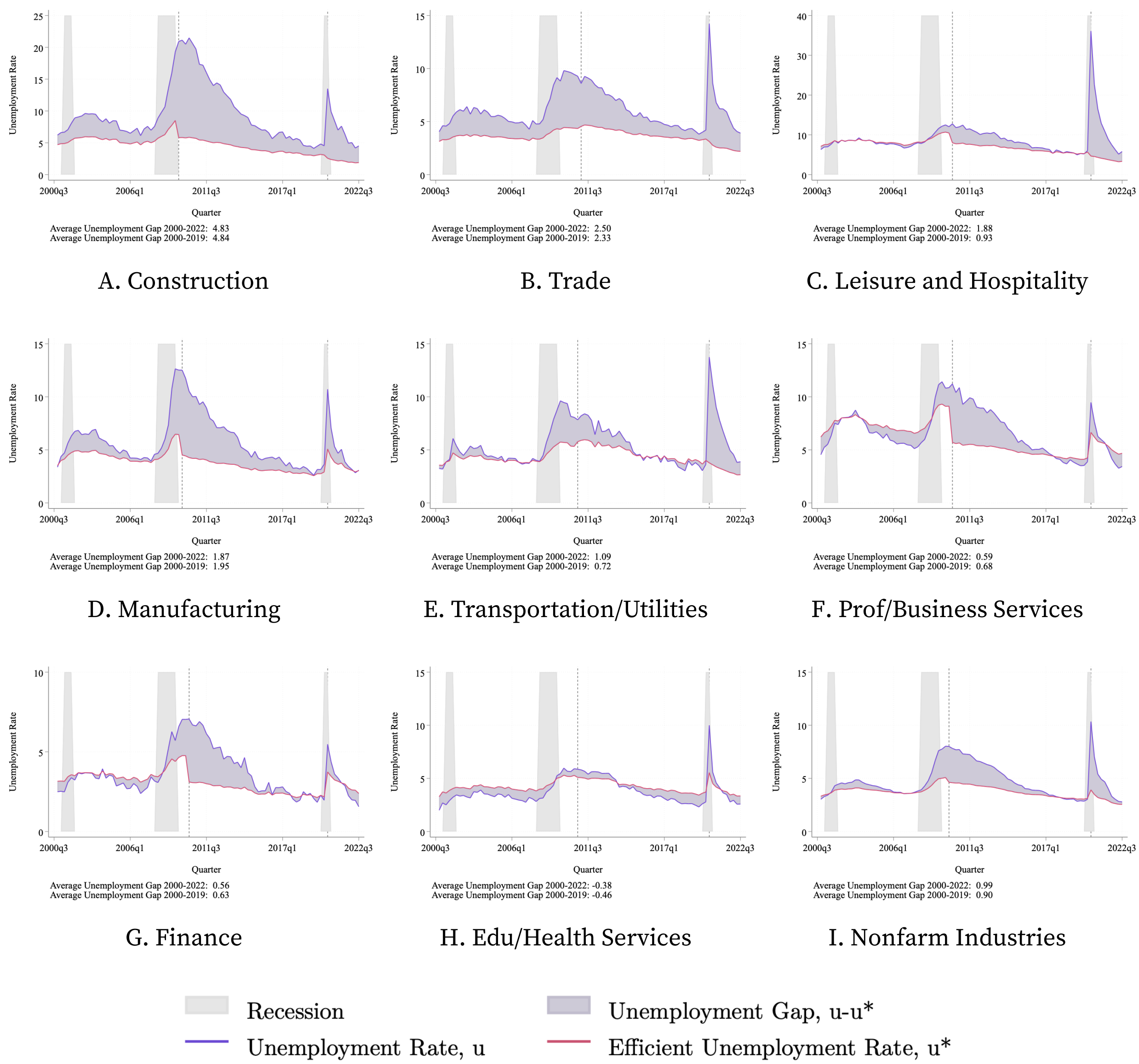
Monetary policy aimed a cooling tight labor markets may differentially impact industries. For industries operating near efficiency, they have the desired effect increasing slack. For consistently slack industries, monetary policy drives the actual unemployment rate farther from efficiency creating an even more slack market. Transfers to industries affected by but not in need of monetary policy cooling could be considered.

Source of Differences. In computing efficient unemployment by industry, I observe heterogeneity in proximity to efficiency. Understanding the source of the variation by industry is an important mechanism for developing policies aimed at moving industry unemployment rates towards efficiency. Mechanisms could include education level of the industry's labor force, wage laws, or characteristics of the industry operation.

This phenomenon could also be used to investigate the role of industry switching and flexibility, and to what extent people in slack industries enter tight industries as an arbitrage. Since industry unemployment rate is calculated using the most recent industry of employment, I am not able to observe if individuals are searching in other industries. This limitation hampers by ability to measure unemployment rate by industry.

Recent work shows Beveridge curves vary by location (Owyang et al. (2022)). Extensions of this work could characterize the extent to which variation in local Beveridge curves results from regional industry composition.

Figure 2. Efficient and Actual Unemployment Rate



This figure presents efficient, u^*, and actual unemployment rate, u, in order of average unemployment gap size from 2000-2022 where average unemployment gap is $\frac{1}{Q}\sum_{q=1}^{Q} u - u^*$. Figure 2A and 2H presents the largest and smallest average unemployment gaps, respectively. The efficient unemployment rate is calculated using the sufficient statistics method defined in Equation 6. The actual unemployment rate is from the CES. Dashed vertical lines indicate quarter of break in elasticity, ϵ, such that after the dashed line a new ϵ is used to estimate the sufficient statistics.

Limitations. My estimates would be improved by updated information on recruiting. The NES was collected in 1997 and may not captured more modern recruiting practices. It also focused on manufacturing firms such that they are overrepresented in the sample, so estimates for non-manufacturing industries may be less precise.

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Table B-1. Employees on nonfarm payrolls by industry sector and selected industry detail, Seasonally adjusted, *U.S. Bureau of Labor Statistics, All Employees by Industry, retrieved from*

FRED, Federal Reserve Bank of St. Louis, 2022.
Unemployed persons by industry and class of worker, Table A-14*, U.S. Bureau of Labor Statistics, retrieved from FRED, Federal Reserve Bank of St. Louis,* 2022.
U.S. Bureau of Labor Statistics, "Job Openings and Labor Turnover Survey," 2000-2022.

Appendix A. Industry Graphs

Panel A

Panel A presents the Beveridge curve. There are two breaks and thus three regimes for the elasticity of the Beveridge curve. Gray dotted lines connect quarters seperated by breaks. Elasticity and constants for regimes 1, 2, and 3, respectively.

Panel B

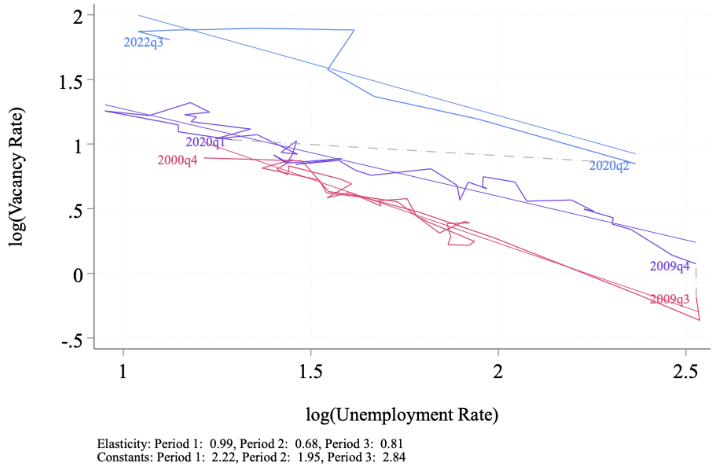
Panel B presents the estimated elasticity of the Beveridge curve for each regime.

Panel C

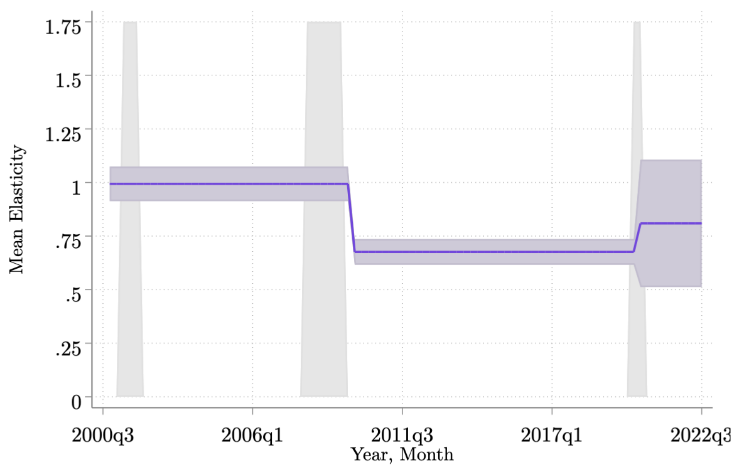
Panel C presents the unemployment rate and the efficient unemployment rate. Breaks are identified by vertical dashed lines.

List of Appendix Figures

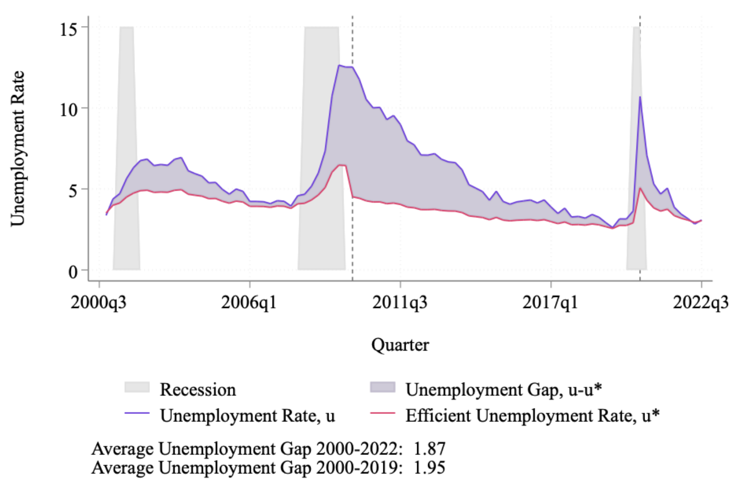
Figure A.1. Manufacturing



A. Beveridge Curve



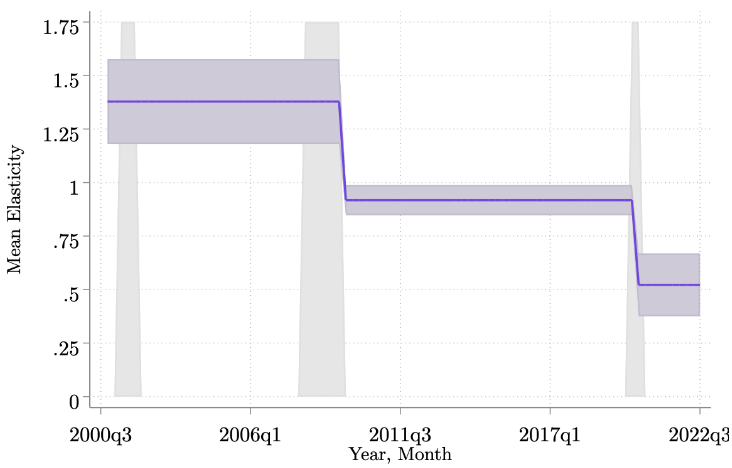
B. Elasticity



C. Efficent and Actual Unemployment

Figure A.2. Construction

A. Beveridge Curve



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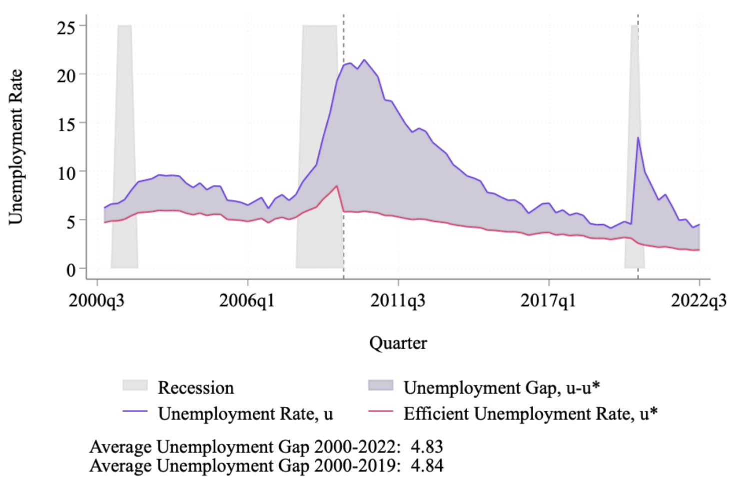
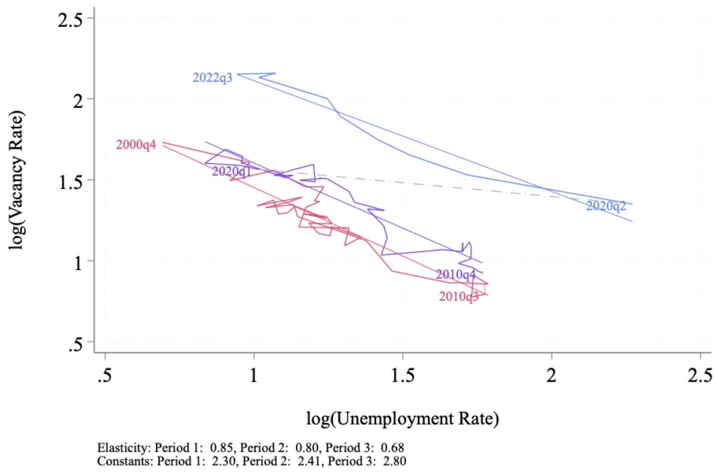
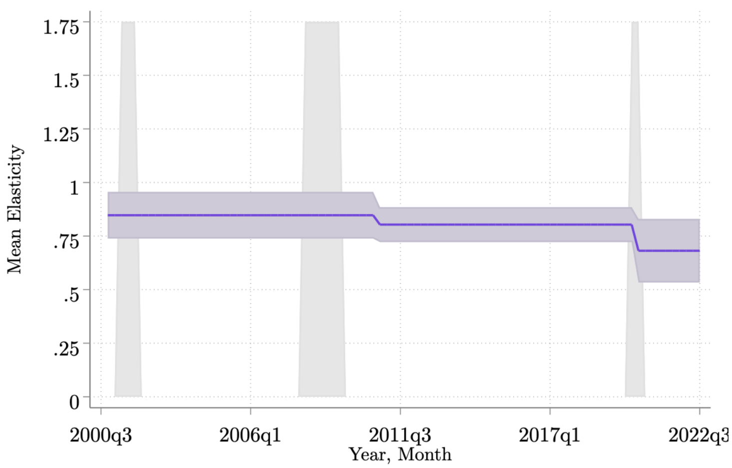


C. Efficent and Actual Unemployment

Figure A.3. Education and Health Services



A. Beveridge Curve



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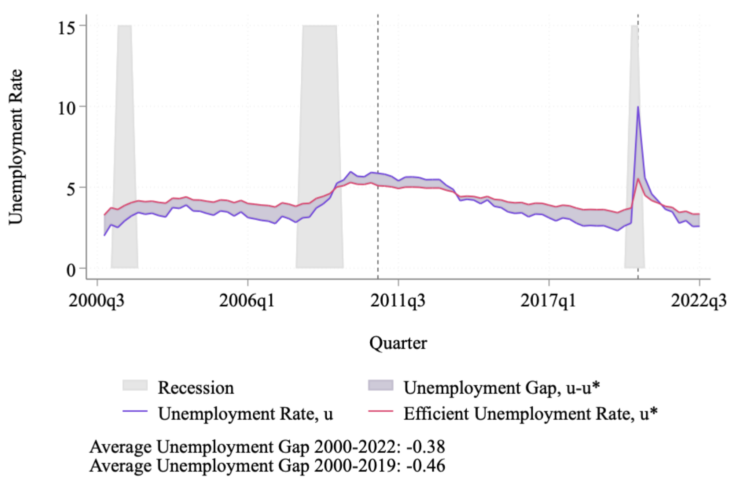
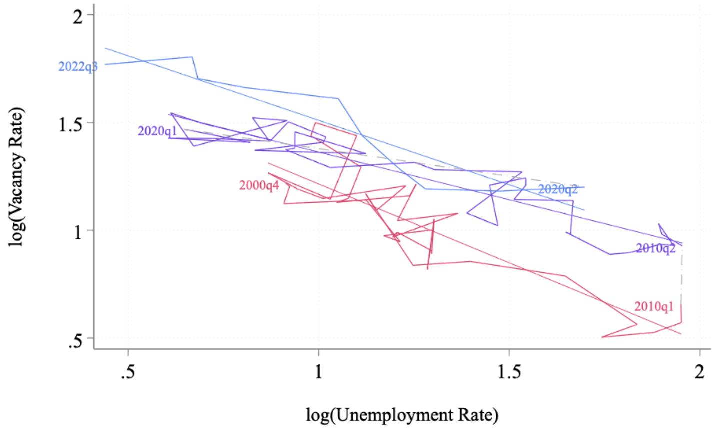


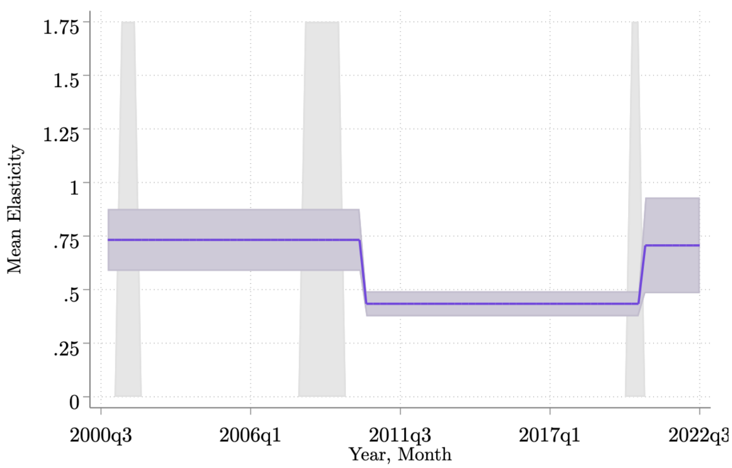
C. Efficent and Actual Unemployment

Figure A.4. Finance

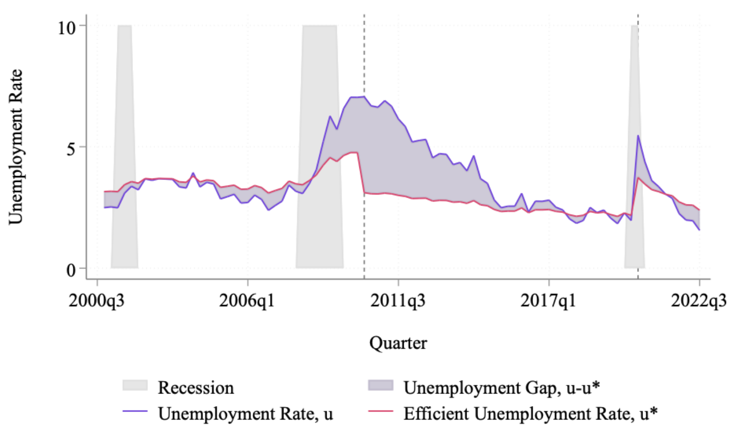


Elasticity: Period 1: 0.73, Period 2: 0.44, Period 3: 0.60
Constants: Period 1: 1.95, Period 2: 1.81, Period 3: 2.11

A. Beveridge Curve



B. Elasticity

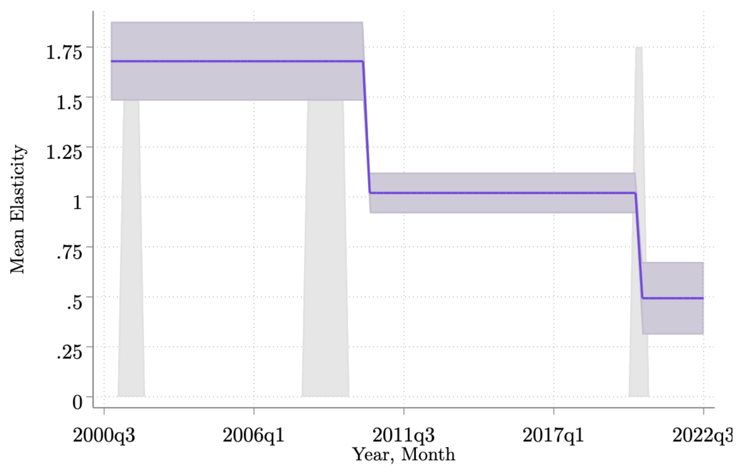


Average Unemployment Gap 2000-2022: 0.56
Average Unemployment Gap 2000-2019: 0.63

C. Efficent and Actual Unemployment

Figure A.5. Leisure and Hospitality

A. Beveridge Curve



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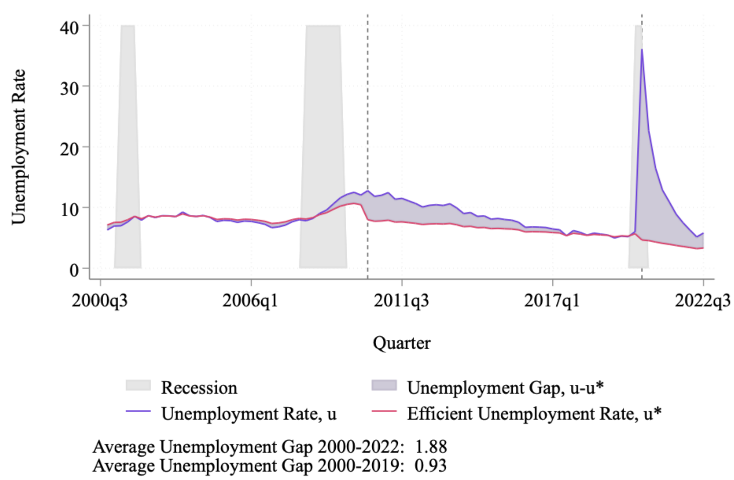
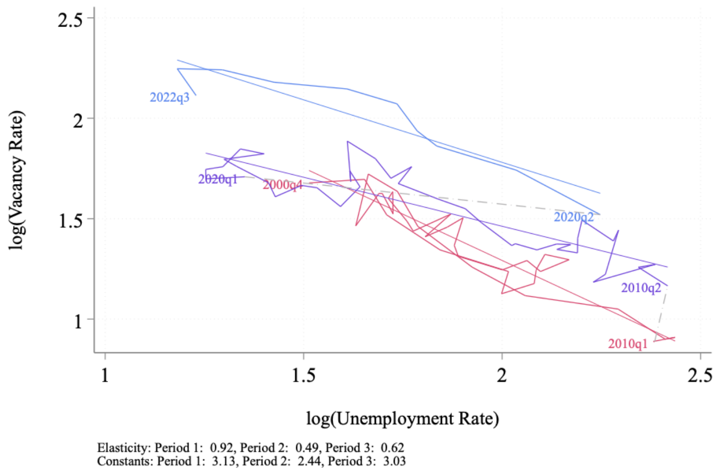


C. Efficent and Actual Unemployment

Figure A.6. Professional and Business Services



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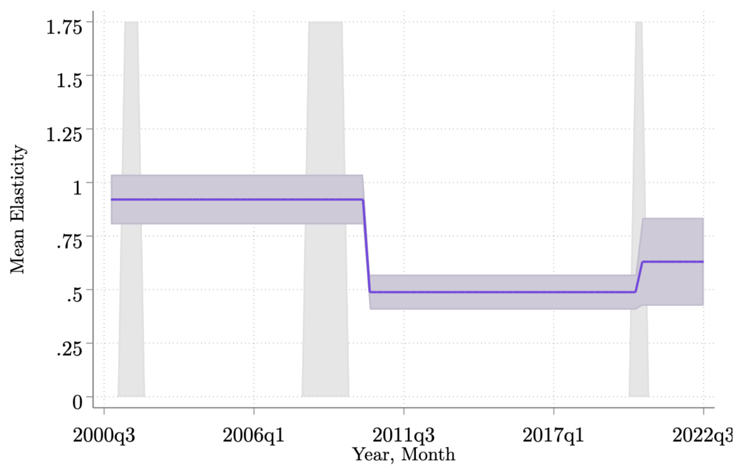
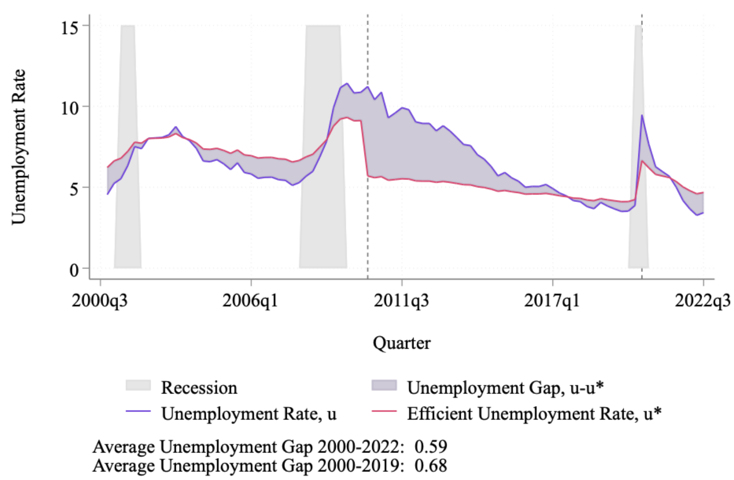
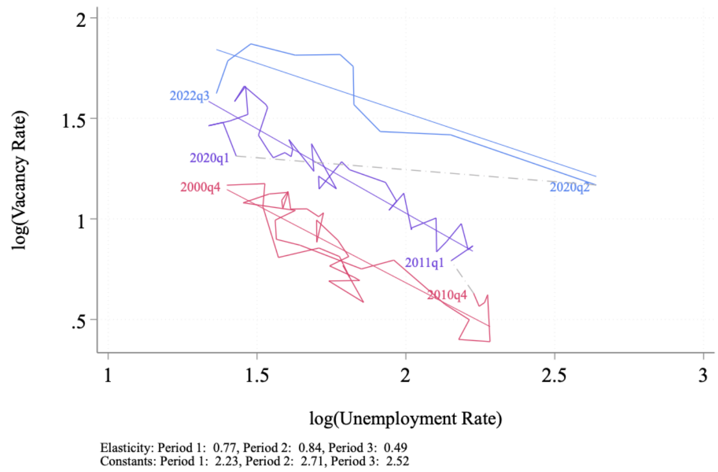


B. Elasticity



C. Efficent and Actual Unemployment

Figure A.7. Trade



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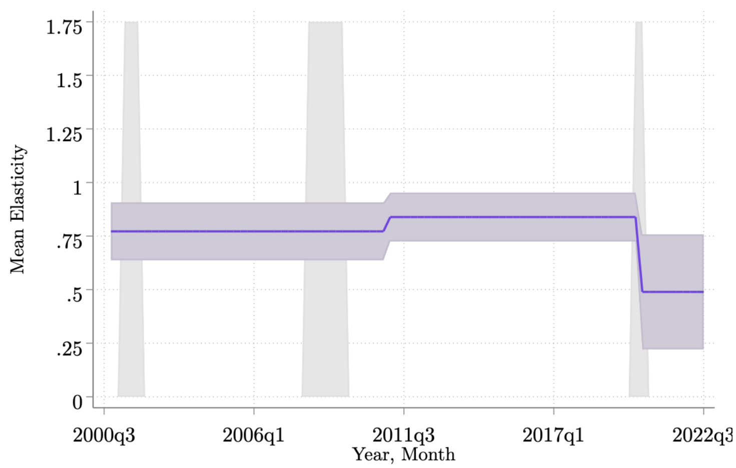
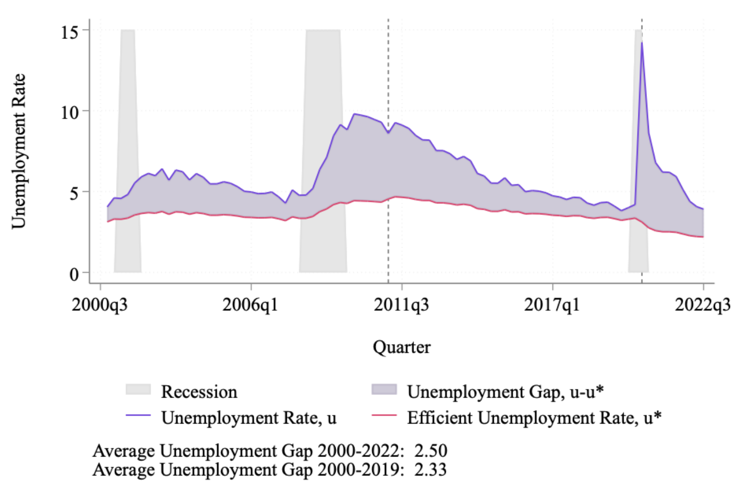
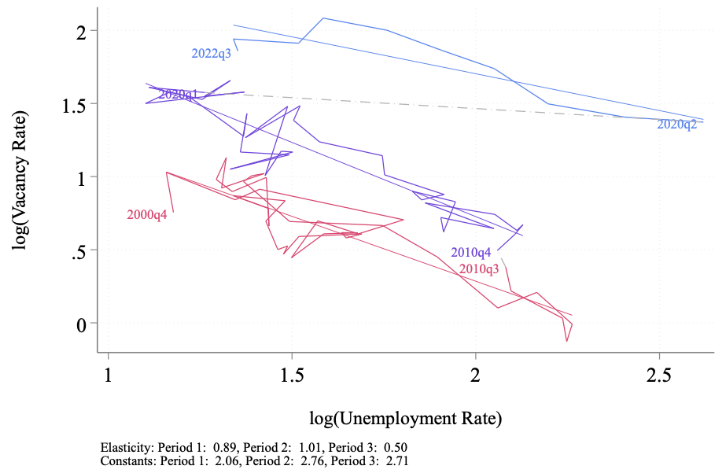


B. Elasticity

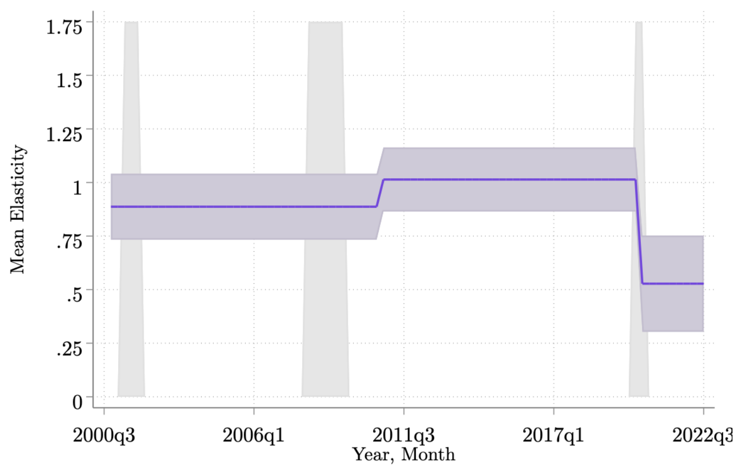


C. Efficent and Actual Unemployment

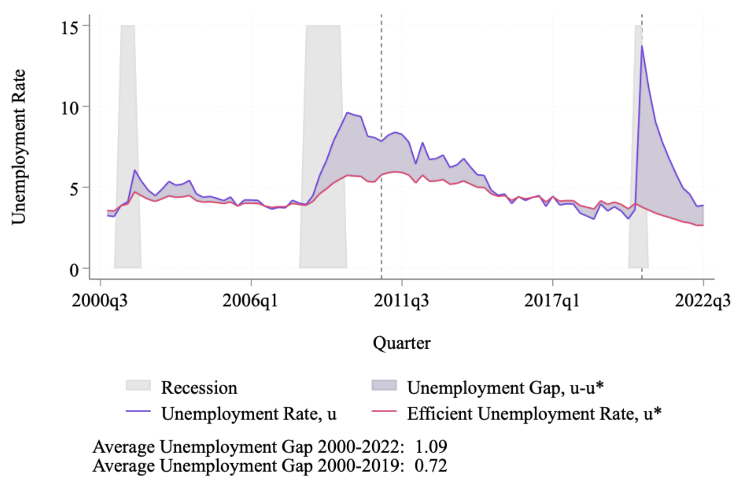
Figure A.8. Transportation and Utilities



A. Beveridge Curve

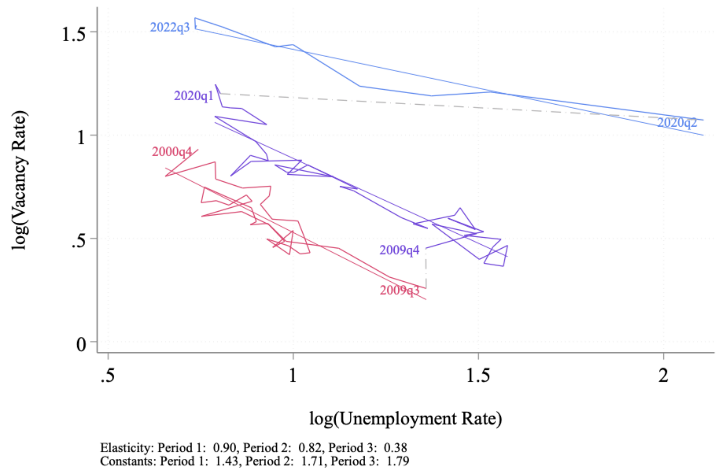


B. Elasticity

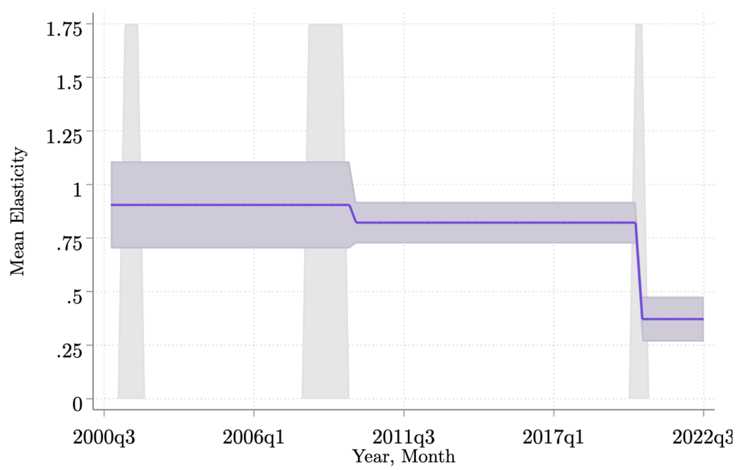


C. Efficent and Actual Unemployment

Figure A.9. Government

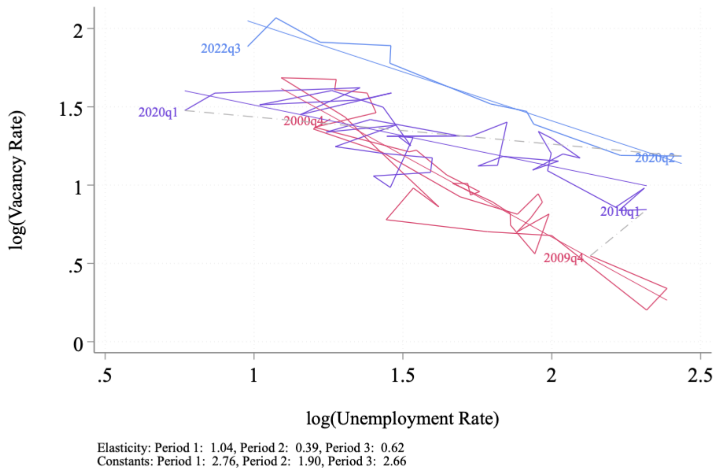


A. Beveridge Curve

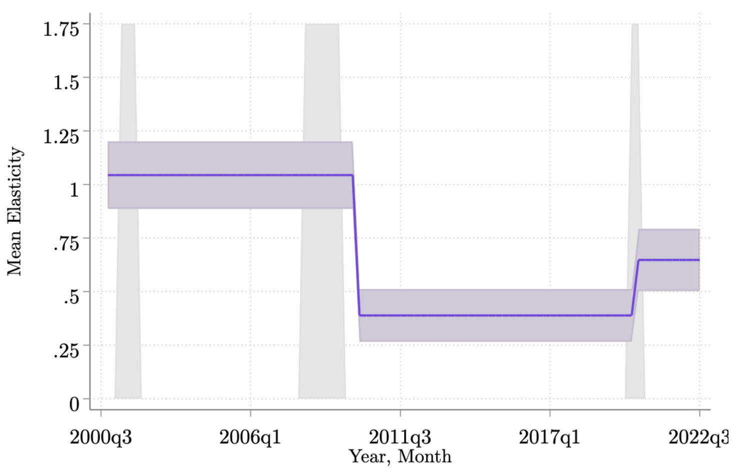


B. Elasticity

Figure A.10. Information



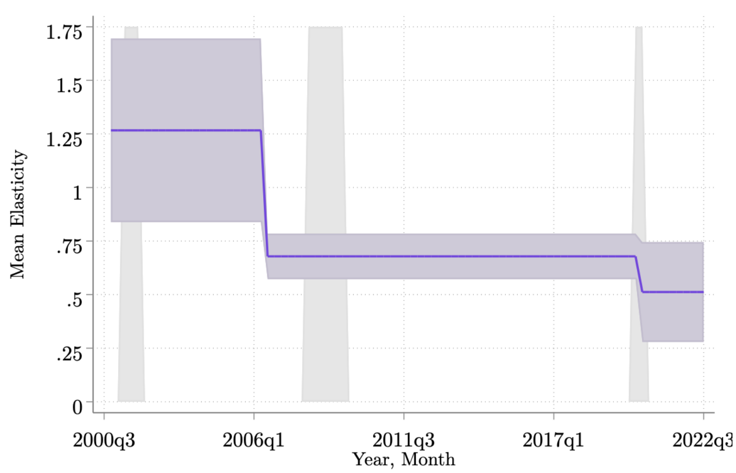
A. Beveridge Curve



B. Elasticity

Figure A.11. Other Services

A. Beveridge Curve



B. Elasticity