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A First Aid Kit to Assess Welfare Impacts

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Abstract

We develop a simple framework to measure the impacts of an economic shock on unemployed workers' welfare quantitatively. We follow the sufficient statistics approach in consulting traditional economic models, and use a standard job search model to derive the sufficient statistics to identify the impacts. We then apply our framework to assess the impacts of the coronavirus disease 2019 (COVID-19) by using regional data of the United States and Japan, and international data. Analysis reveals the regions and countries that are severely damaged by the COVID-19.

Keywords: Sufficient statistics, Job search models, Welfare impacts, COVID-19

1 Introduction

Job search models are now widely used in economics to analyze labor market outcomes (Rogerson et al., 2005; Mortensen, 2003; Shimer, 2010; Wright et al., 2021). Many existing studies have used these models for quantitative analysis through calibration and structural estimation. In this paper, we show that a standard job search model can further provide us a very simple method to quantify the impacts of an economic shock on unemployed workers' welfare.

Although conducting a full-fledged calibration or structural estimation analysis to assess the shock's impacts is undoubtedly significant, this process requires extremely rich data. However, such a requirement is often difficult to meet. The sufficient statistics approach provides a remedy for the difficulty by consulting traditional economics models and showing statistics that are "sufficient" to know the welfare impacts (Chetty, 2009). This approach leaves primitive parameters unidentified and instead identifies a smaller set of reduced-form elasticities. In this paper, we show that the

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standard Mortensen-Pissarides job search model yields sufficient statistics to measure the impacts of an economic shock on the unemployed worker's asset value (discounted expected lifetime income) quantitatively and its decomposition into two components, namely, changes in the job finding rate and changes in the match surplus.

Our approach has two distinct features. First, the approach requires only three numbers: the number of unemployed workers, that of vacancies, and that of new matches, all of which are available in many regions and countries. Hence, it is extremely easy to implement. Second, the approach focuses on the unemployed workers' welfare, which is significant because they are often the most seriously damaged by negative economic shocks. In this respect, this approach is in line with the Rawlsian view, which puts significance on the prospects of the least well-off.

We then implement our approach to measure the within and across country differences in the impacts of the coronavirus disease 2019 (COVID-19). Analysis reveals the most and least seriously damaged regions within a country as well as the most and least seriously damaged countries. The analysis also uncovers the main driving forces of the changes.

Of course, we do not intend to claim that our approach is "sufficient" as quantitative analysis because it does not enable us to conduct counterfactual analysis to find out the necessary policy intervention. Still, we believe that our approach works as a nice starting point.

2 Model

Consider a continuous time job search-matching model with heterogeneous workers (indicated by i) and jobs (indicated by j) a la Pissarides (2000). Let u_i, v_j, and m_{ij} denote the number of type i unemployed workers, that of type j vacancies, and that of new matches between type i workers and type j jobs, respectively. In a standard search model, m_{ij} is given by a matching function (Petrongolo and Pissarides, 2001), although we here need not to specify it explicitly. Let further u, v, and m denote the total numbers of unemployed workers, vacancies, and new matches, respectively: $u = \sum_i u_i$, $v = \sum_j v_j$, and $m = \sum_j \sum_i m_{ij}$.We assume the off-the-job search, that is, only unemployed workers search for jobs.

For each job searcher of type i, a new match with a job of type j arrives according to a Poisson process with the aggregate rate of $p_{ij} = m_{ij}/v_i$. Hence, the asset value function (Bellman equation) of a type i job searcher, U_i, is given by

$$rU_i = \underbrace{\sum_j p_{ij}(W_{ij} - U_i)}_{\text{expected match surplus}}, \tag{1}$$

where r is the discount rate. Here, we normalize the value of home production or unemployment benefits to zero. W_{ij} is the asset value of a type i worker landing at a type j job and depends on the $i - j$ pair, implying that the type i worker's match surplus from landing a job of type j is given by $W_{ij} - U_i$. Because p_{ij} is the rate of finding a type j job, the right hand side of (1) represents the type i worker's expected match surplus, that is, gains from job search.

For each firm posting a vacancy of type j, a new match with a worker of type i arrives according to a Poisson process with the aggregate rate of $q_{ji} = m_{ij}/v_j$. Hence, the asset value function (Bellman equation) of a type j vacant job is given by

$$rV_j = -k + \sum_i q_{ji}(J_{ji} - V_j), \tag{2}$$

where k is the cost of posting a vacancy. J_{ji} is the asset value of a filled type j job with a type i worker and depends on the $i - j$ pair, implying that the type j job's match surplus from employing a worker of type i is given by $J_{ji} - V_i$. Because q_{ji} is the job filling rate, the second term of the right hand side of (2) represents the expected match surplus, that is, gains from posting a type j vacancy.

Note here that we require no assumptions on W_{ij} and J_{ji}. Note also that we allow the possibility of $p_{ij} = 0$, which emerges if $W_{ij} - U_i \leq 0$.

2.1 Equilibrium Conditions

We now introduce two equilibrium conditions that are sufficient to identify the effects on the asset value of unemployment, U_i. First, we assume free entry and exit of firms, which drives the value of posting a vacancy to zero

$$V_j = 0 \iff k = \sum_i q_{ji} J_{ji}. \tag{3}$$

Second, we assume that the wage is determined by the decentralized Nash bargaining between a firm and a worker, which assumes that the total surplus is shared in such a way that the worker receives a fraction β of it, and the firm receives the remaining fraction $1 - \beta$:

$$(1 - \beta)(W_{ij} - U_i) = \beta(J_{ji} - V_j),$$

where β represents the bargaining power of workers. Note that our model includes the competitive search model as a special case. In fact, if we set β equal to the elasticity of the matching function concerning unemployment, then our model becomes a competitive search model. The Nash bargaining, combined with (3), yields the following:

$$
\begin{aligned}
(1-\beta)\sum_i \sum_j m_{ij}(W_{ij}-U_i) &= \beta \sum_i \sum_j m_{ij} J_{ji} \\
&= \beta k \sum_j v_j = \beta k v.
\end{aligned} \tag{4}
$$

The left hand side of (4) represents the worker's matching surplus whereas its right hand side is the firm's match surplus.

2.2 Identification Strategy

From (1), the average flow value of unemployment , $r\overline{U}$, becomes

$$
\begin{aligned}
r\overline{U} &= \frac{\sum_i u_i r U_i}{u} = \frac{\sum_i \sum_j m_{ij}}{u} \frac{\sum_i \sum_j m_{ij}(W_{ij}-U_i)}{\sum_i \sum_j m_{ij}} \\
&= \underbrace{\frac{m}{u}}_{\text{average job finding rate}} \underbrace{\frac{\sum_i \sum_j m_{ij}(W_{ij}-U_i)}{m}}_{\text{average match surplus}},
\end{aligned} \tag{5}
$$

implying that $r\overline{U}$ consists of the average job finding rate and the average match surplus. Moreover, we can use (4) to rewrite the average match surplus as

$$
\frac{\sum_i \sum_j m_{ij}(W_{ij}-U_i)}{m} = \frac{\beta k}{1-\beta}\frac{v}{m}. \tag{6}
$$

Hence, the inverse of the average job filling rate, m/v, reflects the average match surplus. From (5) and (6), we obtain the following:

$$
\ln r\overline{U} = \ln \underbrace{\frac{m}{u}}_{\text{average job finding rate}} + \ln \underbrace{\frac{\beta k}{1-\beta}\frac{v}{m}}_{\text{average match surplus}}. \tag{7}
$$

Unfortunately, we cannot obtain $\ln r\overline{U}$ because we do not observe β and k. However, fortunately, we can observe changes in $\ln r\overline{U}$ caused by a certain shock if such a shock does not affect β and k because m, u, and v are observable.

Let $X(d)$ denote a variable X under a state d, where $d = 1$ represents the state after a particular shock or treatment occurs and $d = 0$ represents the state before it. Moreover, we assume that β and k do not depend on d. Then, we obtain from (7) the following:

$$
\ln \overline{U}(1) - \ln \overline{U}(0) = \ln \frac{m(1)}{u(1)} - \ln \frac{m(0)}{u(0)} + \ln \frac{v(1)}{m(1)} - \ln \frac{v(0)}{m(0)}. \tag{8}
$$

Proposition 1 *Suppose that the bargaining power of workers, β, and the cost of posting a vacancy, k, do not depend on the state, d. Then changes in the average asset value of unemployment, $\overline{U}$, caused by a change in d are given by (8).*

Note here that although agent types are unobservable for researchers, implying that u_i, v_i, and m_{ij} are unobservable, their aggregate values ($u = \sum_i u_i$, $v = \sum_j v_j$, and $m = \sum_j \sum_i m_{ij}$) are observable. Hence, by comparing these values before and after the shock, we obtain its impacts on the average asset value of unemployment. Note further that even if k depends on d, we can observe changes in the average match surplus per vacancy costs $\sum_i \sum_j m_{ij}(W_{ij} - U_i)/k$ from u, v, and m. Moreover, in the case wherein β depends on d, if we use the competitive search model, we can obtain the value of β from estimating the matching function.

3 Estimation

In this section, we adopt our method to measure the impacts of the COVID-19 on the unemployed workers' welfare. We first use regional data of the United States and Japan to examine the intra-national heterogeneity in the COVID-19 impacts, and then use nation level data of European Union countries as well as the United Kingdom, the United States and Japan to examine the international heterogeneity.

3.1 Data

We need data on the number of unemployed workers, u, that of vacancies, v, and that of new matches, m, before and after the shock occurs in order to know its impacts from (8). We consider the year 2019 as the time before the COVID-19 shock occurs (the state with $d = 0$), and the year 2020 as the time after it occurs (the state with $d = 1$).

For the United States, u comes from the Local Area Unemployment Statistics (U.S. Bureau of Labor Statistics) at the state level and from the Labor Force Statistics from the Current Population Survey (U.S. Bureau of Labor Statistics) at the national level. We use the yearly average value for both levels. The numbers of active job openings and hires are available in the Job Openings and Labor Turnover Survey (U.S. Bureau of Labor Statistics), and we use them as v and m, respectively. Here, u and v are stock variables whereas m is a flow variable. Hence, we use the number of hires per month as m. Although the national level data for v and m are available until the end of 2020, the state level data for them are available only until September 2020 at the time of our analysis (on March 11, 2021). Hence, we use their yearly average values for the national level and their average values over nine months (from January to September) for the state level.

For Japan, the Employment Referrals for General Workers (Ministry of Health, Labour and Welfare) reports the number of active job openings and hires every month, from which we obtain v and m. The number of unemployed workers, u, is available in the Labour Force Survey (Statistics Bureau of Japan, Ministry of Internal Affairs and Communication). Again, we use the yearly average values for u and v, and the yearly average hires per month as m.

For European Union countries, all data come from Eurostat. We use the number of unemployed workers (reported in the table of "Unemployment by sex and age") as u, the number of vacancies (reported in the table of "Job vacancy statistics by NACE Rev. 2 activity") as v, and the unemployment to employment flow (reported in the table of "Labour market transitions") as m. All of them are reported quarterly, and for 2020, only values for the first to third quarters are available. Hence, we took the average values over the three quarters. Moreover, we divide the average unemployment to employment flow by three to obtain the average number of hires per month. Because of data availability, we exclude seven countries (Denmark, Estonia, France, Germany, Italy, Latvia, and Malta) from 27 EU countries from our analysis.

3.2 Results

Figure 1 shows the results for states in the United States.[1] Among 50 states and Washington D.C., Colorado, Hawaii, Massachusetts, and Nevada experienced large declines in the asset value of the unemployed worker, having 1.32, 1.77, 1.26, and 1.35 point decreases in log difference (73, 83, 71, and 74 percent decreases in the asset value), respectively, and Washington D.C., Mississippi, and Nebraska experienced relatively small declines in it, having 0.40, 0.42, and 0.46 point decreases in log difference (33, 34, and 37 percent decreases in the asset value), respectively. Most of the declines in the asset value accrue to decreases in the job finding rate.

Figure 2 provides the results for prefectures in Japan. Among 47 prefectures, Tokyo, Aichi, and Mie experienced relatively large declines in the asset value of the unemployed worker, having 0.56, 0.61, and 0.63 point decreases in log difference (43, 45, and 47 percent decreases in the asset value), respectively, and Fukui, Yamanashi, and Shimane experienced relatively small declines in it, having 0.18, 0.12, and 0.02 point decreases in log difference (16, 12, and 1 percent decreases in the asset value), respectively. Most of the declines in the asset value accrue to decreases in the job finding rate.

[1] Data and stata codes for estimation are given as supporting information files. Online Appendix provides tables showing the estimated log and level differences in $\overline{U}$.

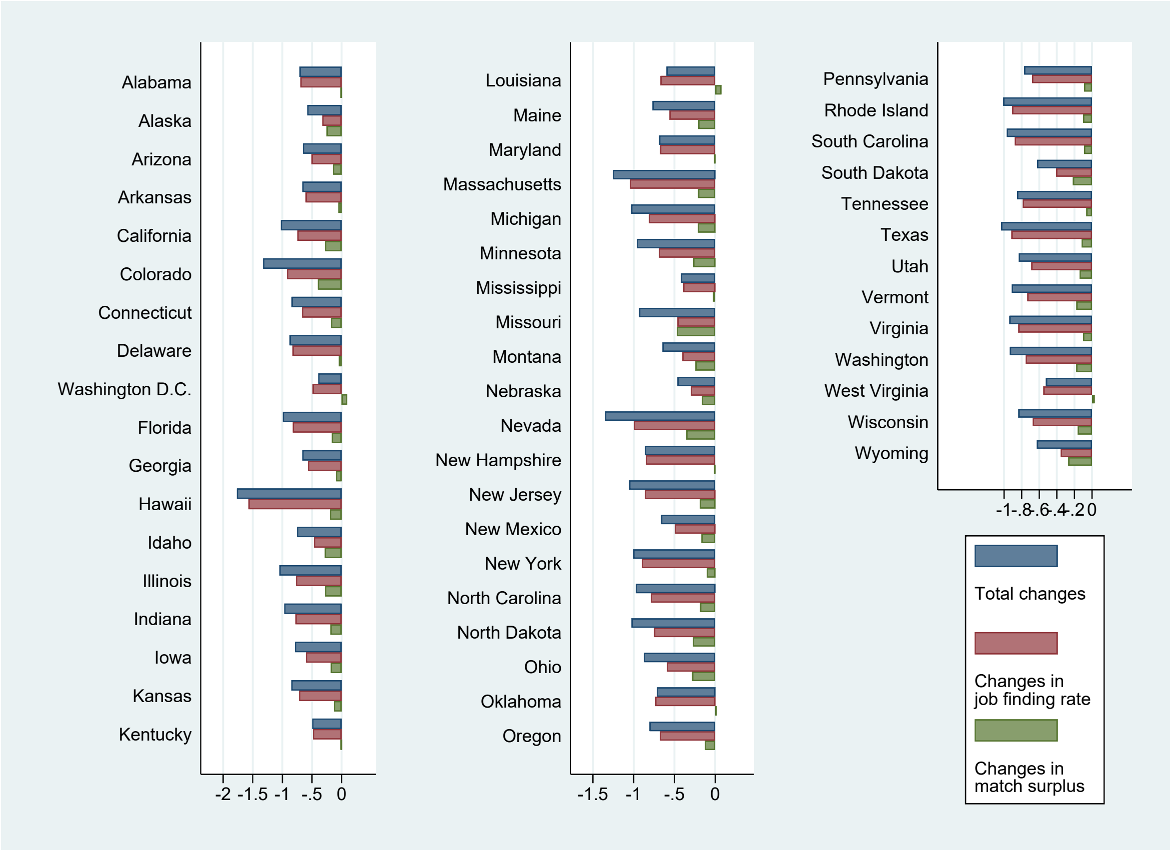

Figure 1: Effects of COVID-19 on the unemployed workers' welfare in U.S. states

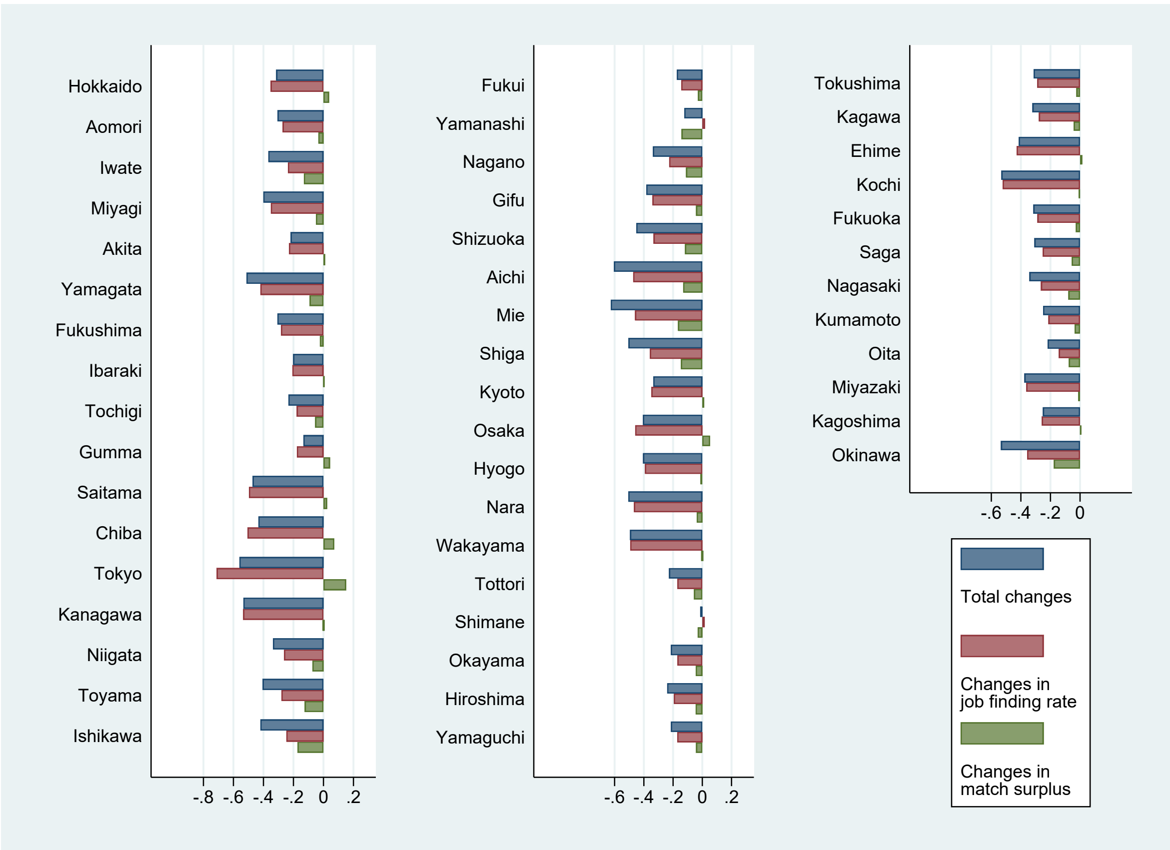

Figure 2: Effects of COVID-19 on the unemployed workers' welfare in Japanese prefectures

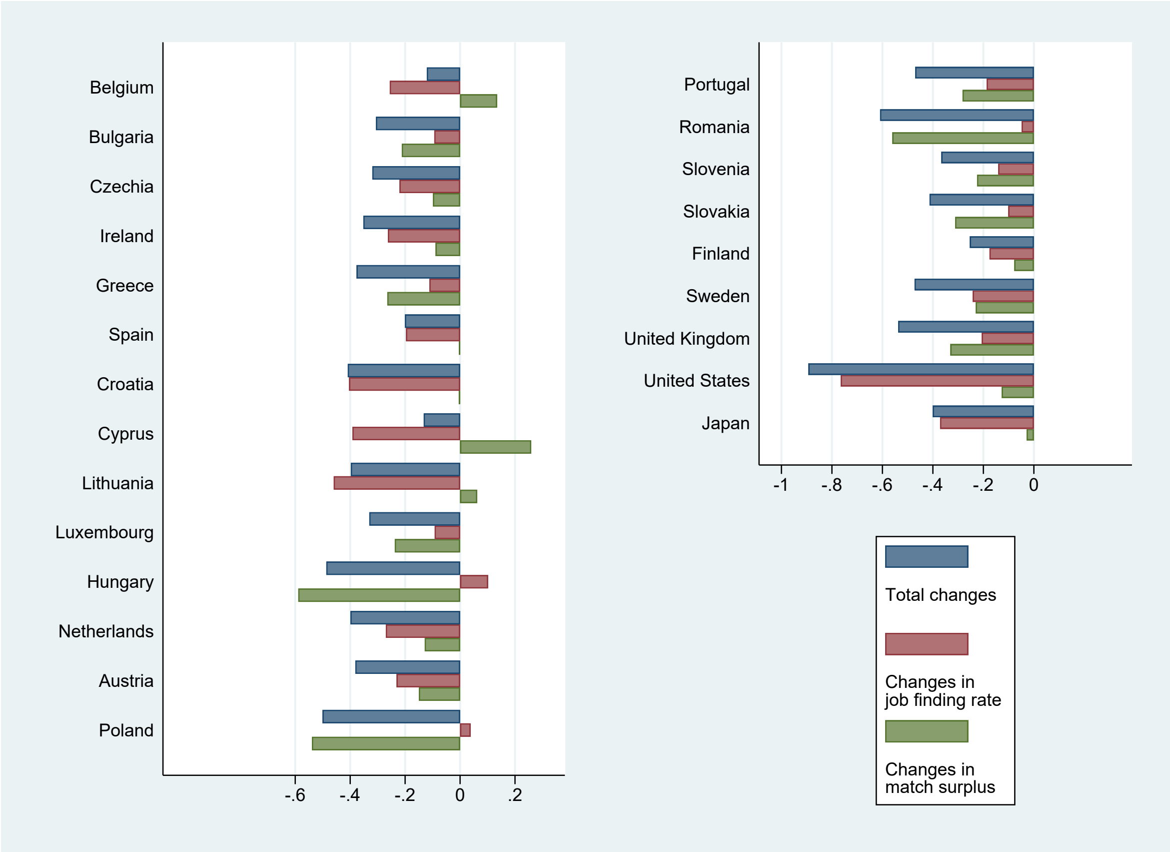

Figure 3: Effects of COVID-19 on the unemployed workers' welfare in selected countries

Figure 3 shows the results for 20 EU countries, the United Kingdom, the United States, and Japan. Among 23 countries, the United Kingdom and the United States experienced relatively large declines in the asset value of the unemployed worker, having 0.54 and 0.89 point decreases in log difference (42 and 59 percent decreases in the asset value), respectively, and Belgium and Cyprus experienced relatively small declines in it, having 0.12 and 0.13 point decreases in log difference (11 and 12 percent decreases in the asset value), respectively. The declines in the asset value accrue to decreases in the job finding rate in countries such as the United States and Japan. However, there also exist countries such as Hungary, Poland, and Romania wherein they accrue to decreases in the match surplus.

4 Conclusions

We showed that the standard Mortensen-Pissarides job search model provides us a simple method to assess the impacts of a particular economic shock on the unemployed workers' welfare. The key feature of this method is its convenience. It requires only a few statistics available in many regions and countries. We implemented this method for the analysis of the impacts of COVID-19 within and across countries, and demonstrated that it can help us to identify regions or countries severely damaged by the COVID-19 as well as the main driving force of the welfare changes. Of course, our method can provide only a rough approximation of the welfare changes and detailed analysis must follow subsequently. However, we believe that our method can work as a nice first aid kit.

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Online Appendix: Estimation Results

State	$\ln\overline{U}(1) - \ln\overline{U}(0)$	$\overline{U}(1)/\overline{U}(0)$	State	$\ln\overline{U}(1) - \ln\overline{U}(0)$	$\overline{U}(1)/\overline{U}(0)$
Alabama	-0.71	0.491	Montana	-0.645	0.525
Alaska	-0.579	0.56	Nebraska	-0.463	0.63
Arizona	-0.654	0.52	Nevada	-1.352	0.259
Arkansas	-0.663	0.516	New Hampshire	-0.862	0.422
California	-1.027	0.358	New Jersey	-1.055	0.348
Colorado	-1.324	0.266	New Mexico	-0.664	0.515
Connecticut	-0.845	0.429	New York	-1.005	0.366
Delaware	-0.878	0.416	North Carolina	-0.975	0.377
Washington D.C.	-0.395	0.674	North Dakota	-1.025	0.359
Florida	-0.993	0.37	Ohio	-0.876	0.417
Georgia	-0.663	0.515	Oklahoma	-0.718	0.488
Hawaii	-1.769	0.17	Oregon	-0.806	0.447
Idaho	-0.753	0.471	Pennsylvania	-0.772	0.462
Illinois	-1.05	0.35	Rhode Island	-1.01	0.364
Indiana	-0.968	0.38	South Carolina	-0.969	0.379
Iowa	-0.789	0.454	South Dakota	-0.625	0.535
Kansas	-0.848	0.428	Tennessee	-0.852	0.426
Kentucky	-0.496	0.609	Texas	-1.034	0.356
Louisiana	-0.597	0.551	Utah	-0.832	0.435
Maine	-0.768	0.464	Vermont	-0.913	0.401
Maryland	-0.688	0.503	Virginia	-0.939	0.391
Massachusetts	-1.257	0.285	Washington	-0.934	0.393
Michigan	-1.031	0.357	West Virginia	-0.523	0.593
Minnesota	-0.962	0.382	Wisconsin	-0.837	0.433
Mississippi	-0.42	0.657	Wyoming	-0.627	0.534
Missouri	-0.934	0.393			

Table A1. Intra-national comparison for the United States

Prefecture	$\ln \overline{U}(1) - \ln \overline{U}(0)$	$\overline{U}(1)/\overline{U}(0)$	Prefecture	$\ln \overline{U}(1) - \ln \overline{U}(0)$	$\overline{U}(1)/\overline{U}(0)$
Hokkaido	-0.315	0.73	Shiga	-0.506	0.603
Aomori	-0.307	0.736	Kyoto	-0.335	0.715
Iwate	-0.368	0.692	Osaka	-0.406	0.666
Miyagi	-0.401	0.67	Hyogo	-0.405	0.667
Akita	-0.219	0.803	Nara	-0.506	0.603
Yamagata	-0.513	0.599	Wakayama	-0.494	0.61
Fukushima	-0.307	0.735	Tottori	-0.228	0.796
Ibaraki	-0.202	0.817	Shimane	-0.015	0.985
Tochigi	-0.234	0.792	Okayama	-0.216	0.806
Gumma	-0.134	0.875	Hiroshima	-0.241	0.786
Saitama	-0.472	0.624	Yamaguchi	-0.215	0.807
Chiba	-0.434	0.648	Tokushima	-0.314	0.73
Tokyo	-0.561	0.571	Kagawa	-0.322	0.725
Kanagawa	-0.534	0.586	Ehime	-0.414	0.661
Niigata	-0.337	0.714	Kochi	-0.532	0.588
Toyama	-0.406	0.667	Fukuoka	-0.316	0.729
Ishikawa	-0.421	0.657	Saga	-0.308	0.735
Fukui	-0.175	0.84	Nagasaki	-0.342	0.71
Yamanashi	-0.123	0.884	Kumamoto	-0.25	0.779
Nagano	-0.338	0.713	Oita	-0.22	0.803
Gifu	-0.384	0.681	Miyazaki	-0.376	0.686
Shizuoka	-0.452	0.636	Kagoshima	-0.251	0.778
Aichi	-0.605	0.546	Okinawa	-0.535	0.586
Mie	-0.627	0.534			

Table A2. Intra-national comparison for Japan

Country	$\ln \overline{U}(1) - \ln \overline{U}(0)$	$\overline{U}(1)/\overline{U}(0)$	Country	$\ln \overline{U}(1) - \ln \overline{U}(0)$	$\overline{U}(1)/\overline{U}(0)$
Belgium	-0.121	0.886	Austria	-0.381	0.683
Bulgaria	-0.306	0.736	Poland	-0.501	0.606
Czechia	-0.32	0.726	Portugal	-0.47	0.625
Ireland	-0.352	0.703	Romania	-0.61	0.544
Greece	-0.377	0.686	Slovenia	-0.367	0.693
Spain	-0.201	0.818	Slovakia	-0.413	0.661
Croatia	-0.409	0.664	Finland	-0.254	0.776
Cyprus	-0.133	0.876	Sweden	-0.473	0.623
Lithuania	-0.398	0.672	United Kingdom	-0.538	0.584
Luxembourg	-0.331	0.718	United States	-0.893	0.409
Hungary	-0.487	0.614	Japan	-0.401	0.67
Netherlands	-0.399	0.671			

Table A3. International comparison