ECON 2080, part 1
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# Quiz 2: Answers

- Question A: 2
- Question B: 2
- Question C: 4
- Question D: 3
- Question E: 5
- Question F: 1
- Question G: 1
- Question H: 3
- Question I: 1

Reference for Question B (https://doi.org/10.1257/jel.39.2.390) with different search intensities. It is found that search intensity is positive and significant in regions that are adjacent to the one where the worker lives, although it is only about 10 percent of the level of search intensity in the region of residence. Constant returns to scale in the matching function are not rejected by either the British or the French data, in contrast to the aggregate study for France in table 3, which found decreasing returns.

In conclusion, although the problem of spatial aggregation has only recently been discussed in the estimation of matching functions, the findings of those who explicitly embody a spatial dimension into the estimation do not invalidate earlier results on aggregate matching functions. Their analysis, however, sheds more light on the regional dimensions of job matching and the spillovers between regions than aggregate studies that include aggregate measures of regional imbalance in unemployment and vacancy distributions.

## 7. *Conclusions*

Like most other aggregate functions in the macroeconomist's tool kit, the matching function is a black box: we have good intuition about its existence and properties but only some tentative ideas about its microfoundations. Yet, those tentative ideas have not been rigorously tested. They have been used only to provide justification for the inclusion or exclusion of variables from the estimation of aggregate or regional matching functions, leaving it to the empirical specification to come up with a convincing functional form.

The early aggregate studies converged on a Cobb-Douglas matching function with the flow of hires on the left-hand side and the stock of unemployment and job vacancies on the right-hand side, satisfying constant returns to scale, and with the coefficient on unemployment in the range 0.5–0.7. In some of the estimates that use total hires as dependent variable (not only hires from unemployment) the coefficient on unemployment is lower, in the range 0.3–0.4, and the coefficient on vacancies correspondingly higher. But estimation of both Beveridge curves and aggregate matching functions points also to other variables that influence the simple Cobb-Douglas relationship. Much of the estimation of matching functions in the last decade has looked for those other variables and for better empirical specifications. Micro studies suggest as additional variables the age structure of the labor force, the geographical dispersion of job vacancies and unemployed workers, the incidence of long-term unemployment (exceeding one year), and unemployment insurance; interestingly, however, although the other variables have been found significant where tested, unemployment insurance has not been identified as a significant influence on aggregate matching rates. We have argued that this may be related to measurement problems and the difficulty of getting reliable time series data for the generosity of unemployment insurance systems.

Recent empirical work has used disaggregate data and modeled the micro matching functions more carefully, paying attention to the issue of consistency between the timing of the flows and the timing of the stocks in the regressions, the regional spillovers in matching, and the consistency between the flow and stock variables, given the observation that many matches involve either employed workers or workers classified as out of the labor force. The precision of the estimation has increased and the relation between hazard function estimation and aggregate matching function

Illustration for Question C (https://doi.org/10.1016/j.pubecp.2021.100009)

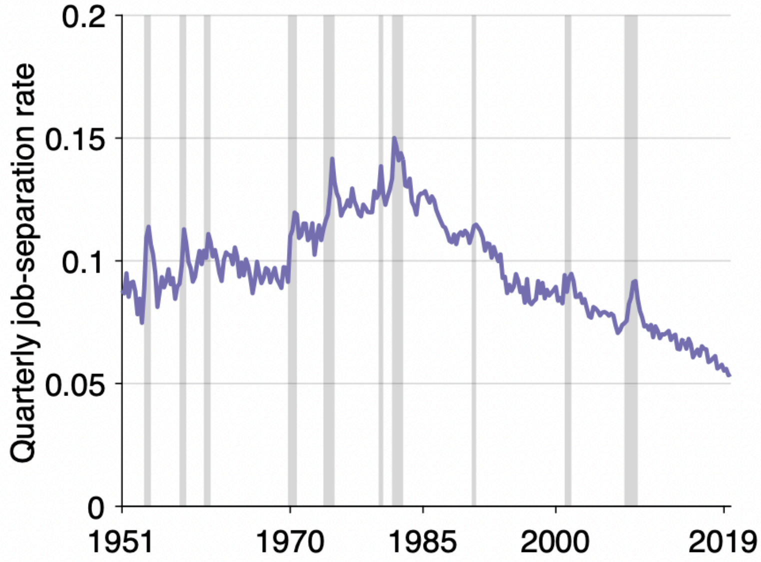
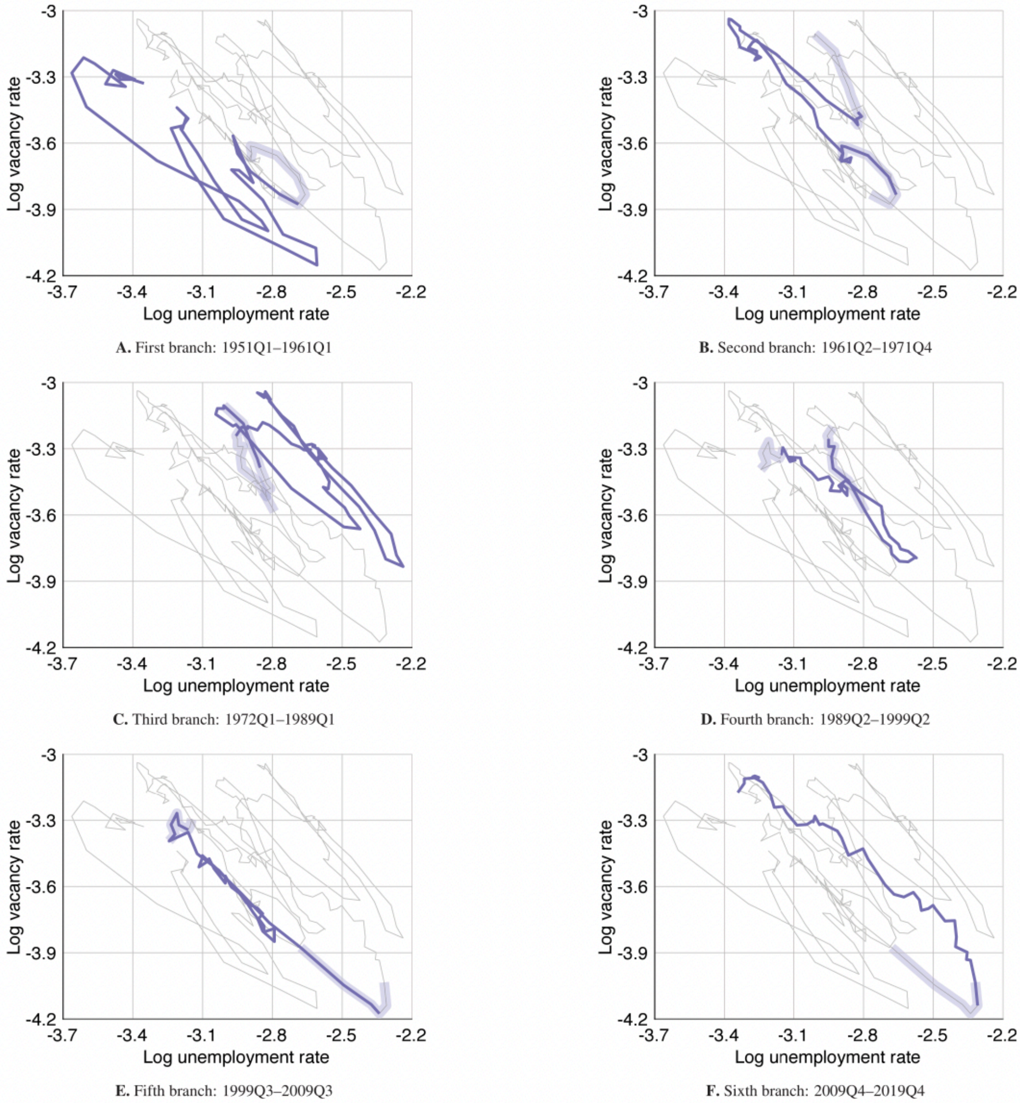



FIGURE A2. Job-separation rate in the United States, 1951–2019

Illustration for Question E (https://doi.org/10.1016/j.pubecp.2021.100009)




**A.** First branch: 1951Q1–1961Q1

**B.** Second branch: 1961Q2–1971Q4

**C.** Third branch: 1972Q1–1989Q1

**D.** Fourth branch: 1989Q2–1999Q2

**E.** Fifth branch: 1999Q3–2009Q3

**F.** Sixth branch: 2009Q4–2019Q4

**Fig. 5.** Beveridge-curve branches in the United States, 1951–2019. *Notes:* The Beveridge curve comes from Fig. 1. The number of structural breaks and their dates are estimated with the algorithm of Bai and Perron (1998, 2003). The 5 break dates delineate 6 Beveridge-curve branches. The wide, transparent lines depict the 95% confidence intervals for the break dates.

Illustration for Question F (https://doi.org/10.1257/mac.1.1.280)

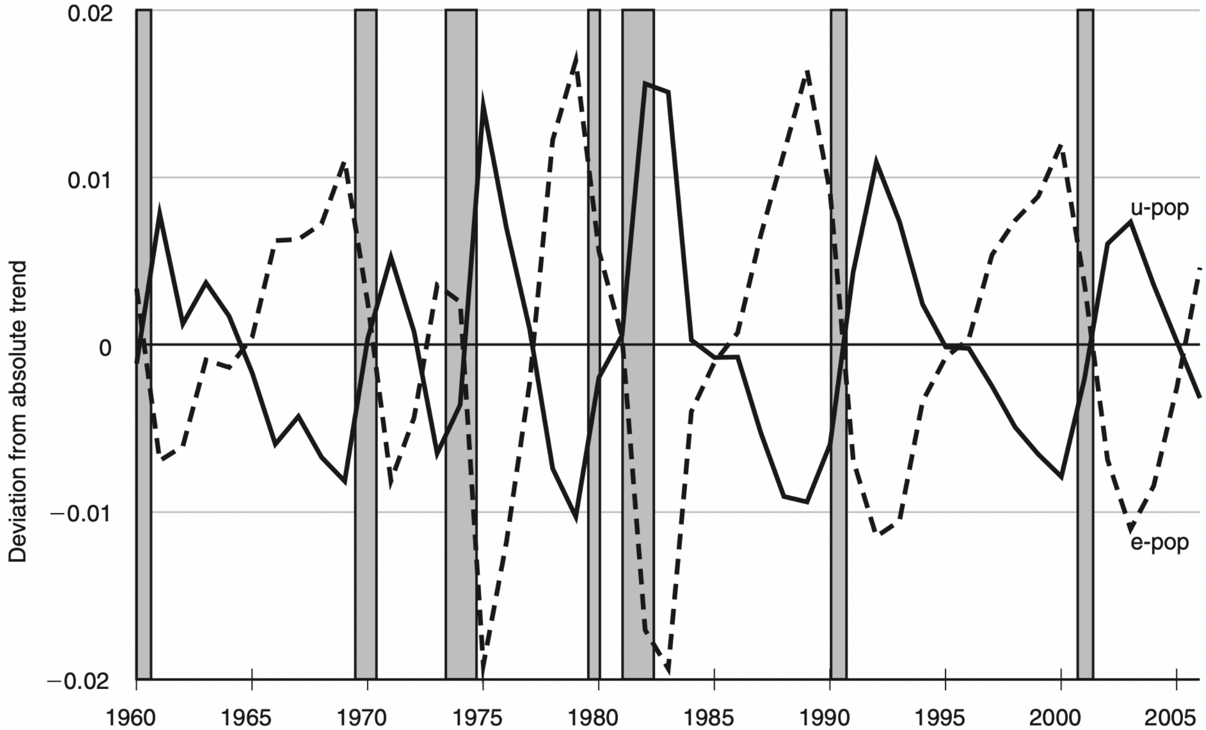



FIGURE 6

*Notes:* Deviation of the e-pop and u-pop ratios from trend, HP filter with parameter 100. The solid line shows the deviation of the u-pop ratio from trend, and the dashed line shows the deviation of the e-pop ratio. The gray bands show NBER recession dates.

Reference for Question I (https://web.stanford.edu/~boyd/cvxbook/bv_cvxbook.pdf)

### Scalar composition

We first consider the case $k = 1$, so $h : \mathbf{R} \to \mathbf{R}$ and $g : \mathbf{R}^n \to \mathbf{R}$. We can restrict ourselves to the case $n = 1$ (since convexity is determined by the behavior of a function on arbitrary lines that intersect its domain).

To discover the composition rules, we start by assuming that $h$ and $g$ are twice differentiable, with $\mathbf{dom}\, g = \mathbf{dom}\, h = \mathbf{R}$. In this case, convexity of $f$ reduces to $f'' \geq 0$ (meaning, $f''(x) \geq 0$ for all $x \in \mathbf{R}$).

The second derivative of the composition function $f = h \circ g$ is given by

$$f''(x) = h''(g(x))g'(x)^2 + h'(g(x))g''(x). \tag{3.9}$$

Now suppose, for example, that $g$ is convex (so $g'' \geq 0$) and $h$ is convex and nondecreasing (so $h'' \geq 0$ and $h' \geq 0$). It follows from (3.9) that $f'' \geq 0$, *i.e.*, $f$ is convex. In a similar way, the expression (3.9) gives the results:

$$\begin{array}{l} f \text{ is convex if } h \text{ is convex and nondecreasing, and } g \text{ is convex,} \\ f \text{ is convex if } h \text{ is convex and nonincreasing, and } g \text{ is concave,} \\ f \text{ is concave if } h \text{ is concave and nondecreasing, and } g \text{ is concave,} \\ f \text{ is concave if } h \text{ is concave and nonincreasing, and } g \text{ is convex.} \end{array} \tag{3.10}$$