THE BEVERIDGE CURVE AND OKUN'S LAW: A RE-EXAMINATION OF FUNDAMENTAL MACROECONOMIC RELATIONSHIPS IN THE UNITED STATES

by

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ABSTRACT

This thesis quantifies and interprets observed trends and cyclical fluctuations in the Beveridge Curve and Okun's Law in the U.S. economy.

The first three chapters investigate the sources of observed shifts in the U.S. aggregate Beveridge Curve since 1970. Previous authors have noted an outward shift of this curve in the 1970s, followed by an abrupt inward shift in the mid 1980s. These movements signify marked changes in the degree of structural unemployment in the U.S. economy since 1970.

Chapter 1 presents and simulates a multi-sector job-matching model. The model provides an analytical framework for interpreting these Beveridge curve shifts, and illustrates the importance of regional Beveridge curve analysis when attempting to identify any underlying changes in the labor market responsible for such shifts. The model demonstrates that aggregate Beveridge curve shifts are the result of changes in the sectoral distribution of labor demand, as well as changes in the efficiency of within-sector job-matching processes. The model shows that regional Beveridge curve analysis allows one to construct sectoral bivariate "mismatch indices." These indices can in turn be used to decompose aggregate Beveridge curve shifts into those accounted for by changes in the regional distribution of labor demand, and those due to changes in within-region job-matching efficiency. I compare the regional mismatch indices developed in this chapter with existing univariate and bivariate dispersion measures. I argue that the mismatch indices provide more accurate indicators of regional labor market influences on the aggregate Beveridge curve than the common dispersion measures. I also demonstrate that mismatch indices can be used to estimate unobserved regional job-matching function parameters.

U.S. regional Beveridge curve analysis has been precluded by the unavailability of either regional vacancy rate data, or appropriate proxy series. In Chapter 2, I develop proxy series for U.S. regional vacancy rates using help-wanted indices for 48 metropolitan statistical areas. I benchmark and adjust these indices so that they may be directly comparable both across regions and over time. Data from several job vacancy collection pilot projects suggest that the adjusted proxy series accurately track time-series and cross-sectional variation in vacancy rates.
Chapter 3 uses these vacancy rate proxy series to study the relationship between U.S. regional and aggregate Beveridge curves since 1970. Confirming previous research, I find that the aggregate Beveridge curve shifted significantly outward in the 1970s and early 1980s, and shifted back in during the late 1980s. I compute regional mismatch indices and conclude that changes in the regional distribution of labor demand are not responsible for these aggregate Beveridge curve shifts. Changes in within-region job-matching efficiency, which resulted in regional Beveridge curve shifts, are primarily responsible for aggregate curve shifts. The regional mismatch indices also suggest that both aggregate and regional job-matching functions exhibit constant returns to scale in U.S. labor markets.

Chapter 4 argues that Okun's Law in the U.S. economy, as it is currently defined, is not a very good "law" at all. My argument is not based on the usual caveat that Okun's Law is merely an empirical regularity, so that the relationship between real GNP growth and unemployment rate changes deviates randomly from that implied by the Okun's Law coefficient. Rather, I argue that the Okun's Law coefficient demonstrates systematic, and not random, fluctuations. I find that these fluctuations are dependent on the state of the business cycle. Using post-war U.S. data, I estimate economically and statistically significant differences in the Okun's Law coefficient in growth cycle expansions and contractions, as well as in cycle trough and peak periods. I show that the relationship between aggregate employment growth and real GNP growth also depends on the state of the business cycle. I develop a growth-accounting framework to interpret the observed state dependence in Okun's Law. I show that cyclical substitution of alternative inputs in the production process, as well as a non-constant relationship between multi-factor productivity growth and output growth, can explain this state dependence. I find little evidence of cyclical production input substitution in the U.S. economy. However, I argue that unobserved labor hoarding behavior, which is a form of cyclical factor substitution, might be responsible for observed state dependence in Okun's Law. In the final section, I argue that business cycle state dependence in Okun's Law or the aggregate production function, may provide new evidence on the empirical validity of alternative models of business cycle fluctuations.

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CHAPTER 1: BEVERIDGE CURVES AND AGGREGATE UNEMPLOYMENT:
A FRAMEWORK FOR ANALYSIS
I. THE BEVERIDGE CURVE, MISMATCH, AND UNEMPLOYMENT: AN INTRODUCTION

Economists have found it useful to decompose aggregate unemployment fluctuations into those resulting from "structural" or "frictional" changes in the labor market, and those caused by cyclical movements in aggregate labor demand. Structural unemployment is the result of rigidities in the job-matching process. The labor market consists of heterogeneous jobs and workers, so that employers and potential employees must search for mutually-beneficial matches. Job and worker heterogeneity implies that this search is time-consuming, resulting in unemployment as workers and jobs are reallocated among different sectors of the economy.¹ As the match between potential employees and job vacancies in terms of skill requirements, employee preferences, or geographic location worsens, structural unemployment increases. Structural unemployment is not due to a lack of available jobs; it arises when jobs are not instantaneously matched with the available supply of unemployed workers.

On the other hand, "demand-deficient" unemployment results when the number of available jobs is low relative to the stock of unemployed workers. Unemployment attributed to a lack of job vacancies is often called "cyclical" unemployment, as it may result from a cyclical downturn in the economy. If there are wage and/or price rigidities, or informational asymmetries, the labor market may not clear at its full-information, full-employment level in the short run, and downward shifts in labor demand increase unemployment.²

The co-movement of unemployment and job vacancy rates, labeled the Beveridge curve, is thus an informative empirical relationship when attempting to identify the sources of aggregate unemployment.³
Increases in unemployment for a given number of job vacancies signify increasing mismatch between unemployed workers and available jobs, and thus increases in structural unemployment. In contrast, increases in unemployment associated with declining job vacancies signify a downturn in labor demand, and thus increases in cyclical unemployment.

A simple example adapted from Mincer (1966) and Yellen (1989) helps to illustrate this point. Suppose that cyclical changes in labor demand move unemployment and vacancies so that the aggregate Beveridge curve is well-approximated by a rectangular hyperbola of the form $uv = k$. $u$ is the unemployment rate, $v$ is the vacancy rate, and $k$ is a parameter. This locus is downward-sloping and convex to the origin in $u$-$v$ space. Points along this curve with high (low) $v/u$ ratios correspond to periods with high (low) cyclical labor demand. The parameter $k$ determines the position of this curve. Increases in $k$ shift the curve away from the origin, implying higher unemployment at any level of job vacancies. $k$ can thus be interpreted as an index of structural mismatch between available jobs and unemployed workers in the economy.

Figure 1-1 illustrates two Beveridge Curves of this form, with different indices of structural mismatch ($k$). Suppose the economy is at point $(u_1,v_1)$ in one period, and moves to point $(u_2,v_2)$ in the next. To decompose the increase in the unemployment rate from $u_1$ to $u_2$ into cyclical and structural components, one must first impose a restriction on the effect changes in $k$, the structural mismatch shock which shifts the Beveridge curve, have on $u$ and $v$. Blanchard and Diamond (1989) present a job-matching model in which such shocks move $u$ and $v$ along a 45-degree line from any point on the original
Beveridge curve. With this assumption, the increase in unemployment from \( u_1 \) to \( u^* \) is identified as the structural change due to increased mismatch, while \( u_2 - u^* \) is the increase due to movements along the Beveridge curve as a result of a cyclical decline in aggregate labor demand. Without information on job vacancies, one could not tell if the increase in unemployment, \( u_2 - u_1 \), was due only to a cyclical disturbance (which would imply that the economy was at point \((u_2,v_3)\) in the second period), a purely structural shock (the economy would be at point \((u_2,v_4)\) in the second period), or some combination of both \((v \) would be between \(v_3\) and \(v_4\)). Information on job vacancies, along with the identifying assumption regarding structural shock effects on \( u \) and \( v \), allows a precise decomposition.\(^5\)

Recent papers by Abraham (1987) and Blanchard and Diamond (1989), using the Conference Board's help-wanted advertising index as a proxy for job vacancies, can be thought of as more sophisticated attempts to decompose aggregate unemployment movements in the United States along these lines.\(^6\) Blanchard and Diamond (1989) find that cyclical shocks account for most of the short and medium run movements in U.S. unemployment, while "reallocation" or mismatch shocks dominate movements in the long run, accounting for a two percentage point increase in the unemployment rate from 1960 to 1984, and a one percentage point decrease from 1984 to 1988. Abraham (1987) provides evidence that mismatch shocks may be an important determinant of increases in unemployment in the U.S. economy throughout the 1970s.

Such evidence is important when formulating policies designed to mitigate unemployment. If unemployment is primarily due to labor demand deficiencies, the government might consider the following
policy options: (1) If wage and price rigidities are prevalent in the labor and goods markets, traditional countercyclical aggregate demand policies are called for; (2) Alternatively, the government may design policies intended to limit wage rigidity and informational asymmetries in the labor market, so that the labor market is more likely to clear at its full-information equilibrium level. Structural unemployment, on the other hand, suggests policies designed to improve the matching process between existing and forecasted job vacancies and the unemployed. These policies include education and training programs, worker relocation assistance, tax incentive programs to draw potential employers to areas with surplus labor, dislocated worker assistance programs, and active involvement in the job-matching process through government employment agency services.

From a policy-making point of view, however, existing unemployment decomposition exercises in the U.S. have been inadequate. As noted above, structural unemployment may result from skill, preference, or geographical mismatch between available jobs and the unemployed. Alternative sources of structural unemployment raise different policy concerns. For example, an upgrading of skill requirements across all industrial sectors might suggest the need for financial support for education and training programs. On the other hand, a terms of trade shock that leads to layoffs concentrated in a particular industry and geographic area of the country could be met with worker and/or business relocation assistance programs.

To identify the sources of fluctuations in structural unemployment as represented by shifts of the aggregate Beveridge curve, a more disaggregated study of industrial, occupational, and/or
regional Beveridge curves is necessary. A simple example illustrates the added information disaggregated analysis provides. Assume that in all sectors of the economy changes in labor demand result in Beveridge curves of the form \( uv = k \), as illustrated in Figure 1-2. If labor demand is distributed across sectors so that all sectors are at the same point on the curve, the aggregate Beveridge curve will be of the same form. What then leads to shifts in the aggregate curve? First, any changes in \( k \), which shift the sectoral curves, also shift the aggregate curve. An increase in \( k \) at the sectoral level represents decreased efficiency in the within-sector job-matching process. Policies to combat unemployment created by such a shift need not be concerned with specialized programs designed to increase labor and job mobility across sectors. Instead, policies should focus on improving the efficiency of within-sector job-matching processes. Examples of such policies include educational reforms, employment service matching programs, and reforms in the unemployment insurance system.

The convexity of the sectoral Beveridge curves in this example suggests that dispersion in labor market outcomes across sectors also leads to outward shifts of the aggregate curve. Suppose aggregate labor demand is unchanged, but is redistributed so that labor demand is relatively high in certain sectors of the economy, while it is low in other sectors. If labor is immobile between sectors\(^7\), the high labor demand sectors move to points like A on the Beveridge curve, with high \( v/u \) ratios, while the low demand sectors move to points like B, with low \( v/u \) ratios. The aggregate vacancy and unemployment rates are given by a point like C, which lies to the right of the identical, convex regional curves. Mismatch between the sectors in which jobs
are available and the unemployed are concentrated, coupled with limited labor mobility across sectoral boundaries, serves to shift the aggregate Beveridge Curve out.\(^8\)

Structural unemployment created by mismatch across, and not within sectors, might call for specialized worker and job relocation programs, and not necessarily general programs to improve within-sector job-matching efficiency. By studying shifts in sectoral Beveridge curves over time, as well as dispersion in labor market outcomes across sectors, economists may be allowed a more precise understanding of the determinants of any observed shifts in the aggregate curve. Economists may then identify the appropriate policy responses to any observed increases in structural unemployment.

These considerations have sparked a great deal of research on the co-movement of unemployment and vacancies at the regional, occupational, and industrial levels in European economies.\(^9\) In general, these studies have concluded that outward shifts of aggregate European Beveridge curves cannot be explained by unemployment and vacancy mismatch across different sectors of the economy. The aggregate curve movements have been driven by outward shifts of sectoral curves.

In the U.S., papers by Abraham (1987) and Blanchard and Diamond (1989) have documented outward shifts of the aggregate Beveridge curve during the 1970s, followed by a pronounced inward shift starting in the mid 1980s. However, with the exception of a brief exploratory analysis in Abraham (1987), economists have not conducted more disaggregated Beveridge curve analyses to identify the sources of shifts in the aggregate curve. Detailed sector-specific study of
Beveridge curves in the U.S. has been precluded by the unavailability of sectoral job vacancy proxy variables.

A major goal of my dissertation research is to overcome these data limitations. In the next chapter, I argue that it is possible to construct reliable proxy series for vacancy rates at the regional level in the U.S., using information from the Conference Board's help-wanted indices for 51 metropolitan statistical areas as my starting point. Construction of these proxy variables allows for the first time a comprehensive study of the importance of geographical unemployment and vacancy mismatch in driving observed shifts in the aggregate Beveridge curve.

In the remainder of this chapter, I present and simulate a simple multi-sector job-matching model of the determinants of regional and aggregate unemployment and vacancy rates. This modeling exercise provides a systematic demonstration of the information on the determinants of aggregate labor market outcomes that follows from careful analysis of regional Beveridge curves. The exercise also allows the development of "mismatch indices," along the lines of Jackman, Layard, and Savouri (1987, 1990), that are grounded in sound economic theory. Furthermore, simulations of the model identify the potential importance of geographical unemployment and vacancy mismatch in explaining aggregate Beveridge curve shifts.

The modeling exercise attempts to make three main points about the informational content of regional Beveridge curve analysis: (1) Measures of geographic mismatch, such as those presented in Jackman, Layard, and Savouri (1990), require information on regional unemployment and vacancy rates at any point in time, as well as
information on the within-region co-movement of these variables over time (i.e., the form of regional Beveridge curves). Univariate regional labor market variable "dispersion" measures, such as those presented in Abraham (1987) or Lilien (1982), are not adequate measures of regional mismatch. (2) Regional mismatch indices that do not take into account possible heterogeneity in regional job-matching processes may provide a distorted picture of fluctuations in mismatch-generated unemployment. For example, the Jackman, Layard, and Savouri (1990) indices assume that the functions determining job-matching processes in different regions are positive monotonic transformations of one another, which has the further implication that all regional Beveridge curves are of the same form. I develop a new mismatch index which allows for heterogeneity in regional job-matching functions, and demonstrate that time-series movements in this index may not closely match those exhibited by the Jackman, Layard, and Savouri (1990) indices. Ultimately, whether this is an important methodological point depends on the degree of heterogeneity in regional job-matching functions and Beveridge curves. This heterogeneity cannot be measured without regional vacancy rate data or proxy series. (3) Regional mismatch indices, along with aggregate matching function estimates, can be used to recover estimates of returns to scale in regional job-matching functions. Theory suggests that job-matching functions should exhibit increasing returns to scale in "island" economies (see Diamond (1982)). If the aggregate labor market consists of many sectoral labor markets with impermeable boundaries in the short run, then these sectoral markets are "island" economies, while the aggregate market is not. This implies that
estimates of returns to scale in these sectoral markets are required to conduct an appropriate test of the Diamond (1982) prediction. It also suggests that estimates from Blanchard and Diamond (1989), showing constant or only slightly increasing returns to scale in the aggregate matching function, do not provide strong evidence against the increasing returns hypothesis. The unavailability of regional hires data has precluded estimation of regional matching functions in the U.S. I demonstrate that mismatch indices can be used to identify regional matching function parameters without the use of disaggregated hires data. Construction of regional mismatch indices thus allows for a cleaner test of the Diamond (1982) prediction than has been previously possible using U.S. data.

In sum, the remaining sections of this chapter serve two purposes: (1) They illustrate the unique information available from study of regional vacancy rates and Beveridge curves, thus pointing out the need for regional vacancy rate proxy series in the U.S. The chapter therefore serves as a justification for the extensive data collection and refinement exercise described in Chapter 2. (2) They highlight the empirical exercises that can be undertaken when appropriate vacancy rate data are available. They thus serve as a guide to Chapter 3's investigation of the empirical importance of geographic mismatch in explaining observed shifts in the U.S. aggregate Beveridge curve.
II. UNEMPLOYMENT AND VACANCIES IN A SECTORAL LABOR MARKET

This section describes a very simple model of a sectoral labor market. The model is related to earlier work by Holt and David (1966), Hansen (1970), Pissarides (1985), and Blanchard and Diamond (1989). Except for minor differences in interpretation and emphasis, it is identical to models presented by Ball (1990) and Jackman, Layard, and Savouri (1990).

The main features of the model include: (1) The lack of a centralized allocation mechanism to match unemployed workers with job vacancies. This implies that firms with job vacancies must identify appropriate applicants, while unemployed individuals must locate firms with job openings. (2) An exogenously determined labor force. This assumption is made for expositional ease, and precludes the study of possible labor migration between sectors in response to divergent labor market outcomes. While relaxing this assumption would allow a much richer description of local labor market dynamics, the mismatch indices developed below are independent of this assumption.\textsuperscript{10} (3) An exogenously determined, fluctuating labor demand. (4) The model ignores wage determination, with the implicit assumption that wages do not play an allocational role in matching workers and jobs (see Blanchard and Diamond (1989) for a discussion of this assumption).\textsuperscript{11,12}

I assume there are L potential workers in the labor force, of which E are employed, and L-E = U are unemployed. At any point in time, there are J productive jobs in the regional market. F of those jobs are filled, and J-F = V are job vacancies. F = E, so job vacancies in the economy are given by J-E.

At any point in time, some proportion of productive jobs become
unproductive, leading to layoffs as well as decreases in job vacancies. At the same time, new jobs are being created which increase job vacancies. For simplicity, I assume that productive job destruction and job creation rates are identical and equal to \( r \). \( rJ \) new vacancies are created each period, while \( rJ \) productive jobs are destroyed, resulting in \( rE \) layoffs and \( rV \) less vacancies.\(^{13}\) \( r \) is therefore a measure of the reallocation rate of jobs among different firms, plants, industrial, or occupational categories.

If there was a centralized mechanism to instantaneously match job vacancies and the unemployed, and if all jobs and workers were homogeneous, employment would always be given by the minimum of \( L \) and \( J \), while job vacancies would be the maximum of \( 0 \) and \( J-L \). Without such an allocation mechanism, however, unemployed workers must search for vacancies, while vacancies must in turn search for unemployed workers. In the literature on search markets, it is standard practice to assume that the number of successful matches is an increasing function of the number of "searchers" on each side of the market. In this model, this implies that "matches," or hires, should be an increasing function of \( U \) and \( V \). Following Ball (1990) and Jackman, Layard, and Savouri (1990), I assume a Cobb-Douglas matching function:

\[
(1-1) \quad H = hu^aw^b \\
\quad \text{with } 0 < a, b < 1 \\
\quad U = L-E \\
\quad V = J-E \\
\quad H = \text{hires} \\
\quad h = \text{"matching efficiency" parameter}
\]

As \( h \) rises, a given amount of unemployment and vacancies leads to more matches, and thus signals an increase in the efficiency of the
search process. With heterogeneous workers and jobs, an increase in h may represent a better match between skill requirements of available jobs and the unemployed, increased search intensity of workers or employers (which could result from changes in the unemployment compensation system on the workers' side, or from changes in the product market on the employers' side), or an actual increase in the efficiency of the search process brought on by the growth of intermediaries in the market which provide matching or labor market informational services (i.e., employment agencies or "head hunters").

A word on the form of the hiring function is in order. As Jackman, Layard, and Savouri (1987) point out, it is not merely an ad-hoc specification, as it can be considered a logarithmic approximation to the matching function derived by Hall (1977). The only restriction I impose on returns to scale is that the function is concave in \( U \) and \( V \). The concavity assumptions \( 0 < a, b < 1 \) imply that the expected duration of unemployment \( (U/H) \) increases with the stock of unemployed workers and decreases with vacancies, while the expected duration of vacancies \( (V/H) \) decreases with unemployment and increases with vacancies. The function also implies that the number of hires approaches zero as either unemployment or vacancies approaches zero. Finally, Blanchard and Diamond's (1989) estimates of the aggregate U.S. matching function suggest that the elasticity of substitution between unemployment and vacancies is approximately one.14

The model's assumptions imply that unemployment and vacancy dynamics are governed by the following differential equations:

\[
(1-2) \quad U = r(L-U) - hU^aV^b
\]
(1-3) \[ V = rJ - rV - hU^aV^b \]

Workers flow into unemployment as productive jobs become unproductive and layoffs ensue. Layoffs are given by the job destruction rate multiplied by employment. Hires, as given by the sectoral job-matching function, determine the flow out of unemployment. Vacancies increase as new jobs are created at rate \( r \). Vacancies decline as previously productive vacancies become unproductive and firms discontinue their search for potential employees (once again at rate \( r \)), and as workers are hired to fill existing job openings.

Steady-state values of \( U \) and \( V \) must satisfy the following condition:

(1-4) \[ r(L-U) = hU^aV^b \]

Changes in labor demand, \( J \), for a given \( r \), move steady-state \( U \) and \( V \) so that a negatively-sloped, convex to the origin, locus results. High values of \( J \) require high steady-state \( V/U \) ratios, while lower \( J \) values are associated with lower \( V/U \) ratios. I call this steady-state relationship between \( U \) and \( V \) for alternative values of \( J \) the regional "Beveridge curve."

In what follows, I use the alternative steady-state relationship given by Equation (1-5):

(1-5) \( \gamma L = hU^aV^b \)
This is the steady-state condition studied by Jackman, Layard, and Savouri (1990). This condition provides a good approximation for Equation (1-4) when the unemployment rate is low. I prefer this specification for two reasons. First, it greatly simplifies the analytical exercises presented in this chapter. Second, by using the Jackman, Layard, and Savouri (1990) framework, geographic mismatch indices developed in this chapter are directly comparable to those presented in previous research.

The steady state given by Equation (1-5) also implies a negatively-sloped, convex Beveridge curve in U-V space as labor demand changes for a given γ. Totally differentiating Equation (1-5) with respect to J and U, I obtain the slope of the Beveridge curve in U-V space:

\[(1-6) \quad \frac{dV}{dU} = -\frac{aV}{bU} \]

The absolute value of this slope is increasing in V, and decreasing in U, indicating a convex locus.

A positive γ shock, indicating an increase in within-region job reallocation, increases steady-state U and V by the same amount, implying that the Beveridge curve shifts out along a 45-degree line in U-V space. This follows easily from the assumption that J and L are given, so that \( dV/d\gamma = dU/d\gamma = -\frac{aE}{d\gamma}. \) By the same logic, a change in the matching efficiency parameter, h, also shifts the Beveridge curve along a 45-degree line. A decline in h shifts the Beveridge curve outward, while an increase shifts it inward.
A high value of $\gamma$ implies that the job reallocation rate is high, so that the flow of new vacancies and unemployment in any period in the steady state is relatively large. If unemployment and vacancies are to be held constant, a large outflow of unemployed workers into vacant jobs is required every period. This outflow requires a relatively "thick" job-search market, with many unemployed workers and vacant jobs, so that the number of matches (hires) is high in every period. Using the same logic, a less efficient matching process (lower $h$) requires a thick job-search market to fill vacancies as they are created at the steady-state rate, $r$.

The main features of this model can be summarized as follows: (1) Changes in steady-state labor demand produce a negatively-sloped, convex Beveridge curve. (2) Changes in within-region job reallocation rates or job-matching efficiency shift this Beveridge curve.  

It is worth mentioning the dynamics of the model, even though my focus will be on these steady-state properties in what follows. Equations (1-2) and (1-3) imply that $U$ and $V$ are always moving along a 45-degree line in $U$-$V$ space, except in the instant a labor demand shock hits the economy. For example, an increase in $J$ immediately increases $V$, and then unemployment and vacancies decline along a 45-degree line into the new steady state with higher vacancies and lower unemployment. Vacancies are the "jump" variable in response to labor demand increases, reacting immediately to an increase in labor demand. Unemployment, on the other hand, cannot change until the hiring process for these new vacancies commences. Vacancies are created the instant $J$ increases. Since flows out of employment remain at $rE$ the instant $J$ increases, and flows into employment only increase
after the increase in vacancies spurs hiring activity, employment increases only after positions start to be filled. Thus employment cannot "jump" upward the moment J increases. For a decrease in labor demand, both U and V are "jump" variables. Vacancies, as well as filled positions, can be destroyed instantaneously, leading to immediate decreases in V and increases in U. Flows out of employment can increase the instant J decreases, but cannot decrease the instant J increases. Decreases in employment are not constrained by a "firing function," while increases are constrained by a "hiring function." Thus employment can "jump" downward the moment J decreases.\textsuperscript{18} For a decrease in J, the model merely predicts that U and V jump to a point so that movement along a 45-degree line in U-V space leads to the new steady-state point on the Beveridge curve. How much unemployment increases as an immediate response to the negative labor demand shock depends on institutional factors such as layoff notification policies. Reallocation rate and matching efficiency shocks move U and V along a 45-degree line to the new steady-state point, just as in Blanchard and Diamond (1989).

In the next section, I consider an economy with several regional labor markets like the one described in this section, and characterize the relationship between regional and aggregate Beveridge curves.
III. THE RELATIONSHIP BETWEEN REGIONAL AND AGGREGATE BEVERIDGE CURVES

Suppose an economy is made up of \( N \) separate regional labor markets, each with a Beveridge curve given by the following steady-state relationship:

\[
(1-7) \quad \gamma_i L_i = h_i U_i^{a_i} V_i^{b_i} \quad \text{where} \quad i = 1, \ldots, N, \quad \text{is a regional index.}
\]

Given these regional curves, a Beveridge curve which relates aggregate unemployment to aggregate vacancies can be derived. In this section, I address the following questions: (1) What form does this aggregate Beveridge curve take when there is an efficient allocation of aggregate labor demand across regions, in the sense that aggregate unemployment is minimized for a given level of aggregate vacancies, and given regional \( \gamma_i', h_i', \) and \( L_i' \)? (2) Once this "efficient" Beveridge curve is identified, is it possible to obtain a measure of the proportion of total unemployment for a given level of aggregate vacancies that can be attributed to inefficient allocations of labor demand across regions? In other words, can one derive a quantitative measure of the importance of geographic mismatch in determining the aggregate unemployment rate and the position of the aggregate Beveridge curve?

Let \( U \) be aggregate unemployment, and \( V \) aggregate vacancies. In order to determine the efficient allocation of labor demand across regions, I solve the following problem:
(1-8) \[ \text{Min} \sum_{i=1}^{N} U_i \quad \text{subject to:} \quad \gamma_i L_i = h_i^{a_i} V_i^{b_i}, \quad V_i \]

\[ \sum_{i=1}^{N} V_i = V \]

Using the steady-state constraints to solve for the \( U_i \) as functions of \( V_i, L_i, \gamma_i, \) and \( h_i \), I restate this problem as:

(1-9) \[ \text{Min} \sum_{i=1}^{N} \left[ \frac{(\gamma_i L_i)}{(h_i V_i)} \right]^{(\epsilon/ a_i)} \quad \text{subject to:} \quad \sum_{i=1}^{N} V_i = V \]

\( \lambda \) is the lagrange multiplier associated with the aggregate vacancies constraint.

The first-order conditions for this problem consist of the constraint function listed in (1-9), as well as Equation (1-10):

(1-10) \[ \frac{-b_i U_i}{a_i V_i} = \lambda, \quad \forall i \]

Beveridge curve slopes are equal in all regions with an efficient cross-sectional distribution of productive jobs (see Equation (1-6)). This in turn implies that marginal rates of technical substitution between vacancies and unemployment in creating hires in the job-matching process are equal across regions. Points along this "efficient" Beveridge curve require productive efficiency in the aggregate job-matching process.

I demonstrate later in this section that as long as regional matching functions are positive monotonic transformations of each other, the efficient Beveridge curve is of the following Cobb-Douglas form:
\[(1-11) \quad u^* v^b = K \quad \text{where} \quad u = \text{aggregate unemployment rate} \]
\[v = \text{aggregate vacancy rate} \]
\[K = \text{parameter which shifts the curve} \]
\[\text{in } u-v \text{ space} \]

If regional matching functions are not positive monotonic transformations of each other, then the efficient Beveridge curve is generally not of this Cobb-Douglas form. However, the efficient Beveridge curve that is drawn out by small changes in labor demand around any original level of aggregate labor demand is always well-approximated by a curve of this form. I discuss the determinants of the parameters \(a^* \) and \(b^* \) later in this section.

Since an efficient regional allocation of labor demand requires that regional Beveridge curve slopes at any given time are equal to some constant \(\lambda \), the slope of the efficient aggregate curve at that time must also equal \(\lambda \). If this efficient curve takes the form given by Equation (1-11), this implies:

\[(1-12) \quad \frac{-b^*U}{a^*V} = \lambda \]

Assuming that the efficient Beveridge curve can be approximated by Equation (1-11), I now develop a geographic mismatch index. This index measures the proportion of aggregate unemployment given vacancies that is attributable to inefficient allocations of labor demand across regions. First, I divide both sides of Equation (1-7) by \(h_i^* \), and sum over all regions to obtain:
\[
(1-13) \quad \Sigma_{i=1}^{N} (L_i \gamma_i / h_i) = \Sigma_{i=1}^{N} U_i^{s_i,v_i^{b_i}}
\]

I then divide both sides of Equation (1-13) by \(L_i^{s_i+b_i}\), where \(L\) is the aggregate labor force, and multiply and divide the right-hand side by \(u_i^{s_i}v_i^{b_i}\), to rewrite this as:

\[
(1-14) \quad \Sigma_{i=1}^{N} \left( f_i \gamma_i / h_i \right) = \left[ \Sigma_{i=1}^{N} U_i^{s_i,v_i^{b_i}} / U_i^{s_i,v_i^{b_i}} \right] \ast u_i^{s_i}v_i^{b_i}
\]

where \(f_i = \frac{L_i}{L_i^{s_i+b_i}}\)

Let the left-hand side of Equation (1-14) be \(s^*\). \(s^*\) is a linear combination of the job reallocation rates and job-matching efficiency parameters which determine the position of each regional Beveridge curve. As \(\gamma_i\) increase, or \(h_i\) decrease, leading to outward shifts of regional Beveridge curves, \(s^*\) increases. Let the term in brackets on the right-hand side of Equation (1-14) be \(g_{mm}^*\). \(g_{mm}^*\) depends on the distribution of \(U\) and \(V\) across regional markets.

I combine Equations (1-11) and (1-14) to obtain:

\[
(1-15) \quad u_i^{s_i}v_i^{b_i} = K = s^* / g_{mm}^*
\]

Given the definition of the efficient aggregate Beveridge curve, \(g_{mm}^*\) must be evaluated with a regional allocation of aggregate labor demand so that Equation (1-10) holds. It is easy to show that \(g_{mm}^*\) reaches its maximum value when aggregate labor demand is distributed in this manner.\(^{19}\) Equation (1-15), evaluated at \(g_{mm}^*\)’s maximum value, implicitly defines \(a^*\) and \(b^*\).
It is now possible to identify the factors leading to shifts in the aggregate Beveridge curve. First, the aggregate Beveridge curve shifts out whenever the efficient curve given by Equation (1-15) shifts out. Increases in within-region job reallocation rates, or decreases in within-region matching efficiency parameters, shift out regional curves, increase $s^*$, and thus lead to outward shifts of the efficient curve as well. Second, the aggregate Beveridge curve shifts whenever the regional distribution of aggregate labor demand changes so that $gmm^*$ changes. As $gmm^*$ decreases away from its maximum value, increased inefficiency in the aggregate job-matching process leads to outward shifts of the aggregate Beveridge curve, while increases in $gmm^*$ indicate increased efficiency in this process and lead to inward shifts of the aggregate curve.

The ratio of the actual aggregate unemployment rate, given $v$ and $s^*$, to the unemployment rate that would be observed if the economy was on its efficient Beveridge curve is given by Equation (1.16):

\[(1.16) \quad u/u_{\text{min}} = \left[\frac{gmm^*}{gmm_{\text{max}}}\right] (1/s^*)\]

where $gmm_{\text{max}}$ = maximum value of $gmm^*$

$u_{\text{min}}$ = $u$ that would be observed, given $s^*$ and $v$, if $gmm^* = gmm_{\text{max}}$

$u/u_{\text{min}}$ is my geographic mismatch index, as it provides a measure of the horizontal shift of the aggregate Beveridge curve that is accounted for by an inefficient regional distribution of labor demand. By tracking $u/u_{\text{min}}$ over time, one can decompose any observed shifts in the aggregate Beveridge curve into those driven by shifts of the regional curves (changes in $s^*$), and those due to shifts in the
regional distribution of unemployment and vacancies (changes in $g_{mm}^*$).

I now consider the specific form of the efficient Beveridge curve, including the determinants of $a^*$, $b^*$ and $g_{mm}^*$, under alternative assumptions regarding returns to scale in the regional matching functions. I also focus on how these values are affected by cross-sectional variation in the matching function parameters, $a_i$ and $b_i$. By calculating explicit values for these parameters, the unemployment rate decompositions suggested by Equation (1-16) become feasible empirical exercises.

CONSTANT RETURNS TO SCALE REGIONAL MATCHING FUNCTIONS THAT ARE MONOTONIC TRANSFORMATIONS OF ONE ANOTHER

I first consider the simplest case in which all regional job-matching functions exhibit constant returns to scale ($b_i = 1 - a_i$), and all functions are monotonic transformations of one another ($a_i = a_j = a, \forall i,j$). This is the assumption used by Jackman, Layard, and Savouri (1987,1990). Equation (1-10) thus implies that $g_{mm}^*$ is maximized when $V/U$ ratios are constant in all regions. Solving for $V_i$ in Equation (1-10), and summing over all regions, I find:

\[(1-17) \quad V/U = (1-a)\lambda/a\]

Equations (1-12) and (1-17) imply that $a^*/b^* = a/(1-a)$, and $V_i/U_i = V/U$ for all $i$, when there is an efficient regional distribution of aggregate labor demand.

Assume $a^* + b^* = 1$, implying that $a^* = a$. A necessary and
sufficient condition for identifying $\alpha^* = a$ and $\beta^* = 1 - a$ as the parameters of the efficient aggregate Beveridge curve is that $u^a v^{1-a} = s^*/\gamma_{\text{max}}^*$, when $\gamma_{\text{max}}^*$ is evaluated with $\alpha^* = a$ and $\beta^* = 1 - a$. I find that $\gamma_{\text{max}}^*$ is equal to one with these parameter assumptions, implying that $u^a v^{1-a}$ must equal $\sum (L_i \gamma_i / h_i)$ if these are the correct parameters. Note that $L_i \gamma_i / h_i = (U_i / V_i)^a V_i$ for all $i$. Since the efficiency conditions imply $U_i / V_i = U / V = \text{some constant C}$ for all $i$, this sum is equal to $C^a V$. This is in turn equal to $u^a v^{1-a}$, which proves that these are in fact the correct parameters for the efficient aggregate Beveridge curve. The efficient aggregate curve in this case is of the same form as each of the regional curves.

In an economy where regional matching functions exhibit constant returns to scale and are monotonic transformations of one another, the aggregate Beveridge curve shifts out when regional $V/U$ ratios diverge. Since $\gamma_{\text{max}}^*$ is equal to one, the $u/u_{\text{min}}$ ratio in this economy is equal to $[\gamma_{\text{max}}^*]^{-(1/a)}$, where $\gamma_{\text{max}}^*$ is given by Equation (1-18):

\[
(1-18) \quad \gamma_{\text{max}}^* = \sum_{i=1}^{N} ((U_i / U)^a (V_i / V)^{1-a})
\]

Jackman, Layard, and Savouri (1990) show that the log of this $u/u_{\text{min}}$ ratio can be approximated by:

\[
(1-19) \quad \log(u/u_{\text{min}}) \approx 0.5a(\sigma_{v1/v}^2 + \sigma_{u1/u}^2 - 2 \rho_{u1/v} \sigma_{u1/u} \sigma_{v1/v})
\]

where $\sigma_{v1/v}$ = standard deviation of regional vacancy rates relative to the aggregate rate
$\sigma_{u1/u}$ = standard deviation of regional unemployment rates relative to the aggregate rate
$\rho_{u1/v}$ = correlation coefficient of $u1/u$ and $v1/v$
Equation (1-19) demonstrates that univariate measures of dispersion in either unemployment rates or vacancy rates provide inadequate measures of geographic mismatch effects on aggregate unemployment and the Beveridge curve. Univariate measures are correct only if regions are identical in all aspects affecting the slopes and positions of the regional Beveridge curves, including job reallocation rates and job-matching efficiency parameters. For example, suppose one region is dominated by industries with particularly high job reallocation rates, leading to higher equilibrium unemployment and vacancy rates at any level of labor demand, while all other regions are identical. Suppose also that productive jobs are efficiently distributed across regions so that $g_{mm}^*$ is equal to one. Univariate measures would suggest that there is geographic mismatch in the economy, and would attribute some proportion of aggregate unemployment to this mismatch. However, the bivariate mismatch measure presented above would not suffer from such a bias. The lesson from this example is clear: in order to develop informative measures of geographic mismatch effects on aggregate unemployment, the co-movement of regional unemployment and vacancy rates must be identified. In other words, regional vacancy data must be assembled, and regional Beveridge curves must be estimated.

Before rushing off to collect local vacancy data, however, it is reasonable to ask just how important geographic mismatch is likely to be in explaining fluctuations in the aggregate Beveridge curve. In order to address this question, I simulate a multi-sector job-matching model which determines regional and aggregate unemployment and vacancy
I provide a detailed discussion of simulation procedures in Appendix 1-A. In this section, I describe only the main features of the simulation exercise. In each simulation, I assume there are ten regional labor markets, each with a Beveridge curve given by Equation (1-7). In keeping with the assumptions of this section, I impose constant returns to scale in all regional matching functions, and assume \( a_i = a_j = a \), for all \( i \) and \( j \). In the first period of each simulation, I assume an efficient regional allocation of aggregate labor demand, so that vacancy/unemployment ratios are equal across regions. I also assume that \( L_i, \gamma_i \), and \( h_i \) are equal across regions in this first period. In subsequent periods, however, regional labor demand, job reallocation rates, and matching efficiency parameters are subject to aggregate shocks (common to all regions) and regional shocks (region-specific). Regional labor demand shocks result in regions moving to different points along any given Beveridge curve, while regional job-matching and job reallocation rate shocks lead to the observation of different regional curves, since these parameters determine the position of these curves in u-v space.

In each period, I draw realizations for each regional and aggregate shock from their respective distributions. I then calculate \( U_i \) and \( V_i \) for each region using the steady-state Beveridge curve relationships (Equation (1-7)). Therefore, I implicitly assume that regions move to their new steady-state positions within the period a shock is realized, and do not incorporate the dynamics suggested by Equations (1-2) and (1-3) in these simulations. Once \( U_i \) and \( V_i \) are recovered, I calculate \( gmm^* \) and \( u/u_{min} \). I run each simulation over 50
time periods, and calculate the average of $u_{\min}$ in those periods. I run each simulation 100 times to obtain a distribution for this average value of $u_{\min}$.

Tables 1-1A through 1-1D provide summary statistics on the distribution of $u_{\min}$ for alternative assumptions regarding the standard deviation of regional and aggregate shocks, as well as the value of $a$ in the model. I highlight the most important results from these tables here, while I provide a more detailed discussion of these tables in Appendix 1-A. I use the following notation in Tables 1-1A through 1-1D: $s_1 = \gamma / h_1$; $\sigma_{\epsilon_j}$ = standard deviation of aggregate labor demand shocks; $\sigma_{\nu_j}$ = standard deviation of regional labor demand shocks; $\sigma_{\epsilon_s}$ = standard deviation of aggregate s shocks; $\sigma_{\nu_s}$ = standard deviation of regional s shocks. See Appendix 1-A for further notational details.

Table 1-1A demonstrates that as the variance of regional shocks increases relative to the variance of aggregate shocks, geographic mismatch unemployment becomes an important determinant of the horizontal position of the aggregate Beveridge curve. For example, in the absence of aggregate shocks, the average value of $u_{\min}$ over the 50-period time horizon is 1.26. Also, in at least one trial, $u_{\min}$ averages over two, suggesting that geographic mismatch results in a doubling of the average aggregate unemployment rate for any given vacancy rate. Even when the variance ratio of aggregate shocks to regional shocks is rather high, I still observe simulations in which the average value of $u_{\min}$ is greater than 1.2. Considering that I start all simulations assuming identical regions and no geographic mismatch, I find this evidence consistent with the view that
geographic mismatch could have a large impact on the aggregate Beveridge curve under reasonable assumptions.

Table 1-B shows that geographic mismatch unemployment increases as the variance of labor demand shocks rises relative to job-matching and job reallocation shocks. This is an intuitive result, since regional labor demand shocks move regions to different $V/U$ ratios on the same Beveridge curve, and thus increase geographic mismatch. Regional job-matching and job reallocation rate shocks, however, lead to movements along a 45-degree line in $U-V$ space, and thus have little effect on $V/U$ ratios when these ratios are near one. The possible empirical relevance of geographic mismatch unemployment is evident in this table as well, since $u/u_{\text{min}}$ ratios are often significantly greater than one.

Table 1-C demonstrates that increased variation in labor demand and $s$ shocks results in greater mismatch measures. Greater variation in the factors determining regional unemployment and vacancy rates implies a wider expected range of outcomes around the initial allocation which minimizes geographic mismatch.

Table 1-D shows distributions of mismatch indices under alternative assumptions regarding the value of $a$ in regional matching functions. As $a$ moves toward zero or one, the variability of mismatch measures increases, so that it is possible to have periods in which mismatch results in enormous horizontal shifts of the aggregate Beveridge curve (see column one, in particular). As $a$ moves away from 0.5, any changes in $J_i$ have a greater impact on $V_i/U_i$ ratios, so that regional variation in $J_i$ results in increased dispersion in $V_i/U_i$ ratios and greater geographic mismatch.
In sum, I read Tables 1-1A through 1-1D as suggesting that regional mismatch unemployment may be a relevant empirical phenomenon, especially if region-specific labor demand shocks are important determinants of regional labor market outcomes. Regional mismatch also plays a more important role in determining the position of the aggregate Beveridge curve as either unemployment or vacancies become dominant in the job-matching process (i.e., as \( a \) goes to one or zero). However, these simulation results maintain the restrictive assumption that regional job-matching processes are determined by constant returns to scale functions that are monotonic transformations of one another. I now relax this constant returns to scale assumption, and later address the monotonicity assumption, to determine if the characterization of geographic mismatch indices presented in this section holds for a broader class of regional labor market models.

**GENERAL COBB-DOUGLAS REGIONAL MATCHING FUNCTIONS THAT ARE MONOTONIC TRANSFORMATIONS OF ONE ANOTHER**

I now consider an economy with regional job-matching functions that are positive monotonic transforms of each other (\( b_{i} / a_{i} = b_{j} / a_{j} \) is some constant \( k_{1} \), \( \forall i,j \)), but which do not necessarily exhibit the same returns to scale. Equations (1-10) and (1-12) continue to imply that \( b_{*} / a_{*} = k_{1} \), and that \( V_{i} / U_{i} = V/U \) is some constant \( k_{2} \) for all \( i \). Positive monotonic transformations do not affect the slopes of the regional Beveridge curves, thus geographic mismatch continues to be minimized when \( V/U \) ratios are equal across regions.

The next step is to find values of \( a^{*} \) and \( b^{*} \), and thus the form
of the efficient aggregate Beveridge curve. These parameters must be consistent with an efficient regional allocation of aggregate labor demand, and with Equation (1-15) evaluated at $\gamma_{\text{max}}$. Furthermore, $b^*/a^*$ must equal $k_1$. Appendix 1-B shows that, under these assumptions, $a^* + b^*$ is given by:

$$
(1-20) \quad a^* + b^* = \frac{\log(\Sigma(s_i L_i))}{\log(\Sigma[(s_i L_i)^{1/(a_i+b_i)}])}
$$

The condition that $b^*/a^* = k_1$ identifies $a^*$ and $b^*$ given Equation (1-20). Appendix 1-B also shows that $\gamma_{\text{max}}^*$ is equal to one when evaluated at these parameters. This implies that $u/u_{\text{min}}$ is equal to $[\gamma_{\text{max}}^*]^{-1/a^*}$, evaluated with $a^*$ and $b^*$ as given by Equation (1-20).²¹

The parameters of the efficient aggregate Beveridge curve depend in an intuitive way upon the the distribution of aggregate hires across regions with divergent job-matching technologies. For the sake of argument, normalize job-matching efficiency parameters ($h_i$) to one in all regions. In this case, $s_i L_i$ is equal to hires in region $i$, and $a^*$ and $b^*$ represent the parameters of the aggregate job-matching function (total hires = $U^{a^*}V^{b^*}$). Equation (1-20) then implies that as aggregate hires become concentrated in regions with greater (lower) returns to scale in the job-matching process, the aggregate job-matching function exhibits increased (decreased) returns to scale. Even if all regions have identical job-matching functions, the distribution of hires across regions affects these aggregate function parameters. If all regions have identical decreasing (increasing) returns to scale functions, then returns to scale in the aggregate function falls (rises) as hires become concentrated in particular
regional markets. This argument implies that shifts in job reallocation rates and labor forces across regions affect the parameters of the efficient aggregate Beveridge curve and aggregate job-matching functions. This is not the case when all regions are assumed to have identical, constant returns to scale matching functions. The lesson learned from this more general case is that the parameters of the equation determining geographic mismatch unemployment may not always be constants. Calculating geographic mismatch unemployment under more general assumptions requires regional hires data, and not just unemployment and vacancy data.

I repeat the simulation exercises described earlier in this section and in Appendix I-A assuming that regional matching functions are positive monotonic transformations of each other, with varying degrees of returns to scale. The results are consistent with the intuition developed in the constant returns to scale simulations. For different assumptions regarding average returns to scale in the regional matching functions, it is invariably the case that geographic mismatch unemployment increases as: (1) The variance of regional shocks rises relative to the variance of aggregate shocks; (2) The variance of labor demand shocks rises relative to the variance of job reallocation and matching efficiency shocks; (3) The total variance of labor demand and job reallocation and matching efficiency shocks rises.

In the next section, I consider an economy in which regional matching functions are not constrained to be positive monotonic transformations of each other.
If regional matching functions are not positive monotonic transformations of one another, appropriate measures of geographic mismatch unemployment change considerably. Identical V/U ratios across regions no longer imply equal marginal rates of technical substitution between vacancies and unemployment in regional job-matching functions. As Equation (1-10) shows, regions in which the elasticity of hires with respect to vacancies ($\beta_1$) is high relative to the elasticity of hires with respect to unemployment ($\gamma_1$), should have relatively high V/U ratios in order to minimize geographic mismatch unemployment.

The intuition behind this result is quite clear. A steady state requires that a certain amount of hiring activity, as determined by the regional job reallocation rates and labor forces, takes place in each regional market. Since hiring requires search behavior by workers and firms, each region must have some stock of unemployed workers and vacant jobs in equilibrium. The search technology may vary from sector to sector, however, as it depends on the recruiting tactics and job-search patterns of firms and workers in that particular sector. New hires in some sectors may depend primarily on the demand side of the search market (job vacancies), while a thick supply side of the market (unemployment) may be necessary to generate a substantial number of hires in other sectors. If labor demand is lowest in regions in which the demand side of the market is of primary importance in determining hiring activity, then increases in unemployment due to this sluggish demand do little to promote
job-matching activity, and vacancies remain relatively high. Alternatively, if labor demand is highest in regions in which the supply side of the search market is most important in determining hires, unemployment remains high despite the relatively large stock of productive job vacancies. It follows that to minimize aggregate unemployment given aggregate vacancies, subject to the steady-state constraints on hiring activity in each region, labor demand and vacancies should be concentrated where they are of primary importance in determining hiring activity. Labor demand relative to the regional labor force, as well as $V_i/U_i$ ratios, should rise as $h_i/a_i$ ratios rise.

Is it likely that regional labor markets have job-matching functions that vary in their marginal rates of technical substitution between vacancies and unemployment? Certain labor market models suggest that there might be considerable regional variation in these matching function parameters. Industrial and occupational employment is not uniformly distributed across regions. Some regions have high concentrations of manufacturing, blue-collar employment, others are dominated by financial sector, white-collar employment, still others thrive on tourism and thus have high concentrations of service sector employment, and so on. "Dual labor market" theories argue that labor markets in different industrial and occupational sectors of the economy may operate quite differently. Economists with widely divergent perspectives on the labor market, from those specializing in the institutional nature of industrial labor markets (Doeringer and Piore (1971)) to neoclassical economists (Bulow and Summers (1986)), have argued that job-matching activity may vary considerably over
industrial and occupational labor markets. For example, Bulow and Summers (1986) argue that hires in the "primary" sector of the economy should be determined primarily by job vacancies, since unemployed workers queue for such openings. This may not be the case in "secondary" sectors of the economy. Evidence from Blanchard and Diamond (1989) suggests that job vacancies are the primary determinant of hires in the manufacturing sector of the U.S. economy. If most manufacturing jobs are part of the "primary" sector of the economy, then this evidence supports the Bulow and Summers (1986) prediction. It is thus feasible that regional differences in employment composition might result in widely divergent regional job-matching processes.

This discussion suggests that measures of geographic mismatch unemployment calculated under an assumption of identical regional job-matching functions, such as those in Jackman, Layard, and Savouri (1987,1990), might provide a distorted picture of the true extent of mismatch in the economy. For example, suppose an economy has two regions. "Primary" sector employment is most prevalent in one region, so that vacancies determine new hires. The other region has a heavier concentration of "secondary" employment (perhaps it is the tourist center of the country, while the first sector is the manufacturing and financial center). Hires in this second region depend to a much greater extent on the pool of unemployed workers. Suppose that initially the V/U ratio is higher in the first region than in the second region, so the condition in Equation (1-10) holds. Now suppose that labor demand or supply is redistributed between the two regions, so that the V/U ratios converge. The Jackman, Layard, and Savouri
(1987,1990) indices would measure a decrease in geographic mismatch unemployment, when in fact mismatch is increasing.

Jackman, Layard, and Savouri (1987,1990) conclude that the proportion of unemployment in Great Britain accounted for by regional mismatch did not increase (and perhaps decreased) during the late 1970s and 1980s. Regions with relatively high V/U ratios prior to the late 1970s, such as Southeast, East Anglia, and East Midlands, saw these ratios fall relative to the national average throughout the 1980s. At the same time, some regions with relatively low V/U ratios, such as Wales, Northwest, Southwest, and West Midlands, saw these ratios rise relative to the national average. This convergence in V/U ratios appears to account for the Jackman, Layard, and Savouri (1987,1990) results. Given the wide diversity in industrial and occupational employment composition across the regions mentioned above, it is likely that job-matching functions are in fact not identical in these regions, and the Jackman, Layard, and Savouri (1987,1990) indices could be substantially underestimating (or even overestimating) changes in mismatch unemployment in Great Britain in the 1980s. In any event, given the strong theoretical arguments suggesting diversity in regional matching functions, an attempt to develop a measure of geographic mismatch unemployment that allows for such diversity is in order. Only careful empirical estimation of regional matching functions will ultimately determine if such a measure is actually relevant.

As usual, construction of the mismatch index involves finding values of $a^*$ and $b^*$ that are consistent with an efficient regional distribution of aggregate labor demand, and with the condition that
Unfortunately, I am unable to derive general functional forms determining these parameters in this case. However, Appendix 1-C presents an algorithm that computes $a^*$ and $b^*$ for any given number of aggregate productive jobs, $J^* = \sum_{i=1}^{N} J_i$. I show that $\frac{s^*}{\gamma_{\text{max}}}$ is equal to one when evaluated with these parameters, so that the mismatch index remains of the form $\frac{u}{u_{\text{min}}} = \left[\gamma_{\text{m}}^*\right]^{-(1/\alpha^*)}$.

I must address some difficult issues regarding the theoretical interpretation and empirical estimation of the geographic mismatch index derived in Appendix 1-C. The efficient aggregate Beveridge curve is not generally of the Cobb-Douglas form $u^* v^* = K$ in this case. $a^*$, $b^*$, and their ratio depend on the state of aggregate labor demand ($J^*$) in the economy. Thus the aggregate Beveridge curve drawn out by changes in $J^*$, given that $J^*$ is distributed between regions to minimize $u$ given $v$, is not a log-linear function of $u$ and $v$ as suggested by Equation (1.11). The slope of this curve in log($u$)-log($v$) space changes as $J^*$ changes. Equation (1.11) describes the efficient aggregate Beveridge curve only when regional job-matching functions are positive monotonic transformations of one another.

Since Appendix 1-C derives a geographic mismatch unemployment index using the assumption that the efficient aggregate curve is of the form $u^* v^* = K$, the validity of this index and its interpretation are called into question. However, for any $J^A = J^*$, the aggregate "efficient Beveridge curve" drawn out by small changes in $J^*$ around $J^A$ is well-approximated by a curve of the form $u^a v^b = K$, where $a^*$ and $b^*$ are calculated using the algorithm from Appendix 1-C. For a given $J^*$, the expression for $\frac{u}{u_{\text{min}}}$ developed in Appendix 1-C is a valid
measure of geographic mismatch unemployment, since $a^*$ and $b^*$ do accurately reflect the curvature of the aggregate efficient Beveridge curve at that level of aggregate labor demand.

A potential problem with the empirical estimation of the mismatch index follows directly from this interpretation issue. In order to generate the most accurate measures of geographic mismatch unemployment in this general case, the algorithm to recover new $a^*$ and $b^*$ must be implemented whenever there is a significant change in aggregate labor demand. Obviously such a procedure is time-consuming, and data-intensive since it requires knowledge of all parameters determining steady states in the regional labor markets. It is useful to determine if a simpler algorithm, with less stringent data requirements, provides accurate approximations for $a^*$ and $b^*$ under most reasonable labor market conditions.

I use simulation exercises to determine if alternative formulations for $a^*$ and $b^*$ exist which provide good approximations for the true values of $a^*$ and $b^*$ under different assumptions regarding returns to scale and parameter heterogeneity in regional matching functions. Equations (1-21) and (1-22) give one of the alternative formulations I consider:

\[(1-21) \quad a^* = \frac{\sum_{i=1}^{N} a_i SL_i}{\sum_{i=1}^{N} SL_i}\]

\[(1-22) \quad b^* = \frac{\sum_{i=1}^{N} b_i SL_i}{\sum_{i=1}^{N} SL_i}\]

This formulation has an intuitive appeal; it suggests that $a^*$ and $b^*$ are hires-weighted averages of the regional $a_i$ and $b_i$ when matching
efficiency parameters are normalized to one in each region. The formulation is strictly correct, however, only in the special case in which regions exhibit constant returns to scale matching functions that are positive monotonic transformations of one another. Empirical implementation of an index based on these values of \( a^* \) and \( b^* \), on the other hand, might be more feasible as \( a^* \) and \( b^* \) must be recalculated when regional job-reallocation rates or labor forces change significantly, but do not need to be recalculated when \( J^* \) changes. It is thus useful to know if such an index closely tracks geographic mismatch unemployment as measured by the "correct" index. In other words, while this index is not strictly correct, if under most labor market conditions it accurately tracks time-series variation in the correct estimates of \( u/u_{\min} \), it may be used with confidence in those circumstances when estimation of the correct index proves infeasible.

To determine the properties of alternative mismatch indices when allowing for general variation in regional matching function parameters, I once again use simulation exercises. Appendix 1-D describes these simulation procedures and results in greater detail.

The main differences between these simulation procedures and those discussed previously can be summarized as follows: (1) I allow for general variation in regional matching function parameters, no longer imposing the monotonicity assumptions of previous sections. (2) I compute three alternative measures of \( u/u_{\min} \). First, there is the "correct" measure, calculated using \( a^* \) and \( b^* \) from the algorithm in Appendix 1-C, which I label \( (u/u_{\min})^c \). The second measure assumes \( a^* \) and \( b^* \) are given by Equations (1-21) and (1-22). I label this measure \( (u/u_{\min})^{\text{avgs}} \), since it is constructed assuming \( a^* \) and \( b^* \) are
hires-weighted averages of $a_i$ and $b_i$. The third measure assumes that all regions have identical matching functions, with $a_i = a^*$ as given in (1.21), and $b_i = b^*$ as given by (1.22), for all i. I label this measure $(u/u_{min})^{JLS}$, since it is the appropriate index under the assumptions Jackman, Layard, and Savouri (1987, 1990) make when developing geographic mismatch indices. (3) I calculate the correlation of the growth rates of $(u/u_{min})^C$ and $(u/u_{min})^{Havg}$, which I call $\rho^{CW}$, and the correlation of the growth rates of $(u/u_{min})^C$ and $(u/u_{min})^{JLS}$, which I call $\rho^{CJ}$, over every sample period. The correlation measures provide information on whether the alternative indices suggest a consistent pattern for the time-series variation in geographic mismatch unemployment.  

Results from these simulation exercises suggest that $(u/u_{min})^{Havg}$ and $(u/u_{min})^{JLS}$ may provide poor estimates of the level of geographic mismatch unemployment in the economy, especially when there is substantial variation in regional matching function parameters. However, the average value of $\rho^{CW}$ over simulation sample periods is often near one, suggesting that the $(u/u_{min})^{Havg}$ index does a very good job of tracking time-series variation in the "correct" index $\rho^{CJ}$, on the other hand, tends to be much lower, especially when regional matching function parameters exhibit significant variation. The Jackman, Layard, and Savouri (1987, 1990) index often identifies decreases in mismatch when in fact mismatch is increasing.

The lessons from this section can be summarized as follows: (1) Strong theoretical arguments suggest that regional matching functions may not be positive monotonic transformations of each other. (2) Simulation exercises show that geographic mismatch unemployment
indices that assume regional matching functions are positive monotonic transformations of one another, when in fact they are not, may do a very poor job of characterizing the extent of mismatch unemployment. (3) The "correct" geographic mismatch unemployment index may be difficult to estimate empirically when regional matching functions are not positive monotonic transformations of each other. However, simulations show that an alternative index that may be easier to use in empirical applications provides accurate measures of time-series variation in mismatch unemployment.

Lessons (1) and (2) illustrate the importance of regional unemployment, vacancy, and hires data in this research agenda. Disparities in regional matching functions and/or Beveridge curves must be identified in order to formulate accurate measures of mismatch unemployment. They also call into question the validity of previous measures of mismatch unemployment which are calculated under very stringent assumptions on the relationship between regional matching functions. Lesson (3) is an important methodological point for empirical studies that intend to use this regional data when and where it is available.

IV. RETURNS TO SCALE IN JOB-MATCHING FUNCTIONS

Economists have often argued that job-matching functions should exhibit increasing returns to scale (for example, see Hall (1989)). These arguments usually rely on predictions from the "coconut" parable in Diamond (1982). When both sides of the job-search market become thicker (higher U and V), the probability of any given person finding
a job increases, so that hires increase more than proportionately with U and V. The Diamond (1982) parable also identifies the relevant search markets in which one would expect to observe increasing returns: its predictions are very much reliant on the assumption that the unemployed and potential employers are on the same "island," searching in the same "market."

As an extreme example, suppose an economy consists of two islands. Production of the sole consumption good in this economy requires one unit of physical capital, and one unit of human capital. Suppose there are two types of people in this economy, "capitalists" and "laborers." Capitalists are endowed with a unit of physical capital, yet no human capital. Laborers are endowed with a unit of human capital, yet no physical capital. Capitalists and laborers therefore must find one another in order to produce the consumption good. Assume that when they do find each other, they split the proceeds of their production. If capitalists and laborers are distributed evenly over the two islands, the usual Diamond (1982) prediction should hold: an increase in the number of capitalists (vacancies) and laborers (unemployed) in the economy should increase job matches, and thus production of the consumption good, more than proportionately. However, if all laborers live on one island, and capitalists live on the other (and you can’t build a boat to connect the islands without a capitalist and laborer as well), an increase in the population of capitalists and laborers has no effect on job-matching. The point is obviously more general: if it is reasonable to think of sectoral labor markets having impermeable boundaries, even in the short run, so that each sectoral market can be
thought of as an "island" economy, these individual markets should demonstrate increasing returns to scale in the job-matching process. However, the returns to scale observed in the aggregate economy job-matching process depends on the distribution of unemployment and vacancies across the separate island economies.

The preceding example suggests that job-matching functions in well-defined regional, industrial, or occupational labor markets should be estimated if one wants to conduct cleaner tests of the Diamond (1982) prediction. It also suggests that evidence from the aggregate matching function estimates in Blanchard and Diamond (1989), showing constant or very slightly increasing returns to scale, is not necessarily inconsistent with increasing returns in sectoral labor market matching functions.

Unfortunately, hires data that would allow estimates of matching functions at the sectoral level in the U.S. are currently unavailable. However, an alternative strategy for determining returns to scale in sectoral markets is available. If factors determining the relationship between returns to scale in aggregate matching functions and returns to scale in sectoral matching functions can be identified, then Blanchard and Diamond (1989) aggregate matching function estimates can be used to recover estimates of returns to scale at the sectoral level.

The job-matching model presented in the previous sections provides some insights on the determinants of the relationship between returns to scale in sectoral and aggregate matching functions. For example, suppose all regional matching functions are identical and exhibit constant returns to scale \((\alpha_i = \alpha_j = \alpha, \text{ and } h_i = h_j = h)\).
Equation (1-23) determines aggregate hires \((h^A)\) under these assumptions:

\[
(1-23) \quad h^A = \sum_{i=1}^{N} (\gamma_i L_i) = h \ast \left[ \sum_{i=1}^{N} \left( \frac{U^i_v^{1-a}}{U^v_{1-a}} \right) \right] \ast U^v_{1-a} \\
= h \ast gmm^* \ast U^v_{1-a}
\]

Suppose one estimates the following aggregate matching function specification:

\[
(1-24) \quad \log(h^A) = \alpha_0 + \alpha_1 \log(U) + \alpha_2 \log(V) + \epsilon \quad \text{where } \epsilon = \text{residual}
\]

This is the baseline specification from Blanchard and Diamond (1989) absent a time trend term.\(^{27}\)

Equation (1-24) is obviously misspecified in this case, however, as it does not include \(\log(gmm^*)\). Consider the auxiliary regression given by Equation (1-25):

\[
(1-25) \quad \log(gmm^*) = \beta_0 + \beta_1 \log(U) + \beta_2 \log(V) + \mu \quad \text{where } \mu = \text{residual}
\]

This missing variable specification bias implies that estimates of \(\alpha_1\) and \(\alpha_2\) are given by Equations (1-26) and (1-27):

\[
(1-26) \quad \hat{\alpha}_1 = \hat{\alpha}_1 + \hat{\beta}_1 \quad \text{where } \hat{\alpha}_1 = \text{OLS estimate of } \alpha_1 \\
\quad \hat{\beta}_1 = \text{OLS estimate of } \beta_1
\]

\[
(1-27) \quad \hat{\alpha}_2 = 1-a + \hat{\beta}_2 \quad \text{where } \hat{\alpha}_2 = \text{OLS estimate of } \alpha_2 \\
\quad \hat{\beta}_2 = \text{OLS estimate of } \beta_2
\]
While each regional matching function exhibits constant returns to scale, the estimate of returns to scale in the aggregate specification depends on \( \hat{\beta}_1 + \hat{\beta}_2 \), the sum of coefficients from the auxiliary regression. These in turn depend on the relationship between \( gmm^* \), \( U \), and \( V \) in the sample. When \( U \) is high given \( V \), or \( V \) high given \( U \), is \( gmm^* \) relatively high or low? Suppose regional job reallocation rates and matching efficiency parameters are quite stable, so that most shifts in the aggregate Beveridge curve are the result of increased geographic mismatch. Increased geographic mismatch implies that \( gmm^* \) is declining, moving away from \( gmm^*_{max} \). In this scenario, \( U \) is high for a given \( V \), and \( V \) high for a given \( U \), when \( gmm^* \) is relatively low. Thus one would expect \( \hat{\beta}_1 + \hat{\beta}_2 \) to be negative, and the aggregate specification would provide an underestimate of returns to scale in regional matching functions. Increased mismatch increases \( U \) and \( V \) without creating steady-state increases in aggregate hiring activity, and thus leads to underestimates of returns to scale in the job-matching function.

If aggregate Beveridge curve shifts are driven primarily by job reallocation and matching efficiency shocks, the aggregate specification would not necessarily underestimate regional returns to scale. Increases in within-region job reallocation rates shift out regional Beveridge curves, and thus increase aggregate \( U \) and \( V \), but also lead to increases in steady-state hiring activity. If geographic mismatch tends to decline whenever regional Beveridge curves shift out, \( gmm^* \) may be positively correlated with aggregate \( U \) and \( V \), leading to an overestimate of returns to scale. If geographic mismatch is
fairly stable over any sample period, there is likely to be little bias in returns to scale estimates since the constant term approximates $g_{mm'}$ in Equation (1-24).

In any event, the lesson appears to be quite clear: To obtain unbiased estimates of regional matching function parameters, and thus test for increasing returns to scale at a more appropriate level of disaggregation, one may either include $\log(g_{mm'})$ in the aggregate matching function specification, or run the auxiliary regression (Equation (1-25)) and use estimates from this regression and the Blanchard and Diamond (1989) estimates to form returns to scale estimates.$^{28}$

This procedure is not as straightforward as it might appear to be at first glance. Computation of $g_{mm'}$ requires knowledge of regional matching function parameters. If the researcher knows these parameters, there is no need to implement the correction procedure. In other words, proper implementation of the correction procedure requires that the researcher already knows the answer to the question that the procedure is designed to address.

However, a simple iterative procedure can be used to identify regional matching function parameters from aggregate estimates and the sample correlation properties of $U$, $V$, and $g_{mm'}$, without requiring prior knowledge of regional matching function parameters. In keeping with the above example, suppose regional matching functions are identical and exhibit constant returns to scale. At the beginning of this procedure, assume $a = a'$. Then run the auxiliary regression given by Equation (1-25) over the same sample period for which the aggregate specification was estimated, using the $g_{mm'}$ series
calculated assuming \( a = a' \). Label the estimates from this regression \( \hat{\beta}_1 \) and \( \hat{\beta}_2' \). If \( a \) is in fact equal to \( a' \), \( \hat{\alpha}_1 \) will equal \( \beta_1 + \hat{\beta}_1' \), and \( \hat{\alpha}_2 \) will equal \( 1-a' + \hat{\beta}_2' \). The true value of \( a \) can be recovered by trying alternative \( a' \) values until this condition holds.

This example assumes that the researcher knows that regional matching functions are identical and exhibit constant returns to scale, and thus only has to recover the \( a \) parameter. However, Appendix 1-E demonstrates that the basic algorithm suggested here can also be used to recover regional matching function parameters when such functions are not identical, and when they exhibit varying degrees of returns to scale.

To identify the possible determinants of biases in returns to scale estimates from aggregate matching function specifications, I once again rely on simulations. I conduct the simulation exercises as described in Appendix 1-A, with one additional step. At the end of each 50-period simulation, I estimate an aggregate matching function of the form given in (1-24) for that 50-period sample. \( \hat{\alpha}_1 + \hat{\alpha}_2 \) minus the average sample values of \( a^* \) and \( b^* \) is then identified as the bias in returns to scale estimates from the aggregate specification. I run one hundred simulations to generate distributions for these bias figures.

Tables 1-3A through 1-3D provide summary statistics for bias figures from the simulation exercises reported earlier in Tables 1-1A through 1-1D, respectively. In all four tables, I assume identical, constant returns to scale regional matching functions.

Table 1-3A presents bias figures under alternative assumptions regarding the variance ratios of aggregate and region-specific shocks.
As the first column shows, if the economy is subject only to aggregate shocks, \( gmm^* \) is constant, and the aggregate matching function estimates are not biased. As regional shocks become more prevalent, however, the possibility of substantial biases in these estimates rises considerably. An increase in the variability of regional shocks relative to aggregate shocks increases sample fluctuations in \( gmm^* \), and thus makes it more likely that \( gmm^* \) exhibits either large positive or negative sample correlations with \( U \) and \( V \).

Table 1-3B presents bias figures under alternative assumptions regarding the variance ratios of \( J \) and \( s \) shocks. If there are no \( s \) shocks in the economy, hires remain constant, and the estimated returns to scale always equals zero. This is an extreme example of the intuition developed above on the role of \( s \) and \( J \) shocks in determining estimated biases; if most shifts in the aggregate Beveridge curve are driven by changes in geographic mismatch, and in this case all are, then returns to scale estimates from the aggregate specification may severely underestimate returns to scale at the regional level.\(^{29}\)

Table 1-3C presents bias figures for alternative assumptions regarding the variance of \( J \) and \( s \) shocks, holding their variance ratio constant. Increased variance in these shocks increases the standard deviation of bias estimates, implying that aggregate returns to scale estimates could severely over- or underestimate returns to scale at the regional level. Table 1-3D shows bias figures as the slope of regional Beveridge curves in \( \log(u) - \log(v) \) space is varied by changing the parameter \( \alpha \). Perhaps the most striking feature of this table, as well as the previous three, is the extreme variability in returns to
scale estimates for a given set of simulation assumptions. This highlights the importance of identifying sample time-series movements in U, V, and gmm when attempting to interpret returns to scale estimates from matching functions estimated with aggregate data. Simulations with alternative assumptions on returns to scale, and the variability of matching function parameters across regions, are all consistent with the general patterns illustrated in Tables 1-3A through 1-3D.

This section provides some important lessons for economists conducting empirical work on the job-matching process: (1) Theory suggests that the job-matching process on an "island" economy should exhibit increasing returns to scale. However, if the aggregate economy consists of many separate "island" economies (i.e., labor markets with well-defined short run boundaries), then returns to scale in the aggregate job-matching process is affected by the distribution of searchers (vacancies and unemployment) across these separate islands. (2) Simulation exercises suggest that estimated returns to scale in the aggregate job-matching function may differ substantially from returns to scale at the regional level under reasonable parameter assumptions. (3) Lessons (1) and (2) suggest that in order to conduct a valid test for returns to scale in "island" economies, disaggregated matching functions should be estimated. However, data limitations in the U.S. preclude estimation of disaggregated functions. Given these limitations, perhaps the most important contribution of this section and Appendix 1-E is the procedure I present to recover regional returns to scale estimates from aggregate matching function estimates. This procedure requires accurate estimates of geographic mismatch.
unemployment, illustrating another important economic issue that can be addressed through careful study of regional and aggregate Beveridge curves.

V. CONCLUSION

This chapter illustrates the importance of regional Beveridge curve analysis in a research agenda designed to improve our understanding of the properties of the U.S. aggregate labor market. Regional analysis allows the computation of accurate measures of geographic mismatch unemployment, and thus allows identification of the role of regional dispersion in labor market outcomes in any observed movements in the "structural" component of aggregate unemployment. I develop general measures of geographic mismatch unemployment, while demonstrating that existing univariate dispersion measures, such as those presented in Lilien (1982), as well as existing bivariate dispersion measures (Jackman, Layard, and Savouri (1987,1990)), may prove to be inadequate. As well as providing information on the nature of aggregate unemployment, these mismatch measures are useful in determining returns to scale in the job-matching process.

Since the publication of Lilien (1982), macroeconomic research has focused extensively on the relative importance of "cyclical" versus "structural" shocks in explaining fluctuations in the aggregate unemployment rate. At the same time, Blanchard and Diamond's (1989) work on the aggregate matching function has sparked renewed interest in the nature of the job-matching process. A detailed study of
regional Beveridge curves, which provides key insights on both of these issues, appears to be particularly timely at this point in the current research agenda.

Until now, however, such analysis has been precluded by the unavailability of U.S. vacancy data, either at the aggregate or regional levels. In the next chapter, I describe a detailed data collection and refinement project I designed to develop proxy variables for regional vacancy rates. I present theoretical arguments and empirical evidence that suggest the proxies I construct do in fact provide accurate estimates of regional vacancy rates. These proxy variables allow me to undertake the detailed study of U.S. regional Beveridge curves that appears to fit so naturally into the current macroeconomic research agenda.
Even in a labor market with seemingly homogeneous "jobs" and "workers," as in Diamond (1982), if workers and jobs are not always in the same geographic location (locational heterogeneity), structural unemployment exists.

See Holzer (1989) for an informative discussion of the distinction between structural and deficient-demand unemployment.

The Beveridge curve is named after Lord William Beveridge, who discussed the co-movement of vacancies and unemployment in his 1893 book, Unemployment: A Problem of Industry.

I derive an explicit functional form for the aggregate Beveridge curve, using a simple job-matching model of the labor market, later in this chapter. This curve is also downward-sloping and convex to the origin.

Alternative assumptions regarding structural shock effects on $u$ and $v$ affect the proportion of any unemployment change attributed to cyclical or structural shocks. However, the conceptual exercise is independent of this identifying restriction.

I discuss use of the help-wanted index as a proxy variable for job vacancies in great detail in Chapter 2.

One can think of prohibitive moving costs when considering geographic sectors, or stark differences in human capital requirements that preclude mobility across industrial and/or occupational sectors.

The example studied here relies on convexity in the sectoral curves to generate the result that labor market dispersion shifts the aggregate Beveridge Curve outward. However, Abraham (1987) argues that even when the curves aren't convex, labor demand dispersion can shift out the aggregate curve. If increases in labor demand are met solely by increases in vacancies in the short run, while decreases in labor demand affect both unemployment and vacancies in the short run, then increases in labor demand dispersion across sectors shift the aggregate Beveridge curve out.

Most of the research has been conducted by a group of macro-labor economists associated with the London School of Economics. For example, see Jackman, Layard, and Pissarides (1984), Jackman and Roper (1987), and Jackman, Layard, and Savouri (1987,1990).

Ball (1990) studies the extent of labor mobility in a model almost identical to the one presented here. He shows that workers' decisions result in a level of labor mobility that does not necessarily match a social planner's optimal allocation, due to both positive and negative externalities that are associated with worker moves.
When working through this chapter, it is useful to think of this as a local labor market, since data limitations preclude a study of disaggregated industrial or occupational labor markets in the U.S. The assumption of an exogenous labor force also seems more tenable when it is geographic boundaries that define the relevant labor force, and not "industrial" boundaries (however, the notion of "occupational" boundaries defining separate labor forces seems reasonable as well). This is especially the case in light of Leonard's (1989) evidence of limited geographic mobility among the unemployed.

All together, these assumptions imply that I ignore three important labor market variables, wages, prices, and the labor force, to focus attention solely on the two remaining variables of interest: employment (unemployment), and job vacancies.

Given the other assumptions of the model, the existence of a steady state, in which both unemployment and vacancies are constant, requires that the job destruction and creation rates are equal. Since the focus of my analysis is alternative steady states, and not unemployment and vacancy dynamics, I impose this steady-state condition from the start.

I find this empirical evidence less compelling than the theoretical arguments, however, as I argue later that the Blanchard and Diamond (1989) matching function specifications may be suffering from a serious omitted variable bias.

Totally differentiate Equation (1-5) with respect to \( U \) and \( \gamma \) to find:

\[
\frac{dV}{d\gamma} = \frac{dU}{d\gamma} - UV/(\gamma L(aV+bU)).
\]

Totally differentiate Equation (1-5) with respect to \( U \) and \( h \) to show:

\[
\frac{dV}{dh} = \frac{dU}{dh} - UV/(aV+bU).
\]

Changes in the labor force may also shift the Beveridge curve. Labor force effects depend on whether one defines the curve in \( U-V \) space, or in unemployment rate-vacancy rate (\( u-v \)) space. For example, if the matching function exhibits constant returns to scale \( (b = 1 - \alpha) \), changes in \( L \) do not shift the curve in \( u-v \) space. However, this obviously implies that both \( U \) and \( V \) are rising with \( L \), leading to an outward shift of the curve in \( U-V \) space.

Abraham (1987) suggests such an asymmetry between labor demand increases and decreases.

To determine conditions under which \( gmm^* \) is maximized, solve the following constrained maximization problem:

\[
\begin{align*}
\text{Max} & \quad \frac{gmm^*}{N} \\
\text{subject to:} & \quad \sum_{i=1}^{N} U_i = U \\
& \quad \sum_{i=1}^{N} V_i = V \\
& \quad \gamma_i L_i / h_i = U_i^{u_i h_i}, \quad \forall i
\end{align*}
\]

The first-order conditions for this problem require that Equation (1-10) holds.
One might also claim that decreases in the maximum value of $gmm$ shift out the efficient curve. However, I demonstrate in the following sections that this maximum value is in fact a constant.

Equation (1-20) implies that $a^* + b^* = 1$ if all regions exhibit constant returns to scale in their job-matching functions, confirming the results from the previous section.

See Leonard (1989) for figures on industrial employment composition in different states in the U.S. Tables 2-8 and 2-9 in Chapter 2 show 1970 and 1980 occupational employment composition for forty-eight metropolitan statistical areas in the U.S.

I have not formally tested this conjecture yet, as I have been unsuccessful in obtaining accurate regional unemployment and vacancy data for Great Britain thus far. In fairness to Jackman, Layard, and Savouri (1987), they mention that separate matching equations were estimated for each region, and tests were performed to check for significant differences across regions. Although these test statistics were not reported, I assume that they accepted the null hypothesis of identical job-matching parameters across regions since they implicitly make that assumption in the remainder of their paper. However, as I demonstrate below through simulations, even small differences in regional matching functions can significantly affect measures of mismatch unemployment. Given the small sample sizes in Jackman, Layard, and Savouri (1987) (18 annual observations for each region), it would hardly be surprising to find no statistically significant differences in parameters across regions if only small differences in parameters existed. While not statistically significant, the simulations show that such differences may have great economic significance.
For example, as $J^*$ rises, given all other parameters, the $a^*/b^*$ ratio rises. Equations (1-10) and (1-12) suggest that changes in $J^*$ that move the economy from one efficient allocation to another must be consistent with the following differential equation:

$$d(V/U)/(V/U) + d(a^*/b^*)/(a^*/b^*) = d(V_1/U_1)/(V_1/U_1), \forall i$$

Equation (1-10) implies that the right-hand side of this equation will be a constant for all $i$ regions when the economy moves from one efficient allocation to another.

If the initial efficient allocation implies constant $V_1/U_1$ ratios in all regions, then a proportional increase (decrease) in these ratios that is constant across regions increases (decreases) the aggregate $V/U$ ratio by the same proportion. Thus the above equation implies that if efficient allocations of aggregate labor demand require equal $V_1/U_1$ ratios, then $d(a^*/b^*)$ is equal to zero as the economy moves from one efficient allocation to another as $J^*$ changes. Efficient allocations require equal $V_1/U_1$ ratios only when regional matching functions are positive monotonic transformations of each other. This confirms the results from the previous two sub-sections which suggest that the $a^*/b^*$ ratio is independent of changes in $J^*$ given all other parameters, so that the efficient aggregate Beveridge curve is of the Cobb-Douglas form, when regional matching functions are positive monotonic transformations of each other.

If regional matching functions are not positive monotonic transformations of each other, then efficient allocations do not require constant $V_1/U_1$ ratios. Starting from an allocation with unequal $V_1/U_1$ ratios, constant proportional changes in regional $V_1/U_1$ ratios result in a less than proportional change in the aggregate $V/U$ ratio. Thus when $J^*$ rises (falls), leading to increases (decreases) in $V_1/U_1$ ratios, $a^*/b^*$ must rise (fall) as well. If regional matching functions are not positive monotonic transformations of each other, then $a^*/b^*$ is not independent of $J^*$, and the efficient aggregate Beveridge curve is not Cobb-Douglas.

I choose to concentrate on correlations in growth rates instead of levels because I am particularly interested in the alternative indices abilities to track the direction geographic mismatch is moving in any given period. The correlations of levels of these alternative mismatch indices are consistent with the arguments I present at the end of this section regarding the alternative indices abilities to track time-series variation in geographic mismatch.

See Appendix 1-D for a detailed discussion of simulation results.

See Blanchard and Diamond (1989) for a discussion of timing issues when estimating this specification.
While I have been focusing on possible biases in returns to scale estimates ($\hat{\beta}_1 + \hat{\beta}_2$), \(\hat{\beta}_1\) and \(\hat{\beta}_2\) individually are also of interest. It is important to obtain unbiased estimates of the role of U and V in generating hiring activity so that the relative importance of demand and supply-side search behavior in the job-matching process can be identified.

However, note that for the other six columns of Table 1-3B, the average returns to scale bias becomes more positive as the variance ratio of J to s shocks increases, which seems to contradict this intuition. As the variance of J shocks increases, holding the the variance of s shocks constant, there are two effects: (1) It becomes more likely that any observed shift in the aggregate Beveridge curve is driven by gmm shifts, which implies an underestimate of returns to scale. (2) Variability in gmm increases, thus the standard deviation of returns to scale bias increases, increasing the probability of both large positive and negative bias estimates. The average bias figures become more positive as one moves to the right in the first six columns of Table 1-3B because this increased variability results in some rather extreme overestimates of returns to scale in certain simulations.

For example, Yellen (1989) writes: "A leading question - perhaps the leading question - in macroeconomics since the publication in 1982 of David Lilien's paper, 'Sectoral Shocks and Cyclical Unemployment,' is whether sectoral, rather than aggregate, shocks are the key factor responsible for fluctuations in the unemployment rate." The italics in this quotation are used by Yellen.
APPENDIX 1-A: Simulation exercises assuming constant returns to scale
matching functions that are monotonic transformations of one another.

In this appendix, I describe simulation procedures for a model
economy assuming constant returns to scale regional matching functions
that are positive monotonic transformations of one another. I also
discuss in greater detail the results from these simulations, as
presented in Tables 1-1A through 1-1D.

I simulate a model economy with the following assumptions:

(1) There are ten regional labor markets in the economy, each with a
Beveridge curve given by Equation (1-7).

(2) All regional matching functions exhibit constant returns to scale,
and $\alpha_i = \alpha_j = \alpha$, for all $i$ and $j$.

(3) $L_i = 100$, for all $i$.

(4) In the first period of all simulations, the regions are identical
in every respect, implying no geographic mismatch unemployment. In
particular, $J_i = 98$ and $\gamma_i/h_i = 0.05$ for all $i$. With $\alpha = 0.5$,
assumptions (1)-(4) imply that first-period regional unemployment
rates are approximately 6.1 percent, while first-period regional
vacancy rates are about 4.1 percent.

(5) After the first period, $J_i$ and $\gamma_i/h_i$ are subject to aggregate and
regional shocks. Let $\gamma_i/h_i = s_i$. $J_i$ and $s_i$ evolve according to
Equations (1A-1) and (1A-2):

\[(1A-1) \quad J_{it} = J_{it-1} + \epsilon_{it}^J + \nu_{it}^J \]

\[(1A-2) \quad s_{it} = s_{it-1} + \epsilon_{it}^s + \nu_{it}^s \]

$t$ and $i$ are time and regional subscripts, respectively. $\epsilon^J$ is a shock
to productive jobs that is constant across all regions. I refer to these as aggregate labor demand shocks. I assume these shocks are iid, and are distributed $N(0, \sigma^2_{\epsilon_j})$. $\nu_j$ is a region-specific shock to productive jobs, and is called a regional labor demand shock. These shocks are iid both over time and across regions, and are distributed $N(0, \sigma^2_{\nu_j})$ in each region. $\epsilon$ is an iid shock to $s_i$ that is constant across all regions, and is drawn from a $N(0, \sigma^2_{\epsilon_s})$ distribution. $\epsilon$ shocks represent changes in job-matching efficiency or job reallocation rates that are uniform across regions. $\nu$ is a region-specific shock to $s_i$, assumed iid over time and across regions, and distributed $N(0, \sigma^2_{\nu_s})$ in each region. Assumptions (4) and (5) imply the following: All regions begin the simulation at the same point on the same regional Beveridge curve. However, regional labor demand shocks lead to regions moving to different points on the same Beveridge curve, while regional job-matching and job reallocation rate shocks lead to the observation of different regional Beveridge curves, since these parameters determine the position of these curves in U-V space.

(6) In each period, I draw realizations for each shock from the relevant distributions, and calculate $U_i$ and $V_i$ for each region using the steady-state Beveridge curve relationships (Equation (1-7)). I assume that regions reach their new steady-state values within the period a shock is realized, and thus do not incorporate the dynamics suggested by Equations (1-2) and (1-3) into these simulations. I then calculate $\gamma^{*}$ and $u/u_{\min}$. I run each simulation over 50 time periods, and calculate the average of $u/u_{\min}$ in those periods. I run the simulation 100 times, and obtain a distribution for this average value of $u/u_{\min}$.

I report summary results from these simulations in Tables 1-1A through 1-1D. In Table 1-1A, I assume $\epsilon = 0.5$, $\sigma_{\epsilon_j} + \sigma_{\nu_j} = 1$, and $\sigma_{\epsilon_s} + \sigma_{\nu_s} = 0.005$. Different columns in Table 1-1A represent alternative assumptions on the variance ratios of aggregate ($\epsilon$) shocks to region-specific ($\nu$) shocks, holding $\sigma_{\epsilon_j} + \sigma_{\nu_j}$ and $\sigma_{\epsilon_s} + \sigma_{\nu_s}$ constant.
For example, in the first column, I assume $\sigma_{\nu J} = \sigma_{\nu s} = 0$, so that $\sigma_{\epsilon J}/\sigma_{\nu J} = \sigma_{\epsilon s}/\sigma_{\nu s} = \infty$. If there are no region-specific shocks, there is no geographic mismatch unemployment in the economy, given the assumption of identical regional labor markets at the beginning of each simulation. Thus $u/u_{\text{min}}$ is always equal to one under these assumptions. However, at the opposite extreme in which there are no aggregate shocks (the last column in Table 1-1A), mismatch unemployment is quite extensive. The average value of $u/u_{\text{min}}$ over the 50-period time horizon is 1.26. In at least one trial, $u/u_{\text{min}}$ averages over two, suggesting that geographic mismatch results in a doubling of the average aggregate unemployment rate for any given vacancy rate.

Table 1-A demonstrates that as the variance of regional shocks increases relative to the variance of aggregate shocks, geographic mismatch unemployment increases. One might argue that intermediate, and perhaps more realistic, values of $\sigma_{\epsilon J}/\sigma_{\nu J}$ and $\sigma_{\epsilon s}/\sigma_{\nu s}$ suggest that geographic mismatch is likely to be of little empirical importance. For example, when these ratios are equal to two, geographic mismatch increases the average unemployment rate by less than four percent. However, note that the standard deviation of this average is relatively large, and in one simulation the average unemployment rate increases by twenty-three percent. Considering that I start all simulations assuming identical regions and no geographic mismatch, I find this evidence consistent with the view that geographic mismatch could have a large impact on the aggregate Beveridge curve under reasonable assumptions.

Table 1-1B demonstrates the effect on geographic mismatch
unemployment as the standard deviation of J shocks \((\sigma_{\varepsilon_J} + \sigma_{\nu_J})\) changes relative to the standard deviation of s shocks \((\sigma_{\varepsilon_S} + \sigma_{\nu_S})\). The table assumes \(s = 0.5\), and \(\sigma_{\varepsilon_J}/\sigma_{\nu_J} = \sigma_{\varepsilon_S}/\sigma_{\nu_S} = 2\). In columns 1-6, I assume \(\sigma_{\varepsilon_S} + \sigma_{\nu_S} = 0.005\), and vary \(\sigma_{\varepsilon_J} + \sigma_{\nu_J}\) from 0 in column 1, to 2.5 in column 2. In column 7, I assume \(\sigma_{\varepsilon_S} + \sigma_{\nu_S} = 0\) and \(\sigma_{\varepsilon_J} + \sigma_{\nu_J} = 1\). Columns 1-6 demonstrate that geographic mismatch unemployment increases as the variance of labor demand shocks rises relative to job-matching and job reallocation rate shocks. This is also an intuitive result. If s shocks drive all regional variation in unemployment and vacancy rates, and if regions start with identical V/U ratios, regional V/U ratios tend to stay very close together, implying no geographic mismatch. s shocks lead to movements along a 45-degree line in U-V space. If the initial V/U ratio is near one for each region, these shocks have little effect on V/U ratios (no effect if the initial V/U ratio is equal to one), and thus have little effect on geographic mismatch. Regional labor demand shocks, on the other hand, move regions to different V/U ratios on the same Beveridge curve, and thus increase geographic mismatch. Column 7 is also mildly consistent with this intuition; the average value of geographic mismatch unemployment is slightly greater when the economy is subject only to J shocks (column 7) than when it is subject only to s shocks (column 1). It is worth noting that the figures in this table once again highlight the possible empirical relevance of geographic mismatch unemployment, as \(u_{\text{min}}/u\) ratios are often substantially greater than one.

In Table 1-1C, I vary the standard deviation of J and s shocks, holding their ratio constant. I assume \(s = 0.5\), \(\sigma_{\varepsilon_J}/\sigma_{\nu_J} = \sigma_{\varepsilon_S}/\sigma_{\nu_S} = 2\).
2, and \((\sigma_{\epsilon j} + \sigma_{\nu j})/(\sigma_{\epsilon s} + \sigma_{\nu s}) = 200\). Not surprisingly, increased variance leads to greater mismatch measures. Increased variation in the factors determining regional unemployment and vacancy rates implies a wider expected range of outcomes around the initial allocation in which geographic mismatch is minimized.

Table 1-1D shows how variation in the slopes of the regional curves (changes in \(a\)) affect geographic mismatch. I assume \(\sigma_{\epsilon j} + \sigma_{\nu j} = 1\), \(\sigma_{\epsilon s} + \sigma_{\nu s} = 0.005\), and \(\sigma_{\epsilon j}/\sigma_{\nu j} = \sigma_{\epsilon s}/\sigma_{\nu s} = 2\). Changes in \(a\) have little impact on median values of \(u/u_{\text{min}}\). However, as \(a\) moves away from 0.5, the variability of mismatch measures increases, and the possibility of a period with an enormous amount of mismatch unemployment arises (see column one, for example). As \(a\) approaches zero, hires are determined almost completely by vacancies, and regional Beveridge curves become flatter in log(U)-log(V) space. This implies that any given \(J_i\) shock leads to a relatively large change in \(U_i\), a small change in \(V_i\), and thus a large change in \(V_i/U_i\). For expositional ease, suppose \(s\) is constant in all regions. Small variations in \(J_i\) then have large effects on the variability of \(V_i/U_i\), and thus large impacts on geographic mismatch unemployment. On the other hand, as \(a\) approaches one, changes in \(J\) lead to large changes in vacancies, with little effect on unemployment, and once again have a substantial impact on \(V/U\) ratios and mismatch unemployment. This exercise again points out the importance of knowing the shape (the parameter \(a\)) of regional Beveridge curves when formulating accurate mismatch measures.
1J shocks with these distributional assumptions imply that the standard deviation of changes in productive jobs in any given region is on average about one percent of total productive jobs in that region. The s shock distributional assumptions imply that the standard deviation of s changes in any given region is on average ten percent of s. These strike me as conservative estimates of variation in J and s at the regional level. Jackman, Layard, and Savouri (1990) cite several studies which support an assumption of $\alpha = 0.5$, including Pissarides (1986), Jackman, Layard, and Savouri (1987), and Blanchard and Diamond (1989).

$^2s_i$ must be greater than zero for all i. The probability of drawing a negative shock large enough to imply a negative $s_i$ increases as the standard deviation of s shocks rises. For example, in the last column of Table 1-1C, the standard deviation of s shocks is one-half the original s for each region. If the shock drawn implies a negative $s_i$, I set $s_i = 0.001$. The same problem does not occur for J shocks, since the standard deviation of J shocks in the last column of Table 1-1C is still only approximately 2.5 percent of the original J for each region.
APPENDIX 1-B: Computing efficient aggregate Beveridge curve parameters when regional matching functions are positive monotonic transformations of one another.

In this appendix, I derive values for $a^*$ and $b^*$ that characterize the form of the efficient aggregate Beveridge curve in an economy with regional job-matching functions that are positive monotonic transformations of each other, but which do not necessarily exhibit the same returns to scale. Under these assumptions, an efficient regional allocation of aggregate labor demand requires that $V_i/U_i = V/U$ for some constant $k_2$ for all $i$. Also, $b_i/a_i = b^*/a^*$ for all $i$.

First, I solve for $V_i$ using the steady-state Beveridge curve (Equation (1-7)) for each region:

\[(1B-1) \quad V_i = (V_i/U_i)^{a_i/(a_i+b_i)} (s_i L_i)^{1/(a_i+b_i)} \]

Regional $V_i/U_i$ are constant with an efficient allocation of aggregate labor demand, while monotonicity of the regional matching functions implies that $a_i/(a_i+b_i)$ are also constant across regions. Imposing these conditions, I rewrite Equation (1B-1) as:

\[(1B-2) \quad V_i = k_3 (s_i L_i)^{1/(a_i+b_i)} \quad \text{where} \quad k_3 = (k_2)^{1/(1+k_1)} \]

Summing Equation (1B-2) over all $i$, I find an expression for aggregate vacancies assuming an efficient regional distribution of aggregate labor demand:
\[(1B-3) \quad V = \left[ \Sigma \left( s_i L_i \right)^{1/(a_i b_i)} \right]_k \]

Next I derive an expression for \( \text{gmm}^* \). \( \text{gmm}^* \) can be rewritten:

\[(1B-4) \quad \text{gmm}^* = \sum_{i=1}^N \frac{\left( U_i / V_i \right)^{a_i b_i + a_i}}{\left( U / V \right)^{a_i b_i + a_i}} \]

To find \( \text{gmm}^* \) \(_{\text{max}} \), I plug the expressions for \( V_i \) and \( V \) from Equations (1B-2) and (1B-3) into (1B-4), and impose the efficiency condition that \( V_i / U_i = V / U = k_2 \) for all \( i \). This results in the following equation for \( \text{gmm}^* \) \(_{\text{max}} \):

\[(1B-5) \quad \text{gmm}^* \_{\text{max}} = \sum_{i=1}^N \frac{\left( k_2^{a_i} s_i \right)^{a_i + a_i} L_i}{\left( k_2 Z \right)^{a_i b_i}} \]

where \( Z = \left[ \Sigma \left( s_i L_i \right)^{1/(a_i b_i)} \right] \)

\( k_3^* b^* = k_2^* \), so that the constant terms in Equation (1B-5) cancel each other out. This leaves the following expression for \( \text{gmm}^* \) \(_{\text{max}} \):

\[(1B-6) \quad \text{gmm}^* \_{\text{max}} = \sum_{i=1}^N \frac{s_i L_i}{Z^{a_i b_i}} \]

Assume \( a^* + b^* \) is given by Equation (1B-7):

\[(1B-7) \quad a^* + b^* = \log(\Sigma(s_i L_i)) / \log(Z) \]

I identify individual \( a^* \) and \( b^* \) parameters using Equation (1B-7)
and the condition that $b^*/a^* = k_1$. If these parameters correspond to those of the underlying efficient aggregate Beveridge curve, then $u^{a^*}v^{b^*}$ must be equal to $s^*/g_{mm}^{max}$ when evaluated using these parameters. Using the parameters suggested by Equation (1B-7), I find that $g_{mm}^{max}$ is equal to one, and $u^{a^*}v^{b^*} = s^*$. Therefore, the parameters of the efficient aggregate Beveridge curve under these assumptions are given by Equation (1B-7) and the condition that $b^*/a^* = k_1$. 
APPENDIX 1-C: Computing efficient aggregate Beveridge curve parameters with general Cobb-Douglas regional matching functions.

In this appendix, I describe a procedure for recovering estimates of $a^*$ and $b^*$ that are consistent with an efficient allocation of aggregate labor demand, and that imply $u^*v^* = s^* / \mu_{\max}^*$, for any given number of aggregate productive jobs $J^*$.

I first determine the efficient regional allocation of labor demand for a given $J^*$. I use the following five-step algorithm to solve for this efficient regional distribution:

1. For region 1, assume $J_1 = r_1 J^*$, where $0 < r_1 < 1$.

2. Given $J_1$, solve for $E_1$ using the steady-state Beveridge curve condition (Equation (1.7)): $(J_1 - E_1)^{b_1}(L_1 - E_1)^{a_1} = s_1 L_1$.

3. Calculate $-a_1 V_1^{b_1} u_1 = \lambda$.

4. For all other $i$ regions, $V_i / U_i = -\lambda b_i / a_i$ by the efficiency conditions. The steady-state Beveridge curves also imply $V_i / U_i = [s_i L_i / ((L_1 - E_1)^{a_1 + b_1})]^{1/b_1}$. Find the $E_i$ that is consistent with both of these conditions. Once $E_i$ is identified, $J_i = E_i + (L_1 - E_1) \lambda b_i / a_i$.

5. If $\sum_{i=1}^{N_1} J_i > J^*$, return to step (1) and assume a smaller value for $r_1$. If $\sum_{i=1}^{N_1} J_i < J^*$, return to step (1) and assume a greater value for $r_1$. Continue this process until a $r_1^* = r_1^*$ is found such that $\sum_{i=1}^{N_1} J_i = J^*$. The $J_i$ (and thus $E_i$, $U_i$ and $V_i$) associated with the $r_1^* = r_1^*$ assumption represent the efficient distribution of $J^*$, in the sense that aggregate unemployment for any given level of aggregate vacancies is minimized.
Let $\Sigma L_i^* = L^*$ and $\Sigma E_i^* = E^*$. Once $E_i^*$ that satisfy the efficiency conditions are identified, aggregate unemployment ($U = L^*-E^*$) and vacancies ($V = J^*-E^*$) consistent with these conditions are also identified. Since the slope of the efficient aggregate Beveridge curve must also equal $\lambda$, the following condition holds:

$$(1C-1) \quad \text{rat}_{ba} = b^*/a^* = V/U\lambda$$

Plugging the value of $\lambda$ recovered in the five-step algorithm above into Equation (1C-1), along with the $V$ and $U$ that are consistent with the efficiency conditions, I find the $b^*/a^*$ ratio for the efficient aggregate Beveridge curve. To find explicit values for $b^*$ and $a^*$ individually, first assume $g_{\text{max}}^\ast$ is equal to one, so that $U^\ast V^b^\ast$ must be equal to $\Sigma(s_i^* L_i^*)$ when evaluated with the correct Beveridge curve parameters. Values of $a^*$ and $b^*$ that ensure that this condition holds are given by Equations (1C-2) and (1C-3):

$$(1C-2) \quad a^* = \frac{\log(\Sigma(s_i^* L_i^*))}{\log(U) + \text{rat}_{ba}} \log(V)$$

$$(1C-3) \quad b^* = \text{rat}_{ba} a^*$$

I evaluate Equations (1C-2) and (1C-3) using the values of $\lambda$, $U$, and $V$ that are consistent with the efficiency conditions recovered in the five-step algorithm.

Evaluating $g_{\text{max}}^\ast$ with the parameter values given by (1C-2) and (1C-3), I find that $g_{\text{max}}^\ast$ is in fact equal to one. Thus the
parameters of the efficient aggregate Beveridge curve for any given $J^*$ are given by Equations (1C-2) and (1C-3) evaluated at those values of $V$, $U$, and $\lambda$ consistent with an efficient regional allocation of $J^*$. It follows that an appropriate measure of geographic mismatch unemployment in this general case is $\frac{u}{u_{\text{min}}} = [gmm^*]^{(1/s^*)}$, evaluated at these same parameter values.

However, the efficient aggregate Beveridge curve is not generally of the Cobb-Douglas form in this case. In fact, simulation exercises show that $rat_{ba}$ falls slightly as $J^*$ rises. In other words, the efficient aggregate Beveridge curve is no longer linear in $\log(u) - \log(v)$ space under these general assumptions. Thus the parameters recovered using the procedure outlined in this appendix provide a good estimate of the curvature of the efficient aggregate Beveridge curve only for values of $J^*$ that are close to the value assumed when calculating $a^*$ and $b^*$ using the above algorithm. Consult the text for further discussion of this issue.
APPENDIX 1-D: Simulation exercises assuming general Cobb-Douglas matching functions.

In this appendix, I describe simulation procedures for a model economy assuming Cobb-Douglas regional matching functions that are not constrained to be positive monotonic transformations of each other. Table 1-2 presents results from a subset of these simulations. These results are also discussed in detail in this appendix.

To allow for more general variation in regional matching function parameters, I assume that $a_i$ and $b_i$ are given by Equations (1D-1) and (1D-2):

\[(1D-1) \quad a_i = \tilde{a} + \mu_i^a \quad \text{where} \quad \mu_i^a \sim N(0, \sigma^2_{\mu_i^a}), \quad \forall \ i; \quad \tilde{a} = \text{constant}\]

\[(1D-2) \quad b_i = \tilde{b} + \mu_i^b \quad \text{where} \quad \mu_i^b \sim N(0, \sigma^2_{\mu_i^b}), \quad \forall \ i; \quad \tilde{b} = \text{constant}\]

The variances of $\mu_i^a$ and $\mu_i^b$ determine variation in $a_i$ and $b_i$ across regions. I assume only cross-sectional variation, and no within-region time-series variation, in $a_i$ and $b_i$. However, time-series variation can be easily accommodated in any future simulations.

I conduct the simulation exercises as described in Appendix 1-A, with several additional steps. At the beginning of each 50-period simulation, I assign each region $a_i$ and $b_i$ parameters by drawing from the distributions for $\mu_i^a$ and $\mu_i^b$. Also, in each period of each simulation, I compute $J^*$ and solve for $a^*$ and $b^*$ using the algorithm presented in Appendix 1-C. I also compute the alternative values for $a^*$ and $b^*$ suggested by Equations (1-21) and (1-22). In each period of
each simulation, I compute three alternative measures of \( u/u_{\text{min}} \). First, there is the "correct" measure, which I label \( (u/u_{\text{min}})^C \). The second measure assumes \( a^* \) and \( b^* \) are given by Equations (1-21) and (1-22). I label this measure \( (u/u_{\text{min}})^{Wav8} \), since I construct it assuming \( a^* \) and \( b^* \) are hires-weighted averages of \( a_1 \) and \( b_1 \). The third measure assumes that all regions have identical matching functions, with \( a_1 = a^* \) as given in (1-21), and \( b_1 = b^* \) as given by (1-22), for all \( i \). I label this measure \( (u/u_{\text{min}})^{JLS} \), since it is the appropriate index under the assumptions Jackman, Layard, and Savouri (1987,1990) make when developing their geographic mismatch indices. I run each simulation over 50 time periods, and I calculate the average value of each of the \( u/u_{\text{min}} \) measures in these periods. I also calculate the correlation of the growth rates of \( (u/u_{\text{min}})^C \) and \( (u/u_{\text{min}})^{Wav8} \), which I call \( \rho^W \), and the correlation of the growth rates of \( (u/u_{\text{min}})^C \) and \( (u/u_{\text{min}})^{JLS} \), which I call \( \rho^J \), over this time period. The correlation measures provide information on whether the alternative indices suggest a consistent pattern for the time-series variation in geographic mismatch unemployment. I run each simulation 50 times to obtain distributions for average \( (u/u_{\text{min}})^C \), \( (u/u_{\text{min}})^{Wav8} \), and \( (u/u_{\text{min}})^{JLS} \), and for \( \rho^W \) and \( \rho^J \).

Table 1-2 reports results from simulation exercises which assume constant returns to scale in the regional matching functions, so that \( a_i \) are given by Equation (1D-1), but \( b_i \) are constrained to be equal to 1-\( a_i \). The baseline parameters are: \( \mu = 0.5 \); \( \sigma_\epsilon + \sigma_\nu = 1 \); \( \sigma_\epsilon + \sigma_\nu = 0.005 \); and \( \sigma_\epsilon / \sigma_\nu = \sigma_\epsilon / \sigma_\nu = 2 \). The first column assumes that \( \sigma_{\mu} = 0.05 \), the second \( \sigma_{\mu} = 0.1 \), and the third \( \sigma_{\mu} = 0.2 \). I impose the following constraint on \( a_i \): \( 0.1 \leq a_i \leq 0.9 \). If \( a_i \) is greater than
0.4, I set \( \alpha = 0.9 \), and if \( \mu_i \) is less than -0.4, I set \( \alpha = 0.1 \). In practice, this constraint is binding only when \( \mu_a \) is relatively large.

First consider the summary statistics for \( (u/u_{\text{min}})^C \), \( (u/u_{\text{min}})^{\text{Hav}} \), and \( (u/u_{\text{min}})^{\text{JLS}} \). The average value and variability of \( (u/u_{\text{min}})^C \) increases as \( \sigma_{\mu_a} \) rises. This is an intuitive result. I start all simulations assuming equal V/U ratios in all regions, which minimizes \( (u/u_{\text{min}})^C \) only when all regions have the same \( \alpha \). Increased variability in \( \alpha \) implies that geographic mismatch unemployment is greater in the initial period, and thus expected to be greater over the entire sample period. This is not the case for \( (u/u_{\text{min}})^{\text{JLS}} \) and \( (u/u_{\text{min}})^{\text{Hav}} \). Recall that \( (u/u_{\text{min}})^{\text{JLS}} \) is minimized when V/U ratios are identical in each region. The initial period value for \( (u/u_{\text{min}})^{\text{JLS}} \) is thus not affected by changes in \( \sigma_{\mu_a} \), and thus the average value of geographic mismatch unemployment using this measure is seemingly independent of \( \sigma_{\mu_a} \). Therefore, \( (u/u_{\text{min}})^{\text{JLS}} \) may not be a good indicator of the level of mismatch unemployment in the economy. \( (u/u_{\text{min}})^{\text{Hav}} \) can actually be less than one, since \( \gamma_{\text{max}} \) is greater than one with these assumptions for \( \alpha^* \) and \( \beta^* \). This and the fact that average \( (u/u_{\text{min}})^{\text{Hav}} \) does not increase with \( \sigma_{\mu_a} \) suggests that \( (u/u_{\text{min}})^{\text{Hav}} \) is also not an accurate measure of the level of geographic mismatch unemployment in the economy.

For most empirical applications, however, perhaps what is most important is the ability of \( (u/u_{\text{min}})^{\text{JLS}} \) and \( (u/u_{\text{min}})^{\text{Hav}} \) to track time-series variation in geographic mismatch unemployment. Table 1-2 suggests that the Jackman, Layard, and Savouri (1987,1990) index may do a very poor job of this when there is significant variation in \( \alpha \).
across regions. For example, when $\sigma_{\mu_a} = 0.2$, the average correlation of the growth rates of $(u/u_{\min})^{JLS}$ and $(u/u_{\min})^C$ over 50-period horizons is only 0.285. In fact, in some simulations, this correlation is significantly negative (reaching -0.598 as its minimum), so that the indices are on average moving in the opposite direction. Even when $\sigma_{\mu_a} = 0.05$, some simulations show negative correlations of these growth rates over the 50-period horizon. On the other hand, $(u/u_{\min})^{WAVS}$ seems to track time-series variation in $(u/u_{\min})^C$ fairly well. With $\sigma_{\mu_a} = 0.2$, correlations of the growth rates of these indices average 0.779, with the standard deviation of that average only 0.16. With $\sigma_{\mu_a} = 0.05$, the two indices demonstrate nearly identical time-series variation.

The basic pattern that $(u/u_{\min})^{JLS}$ and $(u/u_{\min})^{WAVS}$ do a poor job of measuring the level of mismatch in the economy, while $(u/u_{\min})^{WAVS}$ tracks time-series variation in mismatch quite closely, also appears robust to different assumptions regarding parameter baseline values, and returns to scale, in the simulation exercises.
APPENDIX 1-E: Using aggregate matching function estimates to recover regional matching function parameters under general assumptions.

In Section IV of the text, I propose a simple iterative procedure to recover regional matching function parameters using aggregate matching function estimates. However, in developing that procedure, I assume that regional matching functions exhibit identical, constant returns to scale technologies. In this appendix, I demonstrate that a similar procedure can be used to identify hires-weighted averages of regional matching function parameters when such functions are not identical and/or do not exhibit constant returns to scale.

If regional matching functions are not identical, researchers would like to recover returns to scale estimates for all regional markets, if possible. However, in testing the validity of the Diamond (1982) prediction, a measure of the "average" returns to scale in regional markets is probably sufficient. $\alpha^* + \beta^*$ in Equations (1-21) and (1-22) is a hires-weighted average of regional returns to scale. Normalizing $h_1$ to be constant in each region, aggregate hires is given by:

\[
(1E-1) \quad H^a = \sum_{i=1}^{N} \gamma_i L_i = h \star \left[ \sum_{i=1}^{N} \left( \frac{U_i^a V_i^{b_i}}{U_i^{a*} V_i^{b*}} \right) \right] \star U_i^{a*} V_i^{b*} \\
= h \star g_{mm^*} \star U_i^{a*} V_i^{b*}
\]

where $a^*$ and $b^*$ are given by Equations (1-21) and (1-22).

The researcher would like to recover $\alpha^*$, $\beta^*$, and their sum. If the aggregate matching function in (1-24) is estimated, however, estimates of $\alpha_1$ and $\alpha_2$ are given by:

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\begin{align*}
(1E-2) \quad \hat{\alpha}_1 &= \alpha^* + \beta_1 \\
(1E-3) \quad \hat{\alpha}_2 &= \beta^* + \beta_2
\end{align*}

The procedure to find the true \( \alpha^* \) and \( \beta^* \) is as outlined in Section IV for the identical constant returns to scale case. Assume values for \( \alpha_i \) and \( \beta_i \), and thus \( \alpha^* \) and \( \beta^* \). Estimate the auxiliary regression given by (1-25) using a \textit{gmm} \ series constructed under these assumptions, and check the conditions given by Equations (1E-2) and (1E-3). Continue trying alternative values for \( \alpha_i \) and \( \beta_i \) until (1E-2) and (1E-3) hold.

Empirical implementation of this algorithm, however, may be constrained by data limitations. Calculation of \( \alpha^* \) and \( \beta^* \) generally requires regional hires data. If such data were available, regional matching functions could be estimated and this whole exercise would be unnecessary. One of three assumptions will thus be necessary to implement this procedure in empirical work: (1) Job reallocation rates are identical across regions, so that labor-force-weighted averages of \( \alpha_i \) and \( \beta_i \) are equivalent to hires-weighted averages. (2) \( \alpha_i \) and \( \beta_i \) are identical across regions, but their sum is unrestricted. (3) Each region is on its steady-state Beveridge curve at any moment in time. Normalizing \( h_i = 1 \) in all regions, this implies that given an assumption for \( \alpha_i \) and \( \beta_i \), an estimate of hires in region \( i \) is \( U^{a_i} V^{b_i} \). One can then use these regional hires estimates to calculate \( \alpha^* \) and \( \beta^* \).

None of these three assumptions is completely satisfactory, thus returns to scale estimates derived from this procedure will naturally
be suspect. Nonetheless, the procedure should at the very least be able to accurately identify the direction of the bias in aggregate matching function estimates, which should be of interest to macroeconomists working in this literature.
FIGURES AND TABLES: CHAPTER 1
FIGURE 1-1: THE BEVERIDGE CURVE & UNEMPLOYMENT

FIGURE 1-2: DISPERSION & THE BEVERIDGE CURVE
TABLE 1-1A: GEOGRAPHIC MISMATCH UNEMPLOYMENT AND THE VARIANCE RATIOS OF AGGREGATE VERSUS REGIONAL SHOCKS

<table>
<thead>
<tr>
<th>Summary Statistics for $u^*_u$</th>
<th>0</th>
<th>4</th>
<th>2</th>
<th>1.5</th>
<th>0.67</th>
<th>0.25</th>
<th>0</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>1.0</td>
<td>1.02</td>
<td>1.04</td>
<td>1.05</td>
<td>1.10</td>
<td>1.17</td>
<td>1.26</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>0.0</td>
<td>0.03</td>
<td>0.04</td>
<td>0.06</td>
<td>0.07</td>
<td>0.08</td>
<td>0.16</td>
</tr>
<tr>
<td>Minimum</td>
<td>1.0</td>
<td>1.00</td>
<td>1.01</td>
<td>1.01</td>
<td>1.03</td>
<td>1.06</td>
<td>1.06</td>
</tr>
<tr>
<td>Maximum</td>
<td>1.0</td>
<td>1.23</td>
<td>1.23</td>
<td>1.39</td>
<td>1.52</td>
<td>1.55</td>
<td>2.15</td>
</tr>
</tbody>
</table>

Source: Author's calculations from simulation exercises described in Section III of the text and Appendix 1-A.

For each alternative variance ratio assumption, 100 simulations of the model economy described in Section III and Appendix 1-A over a 50-period horizon were conducted. For each simulation, the average value of $u^*_u$ over that 50-period horizon was calculated. The table shows the mean, standard deviation, minimum, and maximum values of this average over the 100 simulations. All figures are rounded.
<table>
<thead>
<tr>
<th>Summary Statistics for $u/u_{\text{min}}$</th>
<th>Assumption for $(\sigma_{c_j} + \sigma_{v_j})/(\sigma_{c_u} + \sigma_{v_u})$ ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0</td>
</tr>
<tr>
<td>Mean</td>
<td>1.01</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>0.02</td>
</tr>
<tr>
<td>Minimum</td>
<td>1.00</td>
</tr>
<tr>
<td>Maximum</td>
<td>1.08</td>
</tr>
</tbody>
</table>

Source: Author’s calculations from simulation exercises described in Section III of the text and Appendix 1-A.

For each alternative variance ratio assumption, 100 simulations of the model economy described in Section III and Appendix 1-A over a 50-period horizon were conducted. For each simulation, the average value of $u/u_{\text{min}}$ over that 50-period horizon was calculated. The table shows the mean, standard deviation, minimum, and maximum values of this average over the 100 simulations. All figures are rounded.
TABLE 1-1C: GEOGRAPHIC MISMATCH UNEMPLOYMENT AND THE VARIANCE OF LABOR DEMAND AND REALLOCATIONAL SHOCKS

Assumption for the variance of shocks: 

\[ (\sigma_{eJ} + \sigma_{vJ}) = \delta^*1.0, \ (\sigma_{eS} + \sigma_{vS}) = \delta^*0.005 \]

<table>
<thead>
<tr>
<th>Summary Statistics for uwmin</th>
<th>( \delta = 0 )</th>
<th>( \delta = 0.5 )</th>
<th>( \delta = 1 )</th>
<th>( \delta = 1.5 )</th>
<th>( \delta = 2 )</th>
<th>( \delta = 2.5 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>1.0</td>
<td>1.01</td>
<td>1.04</td>
<td>1.12</td>
<td>1.26</td>
<td>1.31</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>0.0</td>
<td>0.01</td>
<td>0.06</td>
<td>0.13</td>
<td>0.38</td>
<td>0.59</td>
</tr>
<tr>
<td>Minimum</td>
<td>1.0</td>
<td>1.00</td>
<td>1.01</td>
<td>1.01</td>
<td>1.01</td>
<td>1.01</td>
</tr>
<tr>
<td>Maximum</td>
<td>1.0</td>
<td>1.04</td>
<td>1.43</td>
<td>1.62</td>
<td>3.41</td>
<td>6.50</td>
</tr>
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</table>

Source: Author's calculations from simulation exercises described in Section III of the text and Appendix 1-A.

For each alternative variance assumption, 100 simulations of the model economy described in Section III and Appendix 1-A over a 50-period horizon were conducted. For each simulation, the average value of uwmin over that 50-period horizon was calculated. The table shows the mean, standard deviation, minimum, and maximum values of this average over the 100 simulations. All figures are rounded.
### TABLE 1-1D: GEOGRAPHIC MISMATCH UNEMPLOYMENT AND THE SLOPES OF REGIONAL BEVERIDGE CURVES

<table>
<thead>
<tr>
<th>Summary Statistics for $u/u_{\text{min}}$</th>
<th>Assumption of the value of $a$ in regional curves</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$a=0.1$</td>
</tr>
<tr>
<td>Mean</td>
<td>5.65</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>34.51</td>
</tr>
<tr>
<td>Minimum</td>
<td>1.01</td>
</tr>
<tr>
<td>Maximum</td>
<td>343.8</td>
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</tbody>
</table>

Source: Author's calculations from simulation exercises described in Section III of the text and Appendix 1-A.

For each alternative assumption on $a$, 100 simulations of the model economy described in Section III and Appendix 1-A over a 50-period horizon were conducted. For each simulation, the average value of $u/u_{\text{min}}$ over that 50-period horizon was calculated. The table shows the mean, standard deviation, minimum, and maximum values of this average over the 100 simulations. All figures are rounded.
TABLE 1-2: ALTERNATIVE MEASURES OF GEOGRAPHIC MISMATCH UNEMPLOYMENT AND CROSS-SECTIONAL VARIANCE IN REGIONAL MATCHING FUNCTION PARAMETERS

<table>
<thead>
<tr>
<th>Summary Statistics for alternative measures</th>
<th>Assumption for $\sigma_{\mu a}$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.05</td>
</tr>
<tr>
<td>$(u/u_{min})^c$</td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>1.06</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>0.08</td>
</tr>
<tr>
<td>Minimum</td>
<td>1.01</td>
</tr>
<tr>
<td>Maximum</td>
<td>1.29</td>
</tr>
<tr>
<td>$(u/u_{min})^{wav}$</td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>1.05</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>0.06</td>
</tr>
<tr>
<td>Minimum</td>
<td>1.00</td>
</tr>
<tr>
<td>Maximum</td>
<td>1.29</td>
</tr>
<tr>
<td>$(u/u_{min})^{JLS}$</td>
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</tr>
<tr>
<td>Mean</td>
<td>1.06</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>0.07</td>
</tr>
<tr>
<td>Minimum</td>
<td>1.01</td>
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<tr>
<td>Maximum</td>
<td>1.35</td>
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<tr>
<td>$\rho^c$</td>
<td></td>
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<tr>
<td>Mean</td>
<td>0.86</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>0.17</td>
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<tr>
<td>Minimum</td>
<td>-0.06</td>
</tr>
<tr>
<td>Maximum</td>
<td>0.96</td>
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<tr>
<td>$\rho^c$</td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>0.94</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>0.03</td>
</tr>
<tr>
<td>Minimum</td>
<td>0.81</td>
</tr>
<tr>
<td>Maximum</td>
<td>0.96</td>
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</tbody>
</table>

Source: Author's calculations from simulation exercises described in Section III of the text and Appendix 1-D.

For each alternative variance assumption, 50 simulations of the model economy described in Section III and Appendix 1-D over a 50-period horizon were conducted. For each simulation, the average value for alternative mismatch indices and the correlation of growth rates in these indices over that 50-period horizon were calculated. The table shows the mean, standard deviation, minimum, and maximum values of these statistics over the 50 simulations. All figures are rounded.
<table>
<thead>
<tr>
<th>Summary Statistics for returns to scale bias</th>
<th>Assumption for $\sigma_{\epsilon J}/\sigma_{u J} = \sigma_{\epsilon J}/\sigma_{u J}$ ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\infty$</td>
</tr>
<tr>
<td>Mean</td>
<td>0.0</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>0.0</td>
</tr>
<tr>
<td>Minimum</td>
<td>0.0</td>
</tr>
<tr>
<td>Maximum</td>
<td>0.0</td>
</tr>
</tbody>
</table>

Source: Author's calculations from simulation exercises described in Sections III and IV of the text and Appendix 1-A.

For each alternative variance ratio assumption, 100 simulations of the model economy described in Sections III and IV and Appendix 1-A over a 50-period horizon were conducted. For each simulation, the aggregate matching function was estimated, and the bias in the returns to scale estimate from this function was calculated. The table shows the mean, standard deviation, minimum, and maximum values of this bias figure over the 100 simulations. All figures are rounded.
TABLE 1-3B: RETURNS TO SCALE BIAS IN THE AGGREGATE MATCHING FUNCTION AND THE VARIANCE RATIOS OF LABOR DEMAND VERSUS REALLOCATIONAL SHOCKS

<table>
<thead>
<tr>
<th>Summary Statistics for returns to scale bias</th>
<th>Assumption for $(\sigma_{\epsilon_J} + \sigma_{\mu_J})/(\sigma_{\epsilon_s} + \sigma_{\mu_s})$ ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0  100  200  300  400  500  $\omega$</td>
</tr>
<tr>
<td>Mean</td>
<td>-0.02  0.01  0.04  0.09  0.10  0.12  -1.00</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>0.04  0.03  0.06  0.16  0.18  0.24  0.00</td>
</tr>
<tr>
<td>Minimum</td>
<td>-0.17  -0.02  -0.03  -0.10  -0.11  -0.25  -1.00</td>
</tr>
<tr>
<td>Maximum</td>
<td>0.03  0.14  0.25  0.88  0.91  1.26  -1.00</td>
</tr>
</tbody>
</table>

Source: Author's calculations from simulation exercises described in Section III and IV of the text and Appendix 1-A.

For each alternative variance ratio assumption, 100 simulations of the model economy described in Sections III and IV and Appendix 1-A over a 50-period horizon were conducted. For each simulation, the aggregate matching function was estimated, and the bias in the returns to scale estimate from this function was calculated. The table shows the mean, standard deviation, minimum, and maximum values of this bias figure over the 100 simulations. All figures are rounded.
TABLE 1-3C: RETURNS TO SCALE BIAS IN THE AGGREGATE MATCHING FUNCTION AND THE VARIANCE OF LABOR DEMAND AND REALLOCATIONAL SHOCKS

Assumption for the variance of shocks:

\[(\sigma_{\varepsilon_j}^2 + \sigma_{\varepsilon_j}^2) = \delta^*1.0, (\sigma_{\varepsilon_u}^2 + \sigma_{\varepsilon_u}^2) = \delta^*0.005\]

<table>
<thead>
<tr>
<th>Summary Statistics for returns to scale bias</th>
<th>$\delta=0$</th>
<th>$\delta=0.5$</th>
<th>$\delta=1$</th>
<th>$\delta=1.5$</th>
<th>$\delta=2$</th>
<th>$\delta=2.5$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.0</td>
<td>0.01</td>
<td>0.03</td>
<td>0.08</td>
<td>0.13</td>
<td>0.14</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>0.0</td>
<td>0.02</td>
<td>0.06</td>
<td>0.10</td>
<td>0.18</td>
<td>0.25</td>
</tr>
<tr>
<td>Minimum</td>
<td>0.0</td>
<td>-0.02</td>
<td>-0.09</td>
<td>-0.08</td>
<td>-0.07</td>
<td>-0.09</td>
</tr>
<tr>
<td>Maximum</td>
<td>0.0</td>
<td>0.05</td>
<td>0.22</td>
<td>0.40</td>
<td>0.79</td>
<td>2.12</td>
</tr>
</tbody>
</table>

Source: Author's calculations from simulation exercises described in Sections III and IV of the text and Appendix 1-A.

For each alternative variance assumption, 100 simulations of the model economy described in Sections III and IV and Appendix 1-A over a 50-period horizon were conducted. For each simulation, the aggregate matching function was estimated, and the bias in the returns to scale estimate from this function was calculated. The table shows the mean, standard deviation, minimum, and maximum values of this bias figure over the 100 simulations. All figures are rounded.
### Table 1-3D: Returns to Scale Bias in the Aggregate Matching Function and the Slopes of Regional Beveridge Curves

<table>
<thead>
<tr>
<th>Summary Statistics for returns to scale bias</th>
<th>Assumption of the value of ( a ) in regional curves</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( a=0.1 )</td>
</tr>
<tr>
<td>Mean</td>
<td>0.02</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>0.08</td>
</tr>
<tr>
<td>Minimum</td>
<td>-0.21</td>
</tr>
<tr>
<td>Maximum</td>
<td>0.39</td>
</tr>
</tbody>
</table>

Source: Author's calculations from simulation exercises described in Sections III and IV of the text and Appendix 1-A.

For each alternative assumption on \( a \), 100 simulations of the model economy described in Sections III and IV and Appendix 1-A over a 50-period horizon were conducted. For each simulation, the aggregate matching function was estimated, and the bias in the returns to scale estimate from this function was calculated. The table shows the mean, standard deviation, minimum, and maximum values of this bias figure over the 100 simulations. All figures are rounded.
REFERENCES FOR CHAPTER 1


Beveridge, Lord William, Unemployment: A Problem of Industry, 1893.


CHAPTER 2: CONSTRUCTING PROXY SERIES FOR U.S. REGIONAL VACANCY RATES
I. AGGREGATE AND REGIONAL JOB VACANCIES IN THE U.S.: DATA ISSUES

Economists examining the relationship between unemployment and job vacancies in the United States encounter serious data limitations. Unlike many European countries, government agencies in the U.S. have not collected job vacancy statistics in a systematic, sustained manner. The Bureau of Labor Statistics, the Bureau of Employment Security, and various state employment offices have conducted several pilot programs to collect vacancy statistics through employer surveys. However, these projects have been invariably short-lived and limited in geographic scope. The vacancy statistics provided by these projects allow researchers to observe "snapshots" of the relationship between unemployment and vacancies in various cities and states at different times, identifying a point or two on these regional Beveridge curves. These vacancy data do not allow for a systematic study of either regional or aggregate Beveridge curves, however, since identification of these curves requires consistent time series for job vacancies.

Given these data limitations, economists have increasingly turned to the Conference Board's help-wanted index as a proxy for aggregate job vacancies in the U.S. While use of this index has been questioned in the past, Abraham (1937) presents evidence suggesting that the help-wanted index tracks time-series variation in job vacancies quite closely.

The Conference Board's index is constructed using help-wanted indices from newspapers surveyed in fifty-one different metropolitan statistical areas (MSAs) in the U.S. In this chapter, I use these MSA indices to develop regional vacancy rate proxy series.
In Section II, I argue that MSA help-wanted indices, in their published form, offer little or no information on cross-sectional variation in vacancy rates. All MSA indices share a common base value, and therefore only reflect within-region time-series variation in help-wanted advertising. In order to develop vacancy rate proxies more suitable for cross-sectional comparisons, I benchmark the MSA indices by counting the number of want-ads published in each Conference Board survey newspaper in a given week. I use these benchmark counts and MSA help-wanted indices to construct time series for the volume of help-wanted advertising in each of the survey newspapers. I then compare pilot project job vacancy counts and help-wanted advertising series in those MSAs and time periods for which direct comparisons are possible. These comparisons suggest that help-wanted series track time-series variation in job vacancies within an MSA quite closely. However, consistent evidence of their ability to accurately track cross-sectional variation in job vacancies is lacking.

In Section III, I identify a number of factors that may influence the ratio of job vacancies in an MSA to the number of help-wanted ads appearing in the survey newspaper in that MSA. These factors include: (1) The competitive structure of MSA newspaper advertising markets. Competition in newspaper markets may affect the proportion of job vacancies appearing in newspaper want-ad sections. At the same time, competition may also affect the proportion of total MSA want-ads that appear in survey newspapers. (2) The occupational composition of employment. If vacancies in certain occupations are more likely to be advertised than others, then the occupational composition of
employment and job vacancies affects the ratio of help-wanted ads to vacancies. (3) Employer advertising practices. Variation in recruitment strategies by firms, including their use of job-matching intermediaries such as employment agencies, affects the number of want-ads appearing for any given number of vacancies. (*4*) Institutional features of survey newspapers. Readership demographics, want-ad rate schedules, and classified section formats of survey newspapers may affect the proportion of MSA job vacancies advertised in these papers.

Cross-sectional and time-series variation in these factors implies that help-wanted series may not accurately track variation in job vacancies. Following Abraham (1987), I use an extensive panel data set of MSA newspaper and labor market variables to estimate cross-sectional and time-series variation in many of these factors. I then adjust help-wanted series for this variation. I compare the adjusted help-wanted series with pilot project vacancy counts, and conclude that these series provide accurate proxies for MSA vacancy rates.

The final section briefly summarizes the main conclusions from this proxy-building exercise, and previews the empirical analysis of regional Beveridge curves that follows in Chapter 3.

I now turn to a thorough description of the procedures I follow in constructing regional vacancy proxies. Readers interested in a general overview of the theoretical and empirical issues involved in constructing vacancy rate proxies from help-wanted indices can focus solely on the main body of the chapter. Economists contemplating use of these vacancy rate proxies in further studies should also consult
the chapter's appendices. The appendices describe in much greater detail the data collection and refinement procedures I use in calculating these proxy series.

II. USING THE CONFERENCE BOARD METROPOLITAN HELP-WANTED INDICES TO CONSTRUCT REGIONAL JOB VACANCY PROXIES

The Conference Board collects data on help-wanted ad counts from newspapers in fifty-one MSAs in the U.S. These MSAs account for roughly fifty percent of total nonagricultural employment in the continental United States. Only one newspaper per MSA is included in the Conference Board sample. This paper is always the primary carrier of help-wanted advertising in the MSA. Each month, the participating newspapers report the total number of help-wanted advertisements run in the classified sections of their newspapers during the month. The raw ad counts provided by each newspaper are then adjusted for differences in the number of weekdays and Sundays across months, and for seasonal variation in help-wanted advertising. Each newspaper's adjusted ad count is then converted to an index form, by using a 1967 - 100 base for every MSA. These indices are then published monthly by the Conference Board.

The fact that all MSA indices share the same base level implies that the indices are inappropriate for measuring cross-sectional variation in help-wanted advertising volume. The indices may accurately track time-series variation of job vacancy rates in specific MSAs. However, they provide little or no information on the relative levels of job vacancies in different MSAs.

The raw ad counts used to construct each of the MSA indices,
however, may be more directly comparable across MSAs. Unfortunately, the Conference Board will not release either the help-wanted ad counts supplied by participating newspapers, or the identities of these papers, citing the proprietary nature of these data. To generate estimates of these ad counts, I first identify the newspaper in each of the fifty-one MSAs that is the most likely participant in the Conference Board survey. I then benchmark the MSA indices by manually counting the number of help-wanted ads published in each of these newspapers in a given week.

Appendices 2-A and 2-B describe in detail the methods and data I use to identify the most likely participant in the Conference Board survey in each of the MSAs. The most important assumption in this identification procedure is that the leading help-wanted advertiser in each MSA is also the leading classified advertiser. This assumption allows me to identify the primary carrier of help-wanted advertising in any MSA without requiring manual counts of want-ads placed in all daily newspapers in that MSA.

Each year, Media Records Inc., an advertising consulting firm, and Editor and Publisher, the leading trade magazine in the newspaper industry, publish annual classified advertising volume numbers for virtually every metropolitan daily newspaper in the U.S. I use these sources to determine the leading newspaper in classified advertising volume in each of the fifty-one MSAs, and then assume that this newspaper is also the leading help-wanted advertiser.

Table 2-1 shows the fifty-one MSAs included in the Conference Board survey, as well as the newspaper from each of these areas that I identify as the most likely participant in this survey.
I benchmark the MSA indices by counting the number of want-ads published in the classified sections of the newspapers identified in Table 2-1 during the week of October 9-15, 1967. For each newspaper, I compute a benchmark estimate for the month of October, 1967, by assuming that weekly ad counts do not vary through this month. I use these benchmark counts and the Conference Board's MSA help-wanted indices to construct monthly time series representing the number of help-wanted ads published in each of the sample newspapers. Appendix 2-C provides further details on this benchmarking procedure.

Tables 2-2 and 2-3 display summary statistics for weekly benchmark counts from forty-eight of the original fifty-one newspapers. Close to 250,000 want-ads appeared in these survey newspapers in the benchmark week, including over 12,000 in the Sunday New York Times alone. Table 2-3 demonstrates that limiting benchmark counts to less than a week would be a mistake. The substantial variation in the average number of ads placed across weekdays suggests that one weekday count is not a very good proxy for other weekday counts.

The figures in Table 2-2 suggest that want-ad counts may systematically underestimate job vacancies in these MSAs. For example, it is certainly true that there were more than 665 job vacancies on an average day in October, 1967, in the Boston MSA. However, this does not imply that ad counts are "bad" proxies for regional vacancies. Good proxies must meet the following criteria: They should track the within-region time-series variation of job vacancies, and they should track the between-region cross-sectional variation of vacancies. The ad counts serve as good proxies for
regional job vacancies as long as they underestimate vacancies in a consistent, systematic manner both over time and across regions.

One way of assessing the validity of these ad count series as vacancy proxies is to compare them with vacancy series from employer surveys taken during one or more of the pilot projects mentioned in Section I. Abraham (1983,1987) notes that Minnesota and Wisconsin are the only states for which vacancy time series of any reasonable length exist. Wisconsin collected job vacancy data in 1976 through 1981, while Minnesota collected these data from 1972 through 1981.

Figure 2-1 plots the vacancy rate (VR) and the "help-wanted rate" (HWR), defined as the number of help-wanted ads run in a quarter divided by nonagricultural payroll employment, for the Minneapolis metro area from 1972 through 1981. Figure 2-2 plots these same series for the Milwaukee metro area from 1976 through 1981. The figures clearly show that the HWR accurately track within-region time-series variation in the VR, with the possible exception of the last few quarters in each pilot project. However, Abraham (1987) notes that vacancy rate series from the end of these survey projects may be particularly unreliable.

Correlations between the HWR and VR confirm the ability of the HWR to characterize within-region time-series variation in the VR. The correlation between HWR and VR is 0.77 in Minneapolis, and 0.84 in Milwaukee. The correlation between the growth rates of HWR and VR is 0.82 in Minneapolis, and 0.74 in Milwaukee.

Evidence from Holzer (1989) suggests that the HWR also do a reasonable job of tracking cross-sectional variation in measured VR. Holzer (1989) computes vacancy rates in 1980 for twenty-eight
different geographic areas using data from the Employment Opportunity Pilot Project (EOPP). Seven of those areas are MSAs for which HWR series are also available. Table 2-4 presents VR and HWR for these seven MSAs in 1980. It appears, at the very least, that the HWR identify those MSAs with the highest and lowest VR. In fact, the Spearman rank correlation statistic for the HWR and VR figures from these seven MSAs is 0.79, which is greater than zero at the five-percent significance level. This result suggests that the HWR are capable of identifying low- and high-vacancy MSAs.

On the other hand, the HWR do not accurately reflect the relative levels of job vacancies in Minneapolis and Milwaukee. Figure 2-3 plots the Minneapolis/Milwaukee HWR and VR ratios from 1976 through 1981. It is immediately apparent that HWR systematically understimates VR in Minneapolis relative to Milwaukee. The HWR give the impression that Minneapolis had a low vacancy rate compared to Milwaukee over this time period, while the VR suggest just the opposite was true.

Data from these pilot projects thus offer mixed signals for the validity of the want-ad series as regional job vacancy proxies. The series appear to track within-region time-series variation in VR in Minneapolis and Milwaukee quite closely. However, consistent evidence of their ability to track cross-sectional variation in VR is lacking.

Abraham (1987) identifies factors that may affect the within-region time-series relationship between vacancies and help-wanted advertisements. She notes that shifts in the occupational composition of employment, changes in employer advertising practices, and changes in newspaper competition in regional markets may all
affect the HWR's ability to accurately track VR over time. Differences in these same factors across regions may also limit the HWR's ability to represent cross-sectional variation in VR. In the next section, I develop adjustments to the want-ad series designed to correct for cross-sectional and time-series variation in these three factors. I also consider adjustments to these proxy series based on variation in employment agency activity, newspaper circulation range, and newspaper institutional features both across MSAs and over time. All adjustments are intended to improve the proxy series' abilities to track time-series and cross-sectional variation in job vacancy rates.

III. ADJUSTING THE PROXIES TO ENABLE A MORE ACCURATE DESCRIPTION OF TIME-SERIES AND CROSS-SECTIONAL VARIATION IN VACANCY RATES

NEWSPAPER COMPETITION AND THE EXTENT OF WANT-AD DUPLICATION ACROSS NEWSPAPERS IN AN MSA

Figure 2-3 shows that the Minneapolis HWR/VR ratio was systematically lower than the Milwaukee ratio from 1976 to 1981. Substantial differences in the amount of newspaper competition in these two metro areas during that time period may account for this pattern.

The Milwaukee Journal-Sentinel and the Waukesha Freeman were the only two major daily newspapers in the Milwaukee MSA from 1976 to 1981. Of these two papers, the Journal-Sentinel accounted for approximately 95 percent of the circulation in the metro area, and for 92 percent of the classified advertising volume during this time period. The Journal-Sentinel was clearly the dominant daily newspaper
in Milwaukee at this time. There were also two major daily newspapers in Minneapolis from 1976 to 1981; the Minneapolis Star-Tribune and the St. Paul Dispatch-Pioneer Press. Of these two dailies, the Star-Tribune accounted for 65 percent of metro circulation and classified advertising volume from 1976 to 1981. 15

It is quite likely that ad counts from the Star-Tribune substantially underestimate the total number of separate want-ads placed in the Minneapolis metro area from 1976 to 1981. The Dispatch-Pioneer Press, as a formidable competitor for circulation and advertising revenue in the area, probably ran a number of help-wanted ads that did not also appear in the Star-Tribune. Ad counts from the Journal-Sentinel, however, may more accurately reflect the total number of separate ads placed in Milwaukee at this time. The Freeman, as a relatively small suburban daily, may have run few, if any, help-wanted ads that did not also appear in the Journal-Sentinel. This systematic underestimation of help-wanted counts in Minneapolis versus Milwaukee is one plausible explanation for the bias illustrated in Figure 2-3.

Want-ad series representing only the leading advertisers in competitive newspaper markets obviously underestimate the total number of help-wanted ads placed in these markets. However, the relevant proxy for MSA job vacancies is the number of separate want-ads placed in that MSA's newspapers. If some job openings are advertised in more than one newspaper, total ad counts overestimate the number of separate job vacancies being advertised at any given time. Information on the extent of want-ad duplication across competing newspapers in an MSA is necessary to generate estimates of the number

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of separate vacancies being advertised.

The number of want-ad series appearing in the leading advertiser is a lower-bound estimate of the separate ads. This is the appropriate count only when all ads appearing in secondary advertisers are duplicates of ads appearing in the leading advertiser. Under this "full-duplication" assumption, want-ad series from the leading advertiser do not have to be adjusted for the level of newspaper competition in the metro area.\(^{16}\)

The total number of help-wanted ads run in all newspapers in the MSA is an upper-bound estimate of these separate ads. This is the appropriate count when all ads are placed in only one newspaper in the metro area, so that each paper runs a unique set of help-wanted advertisements. To generate series under this "no-duplication" assumption, I once again utilize advertising volume figures from Media Records and Editor and Publisher. I estimate total help-wanted ads in each MSA by assuming that the leader's share of total help-wanted advertisements run in all newspapers in an MSA is equal to its classified advertising volume share.\(^{17}\)

I also generate separate want-ad series for each MSA under less extreme assumptions on want-ad duplication across competing newspapers. I first identify the probable determinants of want-ad duplication by modeling the relationship between job vacancies and help-wanted advertisements in MSAs with competitive newspaper markets. Appendix 2-D presents a model which predicts that want-ad duplication depends primarily upon the extent to which readership of competing newspapers in an MSA is concentrated among job-seekers with different human capital characteristics.
If workers are identical in every respect, then full duplication is most likely. The leading help-wanted advertiser in an MSA under this assumption is the newspaper with the lowest help-wanted advertising milline rate, or price per line of advertising per 1000 help-wanted section readers. In other words, the leading advertiser is the newspaper that offers the most cost-effective means of recruiting potential employees. Any ads appearing in the secondary advertisers, with higher milline rates, must also appear in the leading advertiser; employers who find it profitable to advertise in a high milline rate paper must find it profitable to advertise in newspapers with lower milline rates as well. Full duplication can occur with heterogeneous workers as well, as long as readership of the competing newspapers in an MSA isn’t concentrated among job-seekers with different characteristics. If total readership for all newspapers is distributed uniformly over different worker types, then the newspaper with the lowest overall milline rate provides the most cost-effective means of recruiting every type of potential employee.

If potential employees with different human capital characteristics tend to read different newspapers in any MSA, however, less duplication of want-ads is likely. For example, suppose blue-collar workers tend to read the Boston Herald, while white-collar workers read the Boston Globe. Employers in the Boston MSA with blue-collar vacancies might find ads placed in the Herald to be most cost-effective, while those searching for white-collar employees may favor Globe want-ads instead. In the extreme, if only blue-collar workers read the Herald, and only white-collar workers read the Globe, then there may be no duplication of want-ads across these two
newspapers.

This discussion suggests that accurate estimates of want-ad duplication require detailed information on the socio-economic characteristics of the readers of alternative newspapers in an MSA. However, the model in Appendix 2-D demonstrates that information on milline rates and advertising shares for competing newspapers in an MSA can also be used to generate estimates of want-ad duplication. I collect help-wanted advertising rate, circulation, and classified advertising volume figures for all competing newspapers in the forty-eight sample MSAs. 18 I use these data to construct five alternative series for the extent of ad duplication in each MSA, ranging from the "no-duplication" series to the "full-duplication" series discussed earlier, with three intermediate series that allow for less-than-full duplication.

It seems unlikely that full- or no-duplication assumptions are valid, so that one of the three series I construct assuming less-than-full duplication should be preferable. In the empirical work I present in Chapter 3, my "preferred" help-wanted rate series are those that imply the median amount of ad duplication from these five alternatives. These series imply that, on average, 70-80 percent of want-ads placed in secondary advertisers in an MSA are also placed in the leading advertiser, a figure that I find reasonable. However, until further primary evidence is obtained documenting the amount of ad duplication in competitive newspaper markets, I cannot be sure that this is an accurate correction. For this reason, I identify those results that are sensitive to want-ad duplication assumptions.
If vacancies in some occupational classifications are more likely to be advertised than others, then the number of help-wanted ads observed for any given level of vacancies depends on the occupational composition of employment. At the same time, variation in recruiting practices by employers also affect the ratio of help-wanted ads to job vacancies. It follows that want-ad series must be corrected for differences in the occupational composition of employment and employer recruiting practices both over time and across MSAs if they are to accurately reflect time-series and cross-sectional variation in job vacancies.

Suppose a vacancy is randomly drawn from the population of total vacancies in MSA i in time period t. The probability that this vacancy is advertised in the help-wanted section of a local newspaper is given by Equation (2-1):

\[
(2-1) \quad \sum_{j} P_{ijt} \times V_{ijt} \quad \text{where} \quad j = \text{occupation index} \\
\quad \quad = \text{city index} \\
\quad \quad = \text{time period} \\
\quad P_{ijt} = \text{probability that a vacancy in} \\
\quad \quad = \text{occupation j, in city i, at} \\
\quad \quad = \text{time t, is advertised}. \\
V_{ijt} = \text{share of total vacancies in} \\
\quad \quad = \text{city i, at time t, in the jth} \\
\quad \quad = \text{occupation}. \\
\]

Abraham (1987) analyzes data from several U.S. job vacancy collection pilot projects and concludes that occupational employment shares provide a very precise proxy for occupational vacancy shares. She notes that Canadian and British data also suggest that occupational employment and vacancy shares are approximately equal.
Therefore, it is possible to rewrite Equation (2-1) as:

\[(2-2) \sum_j (P_{ijt} \times E_{ijt}) \text{ where } E_{ijt} = \text{share of non-agricultural employment in city } i, \text{ at time } t, \text{ in the } j\text{th occupation.}\]

Differences in the occupational composition of employment and employer advertising practices over time and across MSAs imply divergent ad-count/vacancy ratios. However, a simple normalization procedure ensures that differences in measured ad counts across time and regions are not merely reflecting variations in ad-count/vacancy ratios. First, calculate Equation (2-2) for some baseline city and time period. Call this value BASE. Then calculate this expression for all other MSAs and time periods. Call this value for MSA \(i\), at time \(t\), \(B_{it}\). Form a time series for each MSA, \(CF_{it} = \frac{B_{it}}{BASE}\), where \(CF\) stands for "correction factor", and divide the ad count series from that MSA by this \(CF\) series. The resultant series are purged of advertising influences which affect the ratio of ads to vacancies by normalizing ad counts to those that would have been observed in the baseline city and period. The formula for this correction factor is given by:

\[(2-3) CF_{it} = \frac{B_{it}}{BASE} = \frac{\sum_j (P_{ijt} \times E_{ijt})}{\sum_j (P_{ijt}' \times E_{ijt}')} \text{ where } i=\text{baseline city, } t=\text{baseline period.}\]

Suppose that advertising probabilities for a given occupation and time period are equal across regions, so that \(P_{ijt} = P_{kjt} = P_{jt}'\) for all \(i\) and \(k\) cities.\(^{20}\) Let \(P_{bcit}\) be the probability that blue-collar
jobs are advertised in the base period. Define $R_{jt} = P_{jt}/P_{bt}$, the advertising probability in occupation $j$ relative to blue-collar jobs in the base period. Using this new notation, I derive an alternative expression for the correction factor:

$$\text{(2-4) CF}_{it} = \frac{\sum R_{jt} \cdot E_{ijt}}{\sum (R_{jt} \cdot E_{ijt})} + \frac{\sum (R_{jt} \cdot (P_{jt}/P_{bt} - 1) \cdot E_{ijt})}{\sum (R_{jt} \cdot E_{ijt})}$$

I label the first term on the right-hand side of Equation (2-4) the "occupational composition of employment correction" (OCEC). OCEC$_{it}$ measures the effect that employment (and thus vacancy) composition has on the expected ad-count/vacancy ratio in city $i$ and period $t$ relative to the ad-count/vacancy ratio in the baseline city and time period, holding relative and absolute advertising probabilities constant. If OCEC$_{it}$ is greater (less) than one, differences in occupational employment composition alone suggest that one should observe more (less) ads per vacancy in city $i$ and period $t$ than in the baseline city and time period. I label the second term in Equation (2-4) the "advertising practices correction" (APC). APC$_{it}$ measures how changes in occupational advertising probabilities since the baseline period interact with employment composition to change the relative probability that a given vacancy in city $i$ will be advertised. This term is zero in the baseline year by construction, and is positive (negative) when advertising probabilities are high (low) relative to the baseline. If some advertising probabilities are high and some low relative to the baseline, APC$_{it}$ is positive (negative) if increases (decreases) in ad probabilities are
concentrated in the high-employment occupational sectors of city i in period t. 21

Computation of these correction factors requires a series for \( R_j \) in some baseline period, time series for \( P_j \) that include this baseline period, and time series for \( E_{ij} \) that also include the baseline period. Table 2-6 presents three alternative \( R_j \) series identified in Abraham (1987). I use the \( R_j \) estimates from the Walsh, Johnson, and Sugarman (1975) study as my "preferred" estimates. These figures are based on a wider sample of metropolitan areas, and represent a time period closer to the 1970 baseline than the Myers and Creamer (1967) estimates. 22, 23

Following Abraham (1987), I use surveys on recruiting practices from the Bureau of National Affairs (BNA) to construct estimates for the \( P_j \) series. The BNA has conducted such surveys in 1968, 1979, and 1987. Each survey asked personnel officials from a representative sample of U.S. firms about their recruiting practices, including their use of newspaper help-wanted ads. I assume that the proportion of survey firms reporting that they used want-ads to recruit for vacancies in occupation j in year t is a good estimate of \( P_{jt} \). 24

Table 2-7 shows estimates of occupational advertising probabilities I compute from the BNA surveys. 25 The data demonstrate an increase in white-collar advertising probabilities over time, perhaps due to increased equal employment opportunity and affirmative action pressure on employers, as Abraham (1987) suggests. Advertising probabilities in blue-collar, clerical, and service occupations, however, appear to have fallen over time. 26

I obtain estimates of the occupational composition of employment
at the MSA level from 1970 and 1980 Census data. Since the 1990 Census data are not yet available, I assume that the occupational composition of employment has remained unchanged in each of the MSAs since 1980.\textsuperscript{27} Tables 2-8 and 2-9 present estimates of the percentage of total non-agricultural employment accounted for by the six occupational categories identified in Table 2-6 for each of the sample MSAs.\textsuperscript{28,29} A comparison of Tables 2-8 and 2-9 demonstrates a substantial shift away from blue-collar employment in virtually all MSAs in the 1970s. Along with the variance in advertising probabilities across occupational categories that Tables 2-6 and 2-7 illustrate, this suggests that OCEC and APC calculations are potentially quite important when constructing vacancy proxies for this time period.

Table 2-10 displays estimates of OCEC and APC for 1970, 1980 and 1987, using New York City in 1970 as the base city and time period.\textsuperscript{30} I use these three years to estimate time series for CF in each MSA, assuming a constant growth rate of CF between each observation, and assuming 1987 values hold in 1988-89.

Table 2-10 demonstrates that the ratio of want-ads per vacancy has probably trended upward over the sample period, due both to the changing occupational composition of employment and to increased reliance on help-wanted advertising as a recruiting tool. The estimates suggest that in most MSAs, this ratio has increased by 10-15 percent from 1970 to 1987, so that uncorrected want-ad series may exhibit an artificial upward drift over time. The table also demonstrates the importance of these correction factors when making cross-sectional comparisons of want-ad series. The 1970 OCEC suggest
that one would expect to observe eight percent fewer ads per vacancy in Providence (RI) than in New York City because of differences in occupational composition. Failure to correct for this bias would lead to a significant underestimation of vacancies in Providence and other MSAs dominated by blue-collar employment.

EMPLOYMENT AGENCIES AND ADVERTISING PRACTICES

When an employer seeks to fill a job vacancy, she may consider a variety of alternative recruitment strategies, including employee referrals, state or private employment agencies, advertisements in trade journals, or want-ads. Help-wanted advertising probabilities should therefore depend upon the relative cost-effectiveness of this form of recruitment relative to alternative forms of recruitment. I assume that advertising probabilities for a given occupation and time period are equal across MSAs when constructing the APC series. However, it seems likely that the viability of alternative recruitment strategies is not constant across MSAs. In particular, if there are economies of scale in the production of job-placement activities, employment agencies and placement services might be disproportionately centered in major metro areas. This expansion of the recruitment strategy space in larger markets would, all else equal, lead to lower advertising probabilities, and thus lower ad counts for a given level of vacancies. At the same time, divergent trends in employment agency usage across MSAs in the sample period would also suggest different growth rates in advertising probabilities.

One possible proxy variable for the availability of alternative
recruitment strategies in a given MSA and time period is the proportion of total employment accounted for by SIC 736, personnel supply services. Employment agencies, executive placing services, model registries, teacher registries, office help supply services, temporary help services, and employee leasing services are among the establishments included in SIC 736. Table 2-11 presents the percentage of total FICA-covered employment in each MSA that is accounted for by SIC 736 in four sample years. The table demonstrates two potentially important patterns. First, it shows the relative growth of agency employment over time. In 1974, the average sample MSA had 0.84 percent of its employment in SIC 736, while by 1986 this figure had risen to 1.64 percent. Second, it demonstrates wide disparities in the relative availability of employment agency services, as proxied for by the proportion of total employment in SIC 736, across MSAs at any given time. For example, in 1986, SIC 736 accounted for 3.02 percent of employment in Minneapolis, but only 0.88 percent of employment in Detroit.

In Appendix 2-E, I present a procedure designed to identify the extent to which differences in SIC 736 employment shares explain cross-sectional and time-series variation in help-wanted ad counts for given levels of unemployment. I find that these employment shares explain little or none of this variation in my sample. There is no evidence that help-wanted rates are systematically lower in MSAs or time periods with higher levels of employment agency activity. These results suggest that ad-count/vacancy ratios are not significantly affected by the availability of alternative recruitment strategies, at least as proxied for by SIC 736 employment shares. I conclude that
the help-wanted ad count series do not require adjustments for cross-sectional and time-series variation in employment agency activity.

HELP-WANTED ADS REPRESENTING JOBS OUTSIDE THE MSA OF PUBLICATION

Regional and/or national newspapers with low metro/total circulation ratios, such as the New York Times, should attract a higher proportion of ads soliciting applications for jobs outside the metro area of publication. For a given advertising probability for within-MSA job vacancies, this implies that newspapers with low metro/total circulation ratios should have high ad-count/vacancy ratios. However, newspapers with low metro/total circulation ratios might also attract fewer ads for any given number of within-MSA job vacancies, thereby lowering ad-count/vacancy ratios. Since readers living in an MSA are more likely to apply for local job vacancies than readers from outside an MSA, local employers may expect a greater return on help-wanted ads placed in newspapers with high metro/total circulation ratios. While these two effects work in opposite directions, it is still apparent that differences in metro/total circulation ratios across sample newspapers may influence ad-count/vacancy ratios, and thus the comparability of help-wanted rate series across MSAs.

Appendix 2-F implements the two-step procedure described in Appendix 2-E to identify the extent to which differences in newspaper metro/total circulation ratios explain cross-sectional and time-series variation in help-wanted ad counts for given levels of unemployment.
I find no consistent, significant relationship between these circulation ratios and help-wanted ad counts. There is no clear evidence that ad-count/vacancy ratios are dependent on newspaper metro/total circulation ratios. This suggests that the help-wanted ad count series do not need to be adjusted for cross-sectional and time-series variation in newspaper metro/total circulation ratios.

INSTITUTIONAL FEATURES OF DIFFERENT NEWSPAPERS

The metro/total circulation ratio is not the only institutional feature of newspapers participating in the Conference Board survey that may create cross-sectional and time-series variation in ad-count/vacancy ratios. For example, newspaper want-ad pricing policies may significantly affect employers' propensities to use want-ads as a recruitment tool.

In the ad-duplication model of Appendix 2-D, however, I assume that want-ad prices vary within a range narrow enough so that they have no effect on these propensities. Since want-ads appear to be a bargain in even the highest milline rate newspapers, it seems unlikely that variance in rates across newspapers and time has much of an impact on advertising probabilities. For example, the respondents to the 1968, 1979, and 1987 BNA surveys on recruiting practices always identified help-wanted advertising as a "most cost-effective" recruiting source. Within the range of prevailing want-ad rates, the cost of placing ads appeared to have little impact on employers' desires to recruit through want-ads. At the same time, an examination of the milline rates I calculate for sample newspapers suggests that,
at prevailing rates, want-ads are a relatively inexpensive form of recruiting.  

However, even if pricing policies have no impact on advertising probabilities for a given job vacancy, they may still affect ad-count/vacancy ratios. This is due to the nature of the Conference Board index, which is based on the number of help-wanted ads run in a given month, and not the number of separate jobs advertised. These two counts can differ because jobs are advertised on more than one day of the month, and because several jobs may be listed in the same advertisement. It is likely that pricing policies do affect the average duration of ads for a given job and the number of jobs per ad. Newspapers tend to offer a wide range of advertising prices depending on the number of days an ad will run, and on the size of the ad. When collecting rate data for milline rate calculations, I was struck by the variance across newspapers in ad-duration and size discounting schedules. This variance could lead to large differences in the average duration of ads and the number of jobs per ad across sample newspapers.  

Two other institutional features of newspaper want-ad sections may affect ad-count/vacancy ratios. In the early 1970s, most newspapers had a section of want-ads for males, and another for females. Such an arrangement may have led to greater ad-count/vacancy ratios, since employers having no preference over the sex of prospective employees may have placed ads in both the male and female sections. As different newspapers phased out these sex-designated sections at different times, the comparability of ad-count/vacancy ratios across newspapers is once again called into question. It is
also the case that newspapers have different rules about the type of recruitment ad they will run in their help-wanted sections. For example, some newspapers do not include employment agency ads in help-wanted sections. Newspapers also have different policies regarding the placement of military, training program, and commissioned sales recruitment ads. While these rules affect only a small proportion of total potential want-ads, variance in these policies might affect the comparability of ad counts across newspapers and time.

Without an extensive study of the institutional features of sample newspapers, it is impossible to quantify just how important these factors are in driving observed cross-sectional and time-series variation in adjusted help-wanted rates. Since I am unable to correct for such factors in this current study, its vacancy rate proxies provide accurate indicators of local labor market conditions in the U.S. only to the extent that institution-induced variance in help-wanted rates is small in comparison to that which is induced by underlying changes in local labor market conditions. I remain confident that this is the case.

A COMPARISON OF ADJUSTED HELP-WANTED RATES AND VACANCY RATES

I now reconsider the evidence from the Minnesota, Wisconsin, and EOPP vacancy surveys in order to compare time-series and cross-sectional variation in vacancy and adjusted help-wanted rates. It is immediately apparent that ad duplication, employment composition, and advertising practices adjustments have not changed
the within-region time-series variation of help-wanted rates in either Minneapolis or Milwaukee. Plots of vacancy rate and adjusted help-wanted rate time series from these two MSAs are almost identical to Figures 2-1 and 2-2. Correlations between the adjusted help-wanted rates and vacancy rates and their growth rates are virtually unchanged.41

However, the adjustments have changed help-wanted rate ratios across MSAs. Unfortunately, adjusted Minneapolis/Milwaukee HWR ratios continue to systematically underestimate their VR ratios, although not as severely as before adjustment. A plot of these ratios looks much like Figure 2-3, with the horizontal distance between the ratios less than prior to adjustment. The newspaper competition adjustment is chiefly responsible for this slight improvement, as the Minneapolis newspaper market has two major competitors, while Milwaukee only has one. The extent of underestimation is thus dependent on the ad-duplication assumption. As I assume less duplication, the help-wanted count series in Minneapolis rise relative to Milwaukee. In fact, a no-duplication assumption would suggest that the HWR ratio only slightly underestimates the VR ratio. However, I find this assumption to be unrealistic.

While I am concerned that the Minneapolis/Milwaukee HWR ratio underestimates its VR ratio, it is possible that this reflects differences in the way in which the vacancy survey pilot projects were implemented in these two MSAs, and not be indicative of biases in help-wanted counts. For example, Minnesota vacancy data included the construction industry, while Wisconsin data did not. As Holzer (1989) demonstrates, job vacancy rates tend to be relatively high in the
construction industry, presumably because specialized skill requirements for many job openings in this industry imply long vacancy durations. Therefore, the difference in industry coverage between the two pilot projects suggests that measured vacancy rates in Minnesota might be systematically higher than those measured in Wisconsin.\textsuperscript{42}

The adjusted HWR series continue to track 1980 cross-sectional variation in the seven MSAs from the Holzer (1989) study quite well. The Spearman rank correlation statistic of the adjusted HWR and VR figures falls slightly to 0.75, but is still greater than zero at the five-percent significance level.

I believe there is fairly strong evidence suggesting that both the unadjusted and adjusted help-wanted rate series serve as informative proxies for regional vacancy rates. Nonetheless, a great deal of uncertainty remains over how well these series track unobservable regional vacancy rates. Given this uncertainty, I highlight those results in Chapter 3 that are sensitive to alternative adjustment assumptions, or those that seem contrary to other evidence on local labor market performance in the U.S. since 1970.

IV. CONCLUSION AND PREVIEW OF CHAPTER 3

The data collection and refinement procedures I describe in Sections II, III, and the appendices to this chapter produce a variety of alternative help-wanted rate time series for forty-eight U.S. MSAs. Evidence from various pilot projects suggests that these series serve as informative proxies for MSA job vacancy rates. Development of these proxies enables for the first time a thorough analysis of U.S.
regional Beveridge curves. Appendix 2-G illustrates the U.S. aggregate and forty-eight MSA Beveridge curves since 1970 using my "preferred" help-wanted rate series. In the following chapter, I use these curves to quantify U.S. regional mismatch and its role in explaining shifts in the aggregate Beveridge curve and structural unemployment since 1970.
In many European countries, the government provides active employment service offices that act as a clearinghouse for unemployed workers seeking jobs, and employers seeking new hires. These offices tend to centralize job matching activity, and thus provide relatively accurate counts on job vacancies. These employment service vacancy numbers are often supplemented by government-sponsored surveys in which employers are asked to report immediate and expected future job openings. For further information on European job vacancy statistics, consult the OECD's *Sources and Methods, Main Economic Indicators*, series.

See Abraham (1983) for a thorough discussion of the various pilot projects undertaken in the U.S. since the mid-1960s.

It appears that the timing of these pilot projects has been greatly influenced by academic and government economists' views on the importance of structural unemployment in the economy at the time. For example, the most extensive projects were undertaken during the 1960s and early 1970s, when attempts to partition observed unemployment into structural and cyclical components were considered vital exercises in the macroeconomic research agenda. See *The Measurement and Interpretation of Job Vacancies*, the report from a 1965 National Bureau of Economic Research conference on vacancy statistics, for views on the importance of job opening statistics in interpreting and designing macroeconomic policies. The Bureau of Labor Statistics has recently started another job vacancy collection pilot project. It is likely that this project is a direct response to the resurgence of macroeconomic research in the area of structural versus cyclical unemployment, as characterized by Lilien (1982), Abraham and Katz (1986), Blanchard and Diamond (1989), Davis and Haltiwanger (1990), and others.


For skeptical views on the use of the help-wanted index as a vacancy proxy see Robert Solow's comments on Medoff (1983), James Tobin's comments on Abraham (1987), and Zagorsky (1990). I discuss Zagorsky’s (1990) critique of the help-wanted index in Chapter 3. On the other hand, William Nordhaus, in comments on Abraham (1987), argues that even on a conceptual basis, the help-wanted index may be a better indicator of unmet labor demand than employer-reported vacancy statistics. Employers must design and pay for help-wanted advertisements, so that placing a help-wanted ad requires an active response by employers to their unmet labor demand situation. When filling out a survey, however, employers do not have such a concrete metric available to determine unmet labor demand. An employer might report six job openings, for example, but the firm may be in the process of actively recruiting for only three of those positions. Placement of a help-wanted advertisement, on the other hand, signals an active recruitment stance.
The discussion in this paragraph is based on Abraham (1987) and Preston (1977). Consult these sources for further details.

The Sunday edition of each newspaper always runs more help-wanted advertisements than weekday editions. Therefore, a month with five Sundays would show an increase in help-wanted ad volume even if the average volume of each weekday and Sunday edition was unchanged.

According to Preston (1977), the Conference Board uses a seasonal adjustment technique similar to the X-11 method used by the Bureau of the Census.

The national help-wanted index is calculated by aggregating the metropolitan area indices using nonagricultural payroll employment figures as weights.

These series are seasonally adjusted and take into account differences in the number of weekdays and weekends across months since the Conference Board indices embody these adjustments.

I drop Allentown (PA), Gary (IN), and San Bernardino (CA) from the sample because I am unable to obtain copies of their participating newspapers.

I normalize the help-wanted counts by payroll employment because this is the normalization used for vacancy rate numbers. The figures actually show the HWR and VR series divided by their relative sample means and converted to quarterly data. Neither series is seasonally adjusted. I normalize by the sample means because the figures are intended to demonstrate the HWR's ability to track the time-series variation of the VR within each of the metro areas. I thank Katharine Abraham for the data from the Minnesota and Wisconsin VR pilot projects, and for non-seasonally adjusted help-wanted indices for Minneapolis and Milwaukee (Kenneth Goldstein of the Conference Board is the original source for these indices).

I do not normalize the HWR and VR by their respective sample means in this figure. In order to determine if the HWR accurately reflect differences in the VR across regions, the levels of the two variables matter. For example, if HWR systematically underestimates VR in region A, but not in region B, the HWR may lead to the erroneous conclusion that region B is always a "high-demand" sector. The HWR and VR ratios must be at the same level at any point in time, as well as move together over time, if the HWR are to accurately reflect cross-sectional variation in the VR.

I define a "major" daily newspaper to be one which is on average purchased by at least five percent of the households in an MSA each day. See Appendix 2-A for further details on this definition.

Circulation figures are from the Standard Rate and Data Service sources, while advertising volume numbers are from Media Records and Editor and Publisher. See Appendices 2-A and 2-B for details.
The want-ad series do not have to be adjusted as long as the newspapers they are taken from are the leading advertisers in their metro areas for every year of the sample. Assuming that the classified advertising leader is also the help-wanted advertising leader, advertising volume figures from Media Records and Editor and Publisher suggest that the newspapers I have based my ad count series on are the leading help-wanted advertisers in their metro areas in virtually every year of the sample. The only exception is Denver, in 1978 and 1980-88, when the Rocky Mountain News was the classified advertising leader, while my ad counts are based on figures from the Denver Post. To estimate want-ad series for the Rocky Mountain News in 1978 and 1980-88, I assume that the ratio of total help-wanted advertisements in the News relative to the Denver Post in any given year is equal to the ratio of their classified advertising volume in that year, as reported in Media Records.

For example, since the Minneapolis Star-Tribune accounted for 65% of classified advertising volume among newspapers in the Minneapolis-St. Paul MSA between 1976 and 1981, I multiply ad count series from the Star-Tribune during this time period by approximately 1.54 (1/0.65) to generate estimates of total help-wanted ad counts in the MSA.

I discuss sources for these data in Appendix 2-D.

See Table 2, pg. 216, in Abraham (1987) for U.S. and Canadian data, and Jackman, Layard, and Pissarides (1984) for British data. Abraham (1987) argues that this result is expected in labor markets in which high-turnover positions are filled quite quickly, while low-turnover positions take longer to fill.

Data limitations force me to impose this restriction when calculating actual correction factors. The ad duplication model discussed in Appendix 2-D suggests that these probabilities might depend on ad prices, newspaper circulation, and local labor market conditions. Thus it is possible to use my data set on local newspaper markets to form estimates of "P" that are allowed to vary over regions at any given time. However, I suspect that it would be difficult to determine if differences in P estimated in such an exercise were solely the result of model misspecification and random error, or if they actually reflected underlying differences in advertising practices. Therefore, I don't feel such an exercise is warranted, and believe that the assumption of equal P's across regions for a given time period and occupation must be approximately true.
Abraham (1987) argues that increased equal employment opportunity and affirmative action pressures following the 1973 settlement of the AT&T case should have increased advertising probabilities, so that APC should grow over time. However, another 1973 court case may have acted to decrease help-wanted advertising probabilities. On June 21, 1973, the U.S. Supreme Court upheld a Pittsburgh ordinance banning sex-designated newspaper want-ad headings in *Pittsburgh Press vs. Pittsburgh Commission on Human Relations*. Until the early 1970s, almost all daily newspapers in the U.S. had a section of want-ads for males, and another for females. In fact, all help-wanted sections that I study for the week of October 9-15, 1967, had different sections for males and females. It is likely that some job vacancies were being advertised under both sex headings at that time. As ads were consolidated under a single heading, this duplication became unnecessary, and may have led to lower ad counts for a given number of job vacancies.

I choose 1970 as the baseline year for several reasons. It is the first year of my sample for all Beveridge Curve estimation, it is a year in which detailed occupational employment numbers are available at the MSA level, and it is only two years after a Bureau of National Affairs study which provides good estimates for the baseline "P" series.

As Table 2-6 demonstrates, the studies do not provide a consistent picture of the relative probability of professional-technical and managerial vacancies being advertised. Thus it is possible that corrected ad count series depend on the \( R_j \) estimates I choose. As I report results using this "preferred" series, I identify any conclusions that are dependent on the choice of \( R_j \).

These correction factors also assume that occupational employment shares equal occupational vacancy shares. This assumption implies that vacancy rates (defined as vacancies/employment) are equal for all occupations. I also construct correction factors assuming that white-collar vacancy rates are either 2, 1.5, 0.67, or 0.5 times the blue-collar vacancy rates. Once again, I highlight any results that depend on the white-collar/blue-collar vacancy rate assumption.

In fact, it is not necessary that this proportion provides a good estimate of the level of \( P_{jt} \). If \( P_{jt} \) are merely proportional to the fraction of employers reporting they use help-wanted ads over time, then this survey evidence allows accurate estimates of APC, since it is the ratio of \( P_{jt} \) to baseline values which determines APC. This is comforting because it is likely that this proportion overestimates the levels of \( P_{jt} \). If all firms have two vacancies in sales positions in a year, and half use help-wanted ads to recruit for one of those positions, the proportion of firms reporting they use ads would be one-half, while the appropriate estimate of the sales advertising probability would be one-quarter. However, if the ratio of total vacancies to vacancies associated with want-ad recruitment for firms using want-ads is constant over time, the survey evidence will allow accurate estimates of APC.
Several issues arise when constructing the figures in Table 2-7 from the raw advertising probability numbers reported in the BNA surveys. The BNA surveys do not provide estimates for the same occupational categories as the $R_j$ series in Table 2-6. The 1979 and 1987 surveys provide $P_{jt}$ estimates for professional-technical, managerial, clerical, and sales occupations, but group production (blue-collar) and service workers together, while the 1968 survey provides estimates for only college and non-college occupational categories. I proceed as follows: For the 1979 and 1987 surveys, I assume that service and blue-collar workers have the same advertising probabilities. For these surveys, I also compute a college and non-college occupation advertising probability, assuming that professional-technical, managerial, and sales occupations require college degrees, while clerical, blue-collar, and service jobs do not. I then compute the ratio of professional-technical, managerial, and sales advertising probabilities to the total college occupation advertising probability, and assume that the average of these ratios from the 1979 and 1987 surveys held in the 1968 survey. I also compute the ratio of clerical and blue-collar/service advertising probabilities to the total non-college occupation advertising probability, and assume the average of these ratios from the 1979 and 1987 surveys held in 1968. This allows me to estimate occupational advertising probabilities for 1968 at a level of disaggregation consistent with the 1979 and 1987 surveys.

One more correction is necessary to make the 1968, 1979 and 1987 surveys comparable. In the 1968 sample, approximately 70% of the firms employed over 1000 workers, while only 41% and 46% of firms in the 1979 and 1987 surveys, respectively, were this large. The 1968 advertising probabilities for college and non-college graduates were reported separately for small (less than 1000 employees) and large firms (greater than 1000 employees). Instead of taking the overall college and non-college probabilities from the 1968 survey as my estimates, I compute what these probabilities would have been if the sample was comparable to the 1979 and 1987 surveys in terms of the distribution of firm size. In particular, I assume that large firms were only 45% of the sample.

One possible explanation for this is that a greater proportion of clerical and service vacancies have been filled through employment and temporary help agencies over time. However, the BNA surveys provide little or no evidence of increased reliance on these forms of recruiting practices. Nonetheless, I return to this hypothesis in the next section.

It is possible to collect MSA-level occupational employment data between Census years by consulting the annual issues of County Business Patterns. However, data in this publication are published only at the county level, and to get MSA estimates one has to collect data from all counties in each of the MSAs. This is not such a monumental task, however, and I will collect data for 1988 or 1989 soon. Different advertising and occupational composition adjustment assumptions have little or no impact on results presented in Chapter 3, however, thus I doubt that these data will affect my conclusions in any way.
The occupational categories for 1970 and 1980 Census data are not immediately comparable. From the 1970 Census, I collect data for the following occupational categories: (1) Professional, technical, and kindred workers; (2) Managers and administrators, except farm; (3) Clerical workers; (4) Sales workers; (5) Craftsmen, foremen, and kindred workers; (6) Operatives, except transport; (7) Transport equipment operatives; (8) Laborers, except farm; (9) Service workers, except private household; (10) Private household workers. The first four categories correspond directly to occupational categories identified in Table 2-6. Categories (5)-(8) are considered blue-collar occupations, while categories (9) and (10) are labeled service occupations. From the 1980 Census, I collect data for the following occupational categories: (1) Professional specialty; (2) Health technologists and technicians; (3) Technologists and technicians, except health; (4) Executive, administrative, and managerial occupations; (5) Administrative support, including clerical; (6) Sales occupations; (7) Precision production, craft, and repair occupations; (8) Operators, fabricators, and laborers; (9) Service workers. The first three categories are considered professional-technical occupations, categories (7) and (8) are labeled blue-collar occupations, and the other four categories correspond directly to categories identified in Table 2-6.

Between 1970 and 1980, many MSAs were redefined, either adding or deleting suburban counties. I do not correct for these changes, implicitly assuming that the occupational composition of employment in 1970 was the same for those counties that were subsequently added or removed from an MSA as it was for the MSA as a whole. To check this assumption, I will eventually collect data from the 1970 Census at the county level, and use the 1980 MSA definitions to compute 1970 occupational employment numbers for each of the MSAs.

I assume that the $R_j$ series in Table 2-6 as well as the BNA survey from 1968 are appropriate for 1970, that the 1979 BNA survey is appropriate for 1980, and that the occupational composition of employment in 1987 is unchanged from 1980. APC are zero by definition in 1970, the base year, while OCIEC are equal in 1980 and 1987 because I assume that occupational composition is unchanged between these two periods. It is also worth emphasizing that these correction factors are reliant on the $R_j$ series I choose from Table 2-6. The calculations in this table use my "preferred" $R_j$ series.

See the BNA surveys for discussions of recruiting practices of U.S. firms.
Employment agencies and temporary services also place advertisements in the help-wanted sections of papers. Thus one might argue that the proliferation of these services will not decrease want-ads, merely shifting the burden of placing ads from the prospective employer to an agent for that employer. However, each agency ad tends to list several job openings, while employer-placed ads usually list far fewer vacancies per ad (most report one job per ad). Since the Conference Board series from which I construct vacancy proxies are based upon the number of help-wanted ads run, and not the total number of jobs listed, a shift toward agency ads with more vacancies per ad would decrease ad counts. It is also the case (see Appendix 2-C) that many papers publish employment agency ads in a separate section from employer-placed want-ads, and I do not count any ads placed in these sections. Therefore, cities in which agencies place a higher percentage of total want-ads would show lower ad counts per job vacancy. Finally, it could be the case that increased agency activity might increase help-wanted counts. If employers who previously did not rely upon ads as a recruitment device now rely upon agencies who do use recruitment ads, then help-wanted ad counts will rise as long as some proportion of agency ads is included in these counts.

I thank Katharine Abraham for suggesting this proxy.

See the 1972 SIC Manual and its 1977 supplement.

The sources for these data are the 1974, 1978, 1982, and 1986 volumes of County Business Patterns. Employment figures represent all FICA-covered wage and salary employment of private non-farm employers and non-profit organizations in SIC 736. I collect these employment numbers for the county in which the primary city in the MSA is located. Figures from all counties in an MSA are necessary to construct true MSA employment numbers, but this would increase data-collection time considerably. Data-preparation considerations also underlie the choice of limiting collection to four annual observations, chosen to roughly span the sample period.

The standard deviation of figures in column 1, Table 2-11, is 0.38, while it is 0.56 for column 4 figures.

Some of the arguments in Endnote 32 suggest that advertising probabilities may not be significantly affected by employment agency activity.

Circulation of the Sunday edition of the New York Times averaged approximately 1.6 million in 1988, with only about one-third of that circulation in the New York MSA.

As I discuss in Appendix 2-D, however, employers who rely on want-ads only when more informal recruitment techniques fail may be particularly price sensitive. The firms in the BNA surveys tend to be rather large, and may thus rely to a greater extent on formal recruitment methods.
Unfortunately, I have no evidence which allows me to quantify how important rate discount schedules are in determining help-wanted advertising counts. One piece of informal evidence, however, suggests that such factors may not have large differential impacts on ad-count/vacancy ratios across MSAs and time. It appears that those newspapers offering substantial discounts for ad duration, are also the papers offering the most significant size discounts. Since duration discounts increase ad-count/vacancy ratios, and size discounts decrease them (more jobs may be placed per ad), it is possible that together, discounts have little impact on these ratios. In the future, given adequate resources, I hope to shed some light on this issue by collecting information on average ad duration and size. This information may be available directly from newspaper advertising departments. If not, a re-count of newspaper want-ad sections could be undertaken, this time focusing on the number of separate jobs advertised, and not just the number of advertisements.

The correlation between the adjusted HWR and VR in Milwaukee is 0.83, while it was 0.84 before adjustment. This correlation in Minneapolis is 0.71, and it was 0.77 before adjustment. Correlations of the growth rates of adjusted HWR and VR remain at 0.74 for Milwaukee, and 0.82 for Minneapolis.

See Abraham (1983) for a discussion of these two projects.

All MSA-level curves start in 1970, if possible. Unemployment rate series for Albany, Syracuse, and Rochester prior to 1972 are unavailable; these curves start with the 1973 observation. The non-agricultural employment series for Hartford begins in 1972; the 1970 and 1971 Beveridge curve observations for this MSA are unavailable. The aggregate curve is calculated by taking weighted sums of MSA help-wanted and unemployment rates. Non-agricultural employment figures serve as the weights for help-wanted rate calculations, while labor force figures are the weights for unemployment rate computations. MSA labor force series suffer from the same discontinuity problems that non-agricultural employment series do. I correct them in the manner described in Endnote 1 to Appendix 2-E.
APPENDIX 2-A: Identifying the most likely participant in the Conference Board's help-wanted advertising survey in each MSA.

In this appendix, I describe the procedures I follow to identify the most likely participant in the Conference Board's help-wanted advertising survey in each of the fifty-one MSAs. The procedures provide an accurate means for identifying the leading carrier of help-wanted ads in each MSA without having to rely upon manual ad counts.

*Media Records Inc.* collects and analyzes advertising volume numbers for daily newspapers that subscribe to their service. Each year, some 50-100 major metropolitan daily newspapers utilize the *Media Records* service. *Media Records* publishes annual detailed advertising volume figures for each of these subscribing newspapers. For example, display advertising numbers are broken down into retail, automotive, financial, and general sub-categories, while classified advertising and legal advertising are also reported separately. *Editor and Publisher*, the leading trade magazine in the newspaper industry, also conducts an annual survey of advertising volume in daily newspapers. Each year, some 700-800 newspapers, representing over 500 cities, respond to the *Editor and Publisher* survey. The results of the survey for each participating newspaper are published in an annual supplement to the magazine, usually in late May. Just as *Media Records*, *Editor and Publisher* provides a detailed breakdown of display advertising volume, as well as providing separate entries for classified advertising numbers.¹

I use figures from *Media Records* and *Editor and Publisher* to determine the leading newspaper in classified advertising volume in
each of the fifty-one MSAs for which the Conference Board's help-wanted index is published. I then assume that the leading classified advertiser is also the leading help-wanted advertiser. In particular, I proceed as follows: I first identify all newspapers published in a given MSA for each year between 1970 and 1988. From this group, I then identify those papers with daily metropolitan circulation numbers greater than or equal to five percent of the households in their metro area. In other words, I identify those papers that were on average purchased by at least five percent of the households in the area each day. The sources for metro circulation numbers are Standard Rate and Data Service's Newspaper Circulation Analysis and the American Newspaper Markets' Circulation. Overall, 163 different newspapers met this five percent circulation criterion in one of the fifty-one MSAs for at least one year since 1970. For these 163 newspapers, I collect detailed advertising volume numbers as published in the Media Records or Editor and Publisher sources. Out of those papers meeting the circulation criterion, the newspaper with the highest classified advertising volume is identified as the help-wanted advertising leader in the MSA for that year.

It is worth examining this procedure in more detail. I assume that only newspapers published in a given MSA can be the help-wanted advertising leader in that area. A few major dailies meet the five percent circulation criterion in MSAs other than the area in which they are published. For example, in several years since 1970, the New York News meets the circulation criterion in the Hartford (CT), Allentown (PA), and/or Albany (NY) metro areas. It is also the case that in some years total classified advertising in the News is greater
than that found in any dailies published in those metro areas. However, it would be incorrect to conclude that the *News* is the leading carrier of classified advertisements for employment opportunities, rental units, or garage sales *located in the Albany or Hartford metro areas*. In fact, the proportion of help-wanted ads in the *News* directed toward job openings in Hartford is most likely next to zero. Only papers published in the Hartford area are likely to have a substantial proportion of their classified ads directed at consumers and employers in that area.

The five percent circulation criterion also precludes consideration of low-circulation dailies as the leading help-wanted advertiser. This assumption seems fairly uncontroversial; newspapers at this end of the circulation spectrum tend to be small, suburban dailies, or special-interest periodicals that are unlikely to receive broad-based recruitment advertisements.

Perhaps the strongest assumption I make in this selection process is that the leading classified advertiser is also the leading help-wanted advertiser. An informal examination of competing metro dailies across the country suggests that this is a good assumption. An alternative assumption is that the leader in total advertising volume is the help-wanted leader. Total advertising volume figures from *Media Records* and *Editor and Publisher* suggest that in only two of the fifty-one MSAs is there ever a substantial discrepancy between the total and classified volume leaders in any given year.

Finally, if the leading classified advertiser is the same in every sample year, it is likely that this newspaper is the one affiliated with the Conference Board survey. In fact, there is almost
no variation in the leading classified advertisers in these fifty-one MSAs since 1970. The *Denver Post* was the leader during the 1970s, while the *Rocky Mountain News* was the leader in Denver (CO) in the 1980s. The *San Bernardino Sun* and *Riverside Press-Enterprise* shared classified leadership in the Riverside-San Bernardino-Ontario (CA) MSA throughout the sample period. In all other areas, the classified leader remained constant throughout the entire sample period.

Several difficult data issues arise when collecting newspaper advertising and circulation figures for use in this identification procedure. I discuss these issues in Appendix 2-B.
Unfortunately, neither source provides a breakdown of classified ad volume into help-wanted and other sub-categories.

I exclude national newspapers, such as the Christian Science Monitor, USA Today, and various editions of the Wall Street Journal from consideration. It is unlikely that want-ads in national newspapers represent job vacancies in the city of publication.

Along these same lines, one might argue that help-wanted ad counts in major metropolitan dailies, such as the New York Times and the Los Angeles Times, are less reflective of local labor market conditions because a higher proportion of ads may be for jobs outside of the metro area. In other words, these papers may be used in national recruiting campaigns, instead of just local recruitment. Evidence presented in Walsh, Johnson, and Sugarman (1975), however, suggests that newspapers in larger metro areas do not run a higher proportion of ads for employment outside their metro areas. I discuss this point further in Section III of this chapter.

I should stress that I do mean an informal examination. I examine competing papers from several cities in the U.S., and conclude that the leading classified advertiser also always appears to run the most help-wanted ads. I look at papers from Boston (Globe and Herald), New York (News and Times), Chicago (Tribune and Sun-Times), and Los Angeles (Times and Herald-Examiner).

In 1978, the Denver Post was the total advertising leader, while the Rocky Mountain News was the classified leader in the Denver (CO) metro area. The San Antonio Light was the total advertising leader and the San Antonio Express-News was the classified leader between 1970 and 1978 in this Texas market. There are some slight discrepancies in the Albany (NY), Dallas (TX), Philadelphia (PA), and San Bernadino (CA) markets as well.
APPENDIX 2-B: Data issues involved with collecting newspaper circulation and advertising figures.

Several difficult data issues arise in the process of collecting newspaper advertising and circulation figures. This appendix documents some of the problems I encounter, as well as the procedures I follow to ensure that the advertising and circulation series I collect are consistent both across time and MSAs.

The first problem I encounter is that metropolitan circulation numbers are reported given the definition of the relevant MSA at the time of publication. However, there have been three major revisions of the geographical boundaries defining MSAs since 1970. I convert all metro circulation numbers so that they are consistent with current (1990) MSA definitions. This requires collecting circulation numbers at the county level as well as the MSA level.

When collecting circulation and advertising volume numbers, I have to determine if newspapers in a given MSA are competitors. Simpson (1989) and Standard Rate and Data Service's Newspaper Rates and Data contain detailed information on the competitive structure of these fifty-one MSA newspaper markets. These sources indicate that newspapers within an MSA often have the same publisher, sell advertising space together, publish morning and evening editions under different titles, or publish a joint Sunday edition. I assume a group of newspapers with any of these joint publishing or advertising arrangements represents only one newspaper. I calculate the circulation number for these "group newspapers" as the maximum of the circulation for any of its individual editions. Simpson (1989) notes there is also great duplication of advertising in newspapers which
publish multiple editions. This results from advertising pricing schemes which provide strong incentives to place ads in all editions of a given newspaper rather than to target single editions. Therefore, I calculate the advertising number for group newspapers as the maximum value of the advertising volume numbers from its separate editions.

Prior to 1984, advertising volume was measured in "agate lines" of advertising in both Media Records and Editor and Publisher. Unfortunately, these figures are not directly comparable across newspapers with different column widths, and across broadsheet (standard) and tabloid newspaper formats. I convert all lineage figures so that they are comparable across formats. I use standard techniques in the advertising profession to do so. Consult Media Records or Editor and Publisher for details of the adjustment process.

In 1984, Editor and Publisher began publishing advertising volume in "standard advertising units" (SAU), and in 1985, Media Records followed suit. The development of an industry-wide standard for measuring advertising volume implies that all post-1984 numbers are reported on a consistent basis across papers with different formats. However, the 1984 numbers for Media Records papers and Editor and Publisher papers are not consistent in that some are reported in SAUs, and some are reported in agate lines. I convert the 1984 Media Records lineage numbers to SAUs given the methodology described in the 1985 edition of Media Records. The advertising volume time series I construct are not directly comparable pre- and post-1984, as all figures prior to 1984 are measured on a consistent agate line basis, while all figures since 1984 are measured in SAUs.
A final problem is that advertising volume numbers are often not available for all 163 newspapers from the two primary sources. As a result, the advertising series contain numerous missing values. I use linear interpolation to fill in missing values in the time series. It is worth noting that missing values are usually associated with the smallest newspapers, and thus do not affect identification of the leading advertiser in any given metro area.

More thorough documentation on all procedures described in the text, notes, and appendices to this chapter is available upon request.
APPENDIX 2-C: Benchmarking the MSA help-wanted indices.

This appendix describes the procedures I follow, and issues that arise, when benchmarking MSA help-wanted indices.

MSA help-wanted indices are based on monthly want-ad counts from each newspaper. Therefore, the most accurate benchmarks require ad counts from every day in a given month. However, counting want-ads is a very time-consuming, mundane task. It seems infeasible to conduct monthly counts for all sample newspapers without substantial research assistance. I thus limit my benchmark counts to one week. To obtain monthly benchmark estimates from these weekly ad counts, I assume all Mondays in any given month run the same number of want-ads, all Tuesdays run the same number of ads, and so on. This assumption implies that the choice of benchmark month is potentially very important. It is necessary to select a month in which it is likely that the number of want-ads run each week does not vary systematically over the month. In some months, seasonal and holiday job turnover patterns suggest that the number of ads run in the beginning of the month may differ significantly from those run at the end of the month.¹ October is a month that appears to be free of such seasonal and holiday biases.² Since the Conference Board indices use 1967 as their base year, I choose October 9-15, 1967, as the benchmark week.

Forty-four of the fifty-one newspapers are available on microfilm at the Library of Congress for this benchmark week. Another four are available at this library, but holdings do not go back to 1967. For these papers, I choose a week in October in the earliest available year as my benchmark week.³ I am unable to obtain copies of
participating newspapers in Allentown (PA), Gary (IN), and San Bernadino (CA). I thus drop these three MSAs from the sample.

The process of manually counting the ads is not as straightforward as one might imagine. The format in which help-wanted ads are presented in this benchmark week varies considerably across newspapers. In particular, most newspapers publish employment agency ads in a separate category of the classified section. In those cases, I exclude these ads from my help-wanted count. However, in those papers without a separate section for agency ads, I make no attempt to exclude agency ads from my count (this would require reading each ad to determine if it is an agency ad or not). My general sense, however, is that this does not present a serious problem. Newspapers without separate agency sections are concentrated in the smaller metro areas, and appear to run very few agency ads anyway. Therefore, it is unlikely that their ad counts are severely biased upward since only a small proportion of their ad counts are accounted for by agency recruitment efforts. However, one might also argue that ad counts in the largest cities, for which separate agency categories is the norm, are biased downward because employment agency activity is concentrated in the largest metro areas. I discuss this possible bias further in Section III of the chapter.
1For example, near the end of May one might observe a sudden increase in the number of ads soliciting summer employees, so that a weekly count from the beginning of May will underestimate the monthly total. In December, temporary holiday-season jobs are likely to increase ad counts in the beginning of the month relative to the end of the month.

2In rural areas, the timing of the harvest season could systematically affect the number of job openings advertised during different weeks of October. However, such considerations should have little impact on vacancies advertised in the metropolitan areas I am studying.

3These newspapers and their benchmark weeks are as follows: Sacramento Bee, October 13-19, 1975; Albany Times-Union, October 10-16, 1988; Knoxville News-Sentinel, October 14-20, 1985; and Houston Chronicle, October 12-18, 1970.
APPENDIX 2-D: A model that identifies the probable determinants of the extent of want-ad duplication across competing newspapers in an MSA.

This appendix presents a model of the relationship between job vacancies and help-wanted advertisements in MSAs with competitive newspaper markets and heterogeneous workers. I use the model to identify the probable determinants of want-ad duplication across competing newspapers in an MSA. I then collect detailed circulation, and advertising volume and rate data for newspapers in the forty-eight sample MSAs, and use the model's predictions to generate alternative series for want-ad duplication in each of these MSAs.

The model makes the following assumptions:

(a) There are J different occupations, or "worker types", in the economy. The occupations are labeled 1 through J.

(b) There are $N_j$ individuals of type $j$ in the labor force. $N_j$ is constant across all J types, so that the total labor force, $N$, is equal to $J \times N_j$.

(c) $U_j$ is the number of unemployed individuals of type $j$. $U_j$ is also constant across all J types, implying that total unemployment, $U$, is equal to $J \times U_j$, and that the unemployment rate is constant across all J types.

(d) $V_j$ is the number of job vacancies for workers of type $j$. $V_j$ is also constant across types, so that total vacancies, $V$, is equal to $J \times V_j$, and the vacancy rate is constant across all J types.

(e) There are M different newspapers serving the MSA. The papers are labeled 1 through M.

(f) $P_{mj}$ is the probability that a random individual of type $j$ reads
paper \( m \) on a daily basis. Assuming that only individuals in the labor force read newspapers, circulation of paper \( m \) in the metro area, denoted \( C_m \), is thus equal to \( \sum_{j=1}^{J} P_m^{*} N_j \). Circulation of paper \( m \) to type \( j \) workers \( = C_{mj} = P_{mj}^{*} N_j \). I assume all newspaper readers read the want-ad section of the paper.

(g) \( R_m \) is the cost of placing a help-wanted ad in paper \( m \).

(h) \( \Pi_j \) is the present-discounted value of increased profits associated with the filling of a job vacancy of type \( j \) for a given firm. \( \Pi_j \) is distributed between its minimum value, \( \Pi^1_j \), and its maximum value, \( \Pi^h_j \), with a cumulative distribution function \( = G(\Pi_j) \) for all \( J \) worker types.

(i) \( H_j \) is the probability any given reader of type \( j \) will answer a want-ad for a type \( j \) job in a given firm and will be hired. \( H_j = f(U_j/V_j) = f(U/V) \), with \( f' > 0, f'' < 0, f(0) = 0, f(\infty) = 1 \). This probability is constant across worker types because of the assumption of equal \( U/V \) ratios.

(j) Firms are risk-neutral.

Given the above assumptions, firms with a type \( j \) job opening place a want-ad in paper \( m \) if the following condition holds:

\[
(2D-1) \quad C_{mj} * H_j * \Pi_j > R_m
\]

Equation (2D-1) simply states that if the firm's expected benefit from placing an ad in newspaper \( m \) exceeds its cost, the firm advertises its vacancy in paper \( m \). The expected benefit of placing an ad for the risk-neutral firm is the probability the ad leads to a hire \( (C_{mj} * H_j) \) multiplied by the present-discounted value of increased profits.
associated with such a hire \( (\Pi_j) \). The firm places ads in all papers for which Equation (2D-1) holds.

Using Equation (2D-1) and assumptions (d) and (h) from above, expected total help-wanted advertisements in paper \( m \), denoted \( A_m \), is given by Equation (2D-2):

\[
(2D-2) \quad A_m = \sum_{j=1}^{J} \left[ V \ast (1 - G(Z_m^j)) \right] \quad \text{where} \quad Z_{mJ} = \frac{R_m}{(C_{mJ} \ast H_j)}
\]

Labor market conditions, as represented by the unemployment and vacancy rates, are obviously an important determinant of help-wanted advertisements. As vacancies rise, advertisements rise given the probability of advertising any given vacancy. However, this advertising probability may also depend on the vacancy/unemployment rate. This probability may rise during cyclical upturns since the distribution for the expected profitability of hiring, \( G(\Pi_j) \), will probably shift upward, implying that for a given \( Z_{mJ} \), \( G(Z_{mJ}) \) falls. On the other hand, \( Z_{mJ} \) itself should rise during cyclical upturns as \( H_j \) falls, implying a lower advertising probability. For a given value of filling a job vacancy, firms find ads less profitable in tight labor markets because they are less likely to lead to new hires. In sum, advertising probabilities may rise, fall, or stay constant as vacancy/unemployment ratios change.\(^1\) The total effect of an increase in vacancies on help-wanted advertising in a given newspaper is thus theoretically ambiguous as well. However, for the total effect to be negative, the elasticity of the advertising probability with respect to vacancies must be less than -1, which seems highly unlikely.
Advertising rates and circulation are the other determinants of total help-wanted advertising in a given newspaper. In particular, it is the ratio of the price of placing an ad to circulation that determines help-wanted demand. Help-wanted advertising is a decreasing function of the milline rate, or price per line of advertising per 1000 circulation, for a newspaper's classified section.

Consider the amount of ad duplication expected in this model. Assume that $C_{m} = C_{m} = C_{m} / J$, for all $i$ and $j$ worker types, and for all $M$ newspapers. This assumption implies a "general" readership of all newspapers in an MSA, so that no newspaper's circulation is concentrated among a particular worker type. This is also equivalent to assuming homogeneous workers, or $J = 1$. With this assumption, the milline rate associated with placing a help-wanted ad in a given newspaper is the same for every type of worker. This also implies that $Z_{m} = Z_{m}$ for all $i$ and $j$ worker types, so that Equation (2D-2) can be rewritten as:

\[(2D-3) \quad A_{m} = V \times [1 - G(Z_{m})] \quad \text{where} \quad Z_{m} = MR_{m} \times J / (1000 \times H_{j})\]

\[
\begin{align*}
MR_{m} &= R_{m} / 1000 / C_{m} \\
H_{j} &= H = f(U/V), \quad \forall j
\end{align*}
\]

$MR_{m}$ is the milline rate for help-wanted advertising in paper $m$.² Assuming "general" readership, $A_{m}$ differs across newspapers in the MSA only because their milline rates differ. The leading help-wanted advertiser in the MSA is the newspaper with the lowest milline rate, and the advertising share for any remaining newspaper declines as its milline rate rises relative to the others. These assumptions also
imply that all vacancies advertised in the secondary advertisers also appear in the leading advertiser, or "full duplication." This is evident from Equation (2D-1). A firm places an ad for an opening of type $j$ in paper $m$ if the $\Pi_j$ for that opening exceeds $Z_{mj} - Z_m$. Since $Z_m$ is at its minimum in the newspaper with the lowest milline rate, or the leading advertiser, any firm that finds it profitable to place an ad in a secondary advertiser must also find it profitable to advertise in the leading newspaper. The assumption of "general readership" in this model provides theoretical justification for assuming full duplication, and thus for ignoring newspaper competition effects on help-wanted ad counts.

I collect total circulation figures and recruitment advertising rates for all 163 newspapers in my sample from 1969 through 1988, and estimate help-wanted advertising milline rates. The model's prediction that the leading advertiser in an MSA should have the lowest milline rate is generally supported by the data. Of 960 annual observations (20 years for 48 MSAs), 669 are in MSAs with more than one major daily newspaper. In 572 of these observations, or 86 percent, the leading advertiser does have the lowest milline rate.

However, it is likely that this number actually underestimates the number of observations consistent with the model's prediction. The milline rate relevant for potential help-wanted advertisers is the rate per thousand help-wanted ad readers. Let $MR^h_m$ be this milline rate for paper $m$. $MR^h_m$ is related to the observed milline rate for paper $m$ by the following equation:
(2D-4) \[ MR_m = MR^h_m \ast \rho_m \text{ where } \rho_m = \frac{HWRE_m}{C_m} \]

HWRE\_m = help-wanted readership of paper m.

Assumption (f) from above implies that \( \rho_m = 1 \) for all M newspapers. However, it seems likely that \( \rho_m \) may vary across newspapers, with the leading help-wanted advertiser having the highest \( \rho_m \) in an MSA. The leading advertiser has "more to offer" any individual searching for employment, and thus may be read by a higher proportion of total readers of the newspaper. In this case, \( MR^h \) for the leader may be lower than its competitors, even though its observed \( MR \) is not the minimum in the MSA.

This argument, along with the strong negative rank correlation between milline rates and advertising shares across competitive newspapers in sample MSAs, makes it tempting to conclude that the full-duplication assumption is valid, thus precluding the need for any further attempts to correct the ad count series for newspaper competition influences. However, I feel such an assumption is not warranted. It is certainly true that a "general readership", or homogeneous workers, assumption is incorrect. Suburban dailies tend to have "specialized" readerships in the MSA, concentrating their circulation among workers living in the suburbs. Since occupational shares of employment vary considerably over different suburbs and the central city of an MSA, the suburban dailies reach a disproportionate share of some classes of workers. Also, competing metropolitan dailies often offer widely divergent products in the hopes of capturing a specialized share of the circulation market. Neither the tabloid New York News nor the New York Times is meeting the "general
readership" assumption in the New York MSA.

What determines the extent of ad duplication when the general readership assumption is dropped? The number of separate jobs being advertised, denoted $A_s$, is given by Equation (2D-5):

$$
(2D-5) \quad A_s = \frac{\sum_{j=1}^{J} \left[ V \times (1 - G(Z_j^*)) \right]}{J} \quad \text{where} \quad Z_j^* = \text{Min}(Z_{1j}, Z_{2j}, \ldots, Z_{Mj})
$$

The number of separate ads is determined by the minimum milline rate from all M newspapers for each class of worker. The ratio of separate ads to ads in the leader is then given by Equation (2D-6):

$$
(2D-6) \quad \sum_{j=1}^{J} \left[ \frac{(1 - G(Z_j^*))}{(1 - G(Z_{Lj}))} \right] \quad \text{where} \quad Z_{Lj} = \text{leader's} \ Z_j
$$

Equation (2D-6) demonstrates that even when specialized readership is an important feature of newspaper markets, the full-duplication assumption still holds if the leading advertiser maintains the low milline rate for each class of worker. Less-than-full duplication occurs when some paper besides the leader offers the lowest milline rate for a given worker type. Allowing for specialized readership implies that even if a newspaper has a higher milline rate than the leader with respect to total circulation, it might still have lower milline rates for certain classes of workers. For example, a suburban fast-food restaurant looking to hire local teenagers might find that a suburban daily offers the lowest milline rate for this class of worker, while an investment banking firm in the central city looking to hire administrative staff would probably find
that a metropolitan daily provides the lowest milline rate for these workers.

A no-duplication assumption in this model requires that if \( G(Z_{nj}) \) is less than one for some paper \( m \) and class of worker \( j \), \( G(Z_{nj}) \) must be equal to one for all \( n \) not equal to \( m \). In words, no duplication requires that it is profitable to advertise vacancies for each worker type in only one of the newspapers in an MSA. Under this assumption, each paper carries a unique set of want-ads.

The model suggests that information on the socio-economic characteristics of readers of alternative newspapers in an MSA is required to generate accurate estimates of want-ad duplication. Such information allows the calculation of milline rates for alternative worker classes. However, collecting detailed circulation data for all newspapers in my sample is beyond the scope of the current research project.\(^6\)

If more structure is imposed on this ad-duplication model, however, it generates closed-form solutions for the extent of want-ad duplication in an MSA that can be calculated without detailed circulation data. I impose the following further assumptions on this model:

(k) The \( J \) worker types are assembled into two main categories. One group of workers reads the want-ads in only one newspaper, while another group reads ads in two newspapers. No workers read more than two want-ad sections, even when \( M > 2 \). All those reading two papers read the leading help-wanted advertiser.

(l) For \( C_{mj} > 0 \), \( G(Z_{mj}) = 0 \). This assumption implies that it is always profitable to place an ad for a worker of type \( j \) in paper \( m \) as long as paper \( m \) has a non-zero circulation to type \( j \) workers. In
other words, help-wanted advertising rates vary within a range so that they do not affect advertising probabilities. One can also think of this as an assumption on $G(\Pi_j)$. The lower-bound of this distribution is assumed greater than $Z_{m_j}$ for all newspapers $m$ that circulate to workers of type $j$.

(m) Let $b_L$ = the proportion of workers reading one newspaper who read the leading advertiser. Along with assumptions (k) and (l), $b_L$ also represents the proportion of want-ads appearing in only one newspaper listed in the leading advertiser. I assume $b_L$ is given by Equation (2D-7):

$$
(2D-7) \quad b_L = \frac{\gamma \cdot \bar{MR}_{NL}}{MR_L + (\gamma \cdot \bar{MR}_{NL})}
$$

where $\bar{MR}_{NL}$ = mean milline rate for secondary advertisers
$MR_L$ = leader's milline rate
$\gamma$ = parameter

I assume the leader's share of ads appearing in only one newspaper rises as its milline rate falls relative to the average milline rate of its competitors.

Let $AS_L$ represent the share of total help-wanted advertising in an MSA appearing in the leading advertiser. Using these new assumptions, I find that the ratio of separate ads to ads in the leader is given by Equation (2D-8):

$$
(2D-8) \quad \text{Separate/Leader} = 1 + [\delta*(1 - AS_L)/AS_L] \quad \text{with} \quad 0 \leq \delta \leq 1
$$

$$
\delta = \frac{(2*AS_L - 1)*MR_L}{(1 - AS_L)*(\gamma*\bar{MR}_{NL} - MR_L)}
$$

Full duplication occurs when $\delta$ is equal to zero, while no duplication implies $\delta$ is equal to 1. As milline rates in the secondary
advertisers rise relative to the milline rate in the leading advertiser, ad duplication increases. The intuition behind this result is that advertisers turn to the low milline rate paper first when placing ads, and consider higher milline rate papers only after placing an ad in the low-cost alternative.

This result is very much reliant on the assumptions of the model. For example, it may be the case that milline rates in secondary advertisers increase as readership of the alternative newspapers in an MSA becomes more specialized. Specialized readership implies that a newspaper can charge a very high milline rate and still receive want-ads from employers targeting those individuals who read specialized publications. It is possible then that relatively high milline rates in secondary advertisers imply less, and not more, ad duplication.

It is also probably true that variations in help-wanted advertising rates do affect vacancy advertising probabilities for certain jobs. Employers who primarily use informal recruitment techniques, such as employee referrals, may only use want-ads when they are a particularly "good deal."

I intend to examine these issues in much greater detail in future research. Readers who find any of these assumptions particularly objectionable can focus on the no-duplication and full-duplication ad count series. These series are independent of the model's assumptions.

Equation (2D-8) suggests that data on help-wanted advertising shares and milline rates from newspapers in an MSA, along with an estimate of the parameter γ, provide an estimate of ad duplication in
that MSA at any given time. I assume the share of total classified advertising in an MSA appearing in the leading classified advertiser, as reported by Media Records and Editor and Publisher, is a good proxy for \( AS_L \). I construct milline rates for all sample newspapers as described in Endnote 3 of this appendix. These data for any given MSA also provide upper and lower bounds for \( \gamma \). Since \( 0 \leq \delta \leq 1 \), using Equation (2D-8), I find that the following condition must hold for all observations in an MSA:

\[
(2D-9) \quad \text{If } AS_L > 0.5, \quad \gamma \geq (AS_L \times MR_L) / ((1 - AS_L) \times \overline{MR}_{NL}) \\
\text{If } AS_L < 0.5, \quad \gamma \leq (AS_L \times MR_L) / ((1 - AS_L) \times \overline{MR}_{NL})
\]

Let \( AM_L \) be the quotient on the right-hand side of Equation (2D-9). For each MSA, define a new parameter, \( \gamma^* \):

\[
(2D-10) \quad \text{If } AS_L > 0.5, \quad \gamma^* = \text{Max}(AM_L), \\
\text{where Max is taken over all observations with } AS_L > 0.5. \\
\text{If } AS_L < 0.5, \quad \gamma^* = \text{Min}(AM_L), \\
\text{where Min is taken over all observations with } AS_L < 0.5.
\]

Let \( t_{\text{max}} \) be the observation in which \( \text{Max}(AM_L) \) occurs for \( AS_L > 0.5 \), and \( t_{\text{min}} \) be the observation in which \( \text{Min}(AM_L) \) occurs for \( AS_L < 0.5 \). If one assumes \( \gamma = \gamma^* \), \( \delta = 1 \) in periods \( t_{\text{max}} \) and \( t_{\text{min}} \). For all other observations, \( 0 \leq \delta < 1 \). Assuming \( \gamma = \gamma^* \) thus generates a \( \delta \) series implying no duplication in at most two years of the sample, with duplication in the other years determined by Equation (2D-8) evaluated at \( \gamma = \gamma^* \).

Define \( MR^*(t) = MR_L / \overline{MR}_{NL} \) in period \( t \). Consider two new
parameters, \( \gamma^* \) and \( \gamma^{4*} \):

\[
\text{(2D-11) If } AS_L > 0.5, \quad \gamma^{2*} = 2*\gamma^* - MR^* (t_{\text{max}}) \quad \gamma^{4*} = 4*\gamma^* - (3*MR^* (t_{\text{max}}))
\]

\[
\text{If } AS_L < 0.5, \quad \gamma^{2*} = 2*\gamma^* - MR^* (t_{\text{min}}) \quad \gamma^{4*} = 4*\gamma^* - (3*MR^* (t_{\text{min}}))
\]

If \( \gamma = \gamma^{2*} \), \( \delta = 0.5 \) in periods \( t_{\text{max}} \) and \( t_{\text{min}} \), while if \( \gamma = \gamma^{4*} \), \( \delta = 0.25 \) in those periods. \( \delta \) series constructed assuming \( \gamma = \gamma^{2*} \) (\( \gamma^{4*} \)) will on average equal one-half (one-quarter) the \( \delta \) series constructed assuming \( \gamma = \gamma^* \), implying only one-half (one-quarter) as many ads appearing in the secondary advertisers in an MSA are not duplicates of ads appearing in the leader.

I calculate \( \gamma^* \), \( \gamma^{2*} \), and \( \gamma^{4*} \) for each sample MSA, and then the \( \delta \) series associated with each \( \gamma \). I smooth each of the \( \delta \) series by taking a three-year moving average, as the original series exhibit what appears to be excessive year-to-year variation. I then use Equation (2D-8) to estimate the ratio of separate ads to ads in the leader, and multiply the original ad count series by this quotient series to estimate separate ad counts for the MSA.

By construction, the \( \gamma = \gamma^* \) series assume the least amount of ad duplication, while the \( \gamma = \gamma^{4*} \) series assume the most duplication. This is evident in Table 2-5, which shows the mean value of \( \delta \) for two-, three-, and four-or-more-newspaper MSAs under alternative assumptions regarding \( \gamma \). For example, on average, 43 percent of ads placed in the secondary advertiser in a two-newspaper MSA are identified as duplicates of ads run in the leader when \( \gamma = \gamma^* \), while

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85 percent are identified as duplicates when $\gamma = \gamma^4$.

This procedure produces five alternative ad count series for each MSA, representing a wide range of assumptions regarding ad duplication among competitive newspapers in an MSA. Because it seems unlikely that full- or no-duplication assumptions are valid, one of the three series I construct assuming less-than-full duplication should be preferable. I use the $\gamma = \gamma^2$ series as my "preferred" series in the empirical work described in Chapter 3. This is the median series of the five constructed, and, on average, implies 70-80 percent duplication of the leader's ads in secondary advertisers, a figure that I find reasonable. Given the somewhat arbitrary nature of this adjustment procedure, however, I highlight any results that are dependent on ad duplication assumptions.
NOTES FOR APPENDIX 2-D

1 If help-wanted ad counts are to be used as proxy series for vacancies, it is important that these advertising probabilities are not dependent on vacancy/unemployment ratios. In this sense, it is "good news" that the model suggests two effects on advertising probabilities that work in opposite directions whenever the vacancy/unemployment ratio changes. In Section III of the text, I offer a correction for changes in advertising probabilities which may have affected the relationship between ad-counts and vacancies over time. However, I do not attempt to correct for any cyclical tendencies in this relationship, implicitly assuming that vacancy advertising probabilities are independent of cyclical changes in the labor market.

2 Actually, it is the milline rate for help-wanted advertising only if each advertisement requires only one line. The true milline rate is MR divided by the number of lines in a recruitment advertisement.

3 The sources for circulation figures are Standard Rate and Data Service's Newspaper Circulation Analysis and American Newspaper Markets' Circulation. I collect recruitment advertising rates from Standard Rate and Data Service's Newspaper Rates and Data. I use the January edition of this rate periodical in all years but 1974, 1978, and 1979. In those years, I use the July edition because the January issues could not be located. If a newspaper lists a rate specifically for recruitment advertising, I collect this figure. For all other newspapers, I collect the general classified rate. There appears to be little difference between general classified and recruitment rates in those papers listing both rates. I collect both the Sunday edition and weekday rates, and compute the average daily rate by taking a weighted average of the two, with a weight of one-seventh on the Sunday rate. The same weighted average is applied to Sunday and weekday circulation figures to compute an average daily circulation number for each paper. Many newspapers offer a variety of line rates for classified and recruitment advertising depending on the size and/or duration of the ad, and on whether the ad will appear in all zoned editions of the paper. I select the rate for a full-run (all editions), single insertion of one line in the classified section. The rates are deflated by the media cost per thousand index, which is an index of the cost per thousand consumers reached of advertising through television, radio, magazines, newspapers, and billboards. The sources for this index are Table 4.4b, page 67, in Compaine (1980), and the Fall 1984 and August 1989 issues of Marketing and Media Decisions. I calculate milline rates by dividing the deflated daily ad rates by total daily circulation in thousands. I also calculate milline rates based on metropolitan area daily circulation in thousands.
However, if everyone searching for employment buys and reads the help-wanted section in all newspapers in the MSA, and only job seekers read the want-ads, the lowest circulation paper will have the highest $\rho_m$. Since secondary advertisers usually have lower metropolitan circulation shares than the leader, this would imply that $\rho_m$ is not highest among the leading advertisers.

This scenario suggests extreme persistence in the identity of the leading advertiser over time. As job seekers turn to the leader for vacancy listings, employers respond by placing an even greater percentage of their ads in the leader, which in turn sparks increased readership, and so on. The fact that Denver is the only MSA in the sample for which the leading classified advertiser varies from 1969 to 1988 is strong evidence of such persistence.

However, I do not believe that it is an infeasible project. Most major newspapers conduct demographic studies of their readership base on a periodic basis, the majority relying on outside consulting firms that specialize in such research. These studies are important marketing tools for newspapers when selling advertising space.

If $AS_L$ is always $> 0.5$, or always $< 0.5$, for a given MSA, $\delta = 1$ in only one observation in the sample period. This is obviously the case for MSAs with only two newspapers. If $AS_L$ is both above and below 0.5 in the sample period for an MSA, $\delta = 1$ for two observations.
APPENDIX 2-E: The relationship between employment agency activity and help-wanted counts for any given level of unemployment.

This appendix attempts to answer the following question: To what extent do differences in employment agency activity over time and across MSAs explain differences in help-wanted ad counts for given levels of unemployment? I use a two-step procedure to address this question. The first step is to pool annual unemployment rate and adjusted help-wanted rate data for all sample MSAs from 1970 to 1988.\(^1\) I then estimate the following log-linear Beveridge curve equation:

\[
\ln(HWR_{it}) = \alpha + \beta \ln(UR_{it}) + \epsilon_{it}
\]

where \(UR_{it}\) = unemployment rate in MSA i at time t.

\(HWR_{it}\) = adjusted help-wanted rate in MSA i at time t.

I interpret a residual from this equation, \(\epsilon_{it}\), as that component of the help-wanted rate in city i at time t that cannot be explained by local labor market conditions, as summarized by the local unemployment rate.

The second step is to determine the extent to which SIC 736 employment shares explain differences in these residuals across time and MSAs. I calculate the five-year moving average of these residuals for each MSA. I then pool the 1974, 1978, 1982, and 1986 values of these smoothed residual series for each MSA and estimate the following equation:

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\[ (2E-2) \quad \hat{e}_{it} = \delta + \phi \ln(E_{736\_it}) + \nu_{it} \]

where \( \hat{e}_{it} = \) five-year moving average of \( e_{it} \) from Equation (2E-1) for MSA \( i \) at time \( t \).

\( E_{736\_it} = \) proportion of total FICA employment accounted for by SIC 736 in MSA \( i \) at time \( t \).


Estimates of Equations (2E-1) and (2E-2) for alternative adjusted help-wanted rate series, with different assumptions regarding ad duplication and advertising probabilities corrections, tell a remarkably consistent story. Estimates of \( \beta \) from Equation (2E-1) are approximately -0.70, with \( t \)-statistics of about 18. \( R^2 \)'s from these regressions are approximately 0.26. Estimates of \( \phi \) from Equation (2E-2) fluctuate between -0.05 and -0.07, with \( t \)-statistics of less than 1, and \( R^2 \)'s less than 0.01. While the estimated sign of \( \phi \) is consistent with arguments suggesting lower advertising probabilities in MSAs with greater employment agency activity, I cannot reject the null hypothesis that \( \phi \) is in fact equal to zero. I estimate other linear and log-linear variants of equations (2E-1) and (2E-2), and in all cases the relationship between agency employment share and help-wanted rate residuals is found to be statistically insignificant.

It seems likely, however, that the specification given by Equation (2E-2) suffers from a missing variable problem that biases the estimates of \( \phi \) toward zero. According to the job-matching model from Chapter 1, positive residuals from Equation (2E-1) may represent increases in sectoral reallocation within an MSA. Increases in sectoral reallocation may in turn increase the demand for employment agency services, as displaced workers move to jobs in sectors in which they have little previous knowledge of job search techniques and
hiring practices. Agency employment shares might then be positively correlated with sectoral reallocation shocks, the missing variable from this regression, and estimates of $\phi$ will be biased towards zero.

Suppose that the pace of sectoral reallocation within an MSA is fairly constant across MSAs at any given time, and it is only over time that substantial fluctuations in such reallocation intensities are observed. Under this assumption, if one estimates Equation (2E-2) for a cross-section of MSAs in any given time period, then the missing variable problem described above becomes inconsequential, and there is less reason to believe that $\phi$ is biased toward zero. Therefore, I re-estimate Equations (2E-1) and (2E-2) for the cross-section of MSAs for the years 1974, 1978, 1982, and 1986. In each year, and for every alternative help-wanted rate series, the t-statistic on the estimate of $\phi$ is less than one. Once again, the insignificance of $\phi$ is robust to alternative linear and log-linear forms of these regression equations.

There is little or no evidence that for a given unemployment rate, adjusted help-wanted rates tend to be lower in MSAs with higher levels of employment agency activity. I conclude that a correction factor based upon employment agency effects on ad-count/vacancy ratios is not necessary.
I compute help-wanted rates given adjustments for newspaper competition, advertising practices, and occupational composition as described in the text. In keeping with the general practice in this literature, I define the help-wanted rate to be total help-wanted advertising counts divided by non-agricultural employment in millions, and then multiplied by 100. The unemployment rate is normalized by the labor force as usual. Sources of these data are as follows: MSA-level non-agricultural employment numbers are available monthly from 1965 in DRI’s USREG database. Annual figures represent the annual average of monthly data. However, there are some major problems with these data. As noted in Appendix 2-B, there have been three major revisions of the geographic definitions of MSAs in the U.S. since 1970. Unfortunately, the MSA-level series in DRI’s database are not reported on a consistent basis, and reflect non-agricultural employment for the geographic area of the MSA at the date of each observation. Thus there are stark discontinuities in these series in years in which MSA definitions were changed. Typically, these discontinuities occur in the January observation of the years in which new definitions were implemented, suggesting infeasible December-January monthly growth rates for employment. I convert all series to reflect the current (1990) geographic definition of each MSA by assuming that the December-January growth rate of employment in years in which discontinuities were evident equaled the average December-January growth rate for all other years in the MSA. MSA-level unemployment rates are available monthly from 1976 in DRI’s USREG database. Unemployment rates for MSAs from 1970 to 1975 are taken from the 1976 through 1978 editions of the Employment and Training Report of the President. I assume that changes in MSA definition do not affect measured unemployment rates. This is equivalent to assuming that any counties that are added to or dropped from an MSA over time have on average the same unemployment rates as the MSA as a whole.
APPENDIX 2-F: The relationship between newspaper metro/total circulation ratios and help-wanted counts for any given level of unemployment.

In order to identify the possible effects differences in newspaper metro/total circulation ratios have had on measured help-wanted ad counts, I implement a two-step procedure much like that described in Appendix 2-E. The procedure is designed to determine the extent to which cross-sectional and time-series variation in newspaper metro/total circulation ratios explains variation in adjusted help-wanted rates for given levels of unemployment.

The first step is to estimate the "Beveridge curve" relationship given by Equation (2E-1), using annual data from 1970 to 1988.\(^1\) Given the residuals from this equation \((\epsilon_{it})\), I then estimate the following equation:

\[
(2F-1) \quad \epsilon_{it} = \delta + \xi \ln(\text{MTR}_{it}) + \nu_{it}
\]

where \(\text{MTR}_{it}\) = metro/total circulation ratio for the leading help-wanted advertiser in MSA \(i\) at time \(t\).

Estimates of \(\xi\) range between 0.40 and 0.50, depending on the help-wanted rate series I use in estimating the residual series, with \(t\)-statistics of about 5. Ad counts for a given level of unemployment appear to be significantly higher in newspapers with circulation concentrated within the metro area of publication. One interpretation of these estimates is that as circulation becomes concentrated in a metro area, advertising probabilities for local vacancies increase to a much greater extent than advertising probabilities for vacancies outside the MSA decrease.
However, these estimates of $\xi$ are highly suspect. In particular, when I exclude New York City from the sample, estimates of $\xi$ drop to approximately 0.17, and are no longer statistically significant. In fact, there is very little variation in metro/total circulation ratios across the other forty-seven MSAs in my sample. New York City has low help-wanted rates given unemployment, while the New York Times has by far the greatest "national" circulation of any of the sample newspapers. These two facts result in a significant positive estimate of $\xi$ that disappears when New York is dropped from the sample.

If the explanation for New York's relatively low help-wanted rates is merely that local employers don't want to advertise vacancies in a "national" newspaper like the Times, then it would be appropriate to correct help-wanted ad series for metro/total circulation ratio influences, assuming $\xi$ between 0.4 and 0.5. However, it is likely that there are many other local labor market influences responsible for low help-wanted rates in New York, chief among them increasing returns to scale in the job-matching process. Therefore, I decide to assume that $\xi$ is equal to zero, and avoid making a correction for metro/total circulation ratio effects on ad-count/vacancy ratios. It is important to realize that changing this assumption would only significantly alter the relationship between help-wanted rates in New York and other MSAs, since there is so little variation in metro/total circulation ratios across the other MSAs.
See Appendix 2-E for a discussion of the data used in estimating this equation, as well as an interpretation of its residuals.
BEVERIDGE CURVE: LOS ANGELES

BEVERIDGE CURVE: LOUISVILLE
FIGURES AND TABLES: CHAPTER 2
FIGURE 2-1: HWR AND VR, MINNEAPOLIS, 1972-81

HWR
VR

0.25  0.50  0.75  1.00  1.25  1.50  1.75  2.00
72  73  74  75  76  77  78  79  80  81
FIGURE 2-2: HWR AND VR, MILWAUKEE, 1976-81
FIGURE 2-3: MINNEAPOLIS/MILWAUKEE HWR AND VR, 1976-81
<table>
<thead>
<tr>
<th>MSA</th>
<th>NEWSPAPER</th>
</tr>
</thead>
<tbody>
<tr>
<td>Albany (NY)</td>
<td>Albany Times-Union/Knickerbocker News</td>
</tr>
<tr>
<td>Allentown (PA)</td>
<td>Allentown Call-Chronicle</td>
</tr>
<tr>
<td>Atlanta (GA)</td>
<td>Atlanta Constitution-Journal</td>
</tr>
<tr>
<td>Baltimore (MD)</td>
<td>Baltimore Sun</td>
</tr>
<tr>
<td>Birmingham (AL)</td>
<td>Birmingham News-Post-Herald</td>
</tr>
<tr>
<td>Boston (MA)</td>
<td>Boston Globe</td>
</tr>
<tr>
<td>Charlotte (NC)</td>
<td>Charlotte News-Observer</td>
</tr>
<tr>
<td>Chicago (IL)</td>
<td>Chicago Tribune</td>
</tr>
<tr>
<td>Cincinnati (OH)</td>
<td>Cincinnati Enquirer</td>
</tr>
<tr>
<td>Cleveland (OH)</td>
<td>Cleveland Plain Dealer</td>
</tr>
<tr>
<td>Columbus (OH)</td>
<td>Columbus Dispatch-Citizen-Journal</td>
</tr>
<tr>
<td>Dallas (TX)</td>
<td>Dallas News</td>
</tr>
<tr>
<td>Dayton (OH)</td>
<td>Dayton News-Journal-Herald</td>
</tr>
<tr>
<td>Denver (CO)</td>
<td>Denver Post</td>
</tr>
<tr>
<td>Detroit (MI)</td>
<td>Detroit News</td>
</tr>
<tr>
<td>Gary (IN)</td>
<td>Gary Post-Tribune</td>
</tr>
<tr>
<td>Hartford (CT)</td>
<td>Hartford Courant</td>
</tr>
<tr>
<td>Houston (TX)</td>
<td>Houston Chronicle</td>
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<tr>
<td>Indianapolis (IN)</td>
<td>Indianapolis Star-News</td>
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<td>Jacksonville (FL)</td>
<td>Jacksonville Times-Union</td>
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<td>Kansas City (MO)</td>
<td>Kansas City Star-Times</td>
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<td>Louisville Courier-Journal</td>
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<td>Memphis Commercial Appeal-Press-Scimitar</td>
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<td>Milwaukee Journal-Sentinel</td>
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<td>Minneapolis (MN)</td>
<td>Minneapolis Star-Tribune</td>
</tr>
<tr>
<td>Nashville (TN)</td>
<td>Nashville Banner-Tennessean</td>
</tr>
<tr>
<td>New Orleans (LA)</td>
<td>New Orleans Times-Picayune</td>
</tr>
<tr>
<td>New York (NY)</td>
<td>New York Times</td>
</tr>
<tr>
<td>Oklahoma City (OK)</td>
<td>Oklahoma City Oklahoman-Times</td>
</tr>
<tr>
<td>Omaha (NE)</td>
<td>Omaha World-Herald</td>
</tr>
<tr>
<td>Philadelphia (PA)</td>
<td>Philadelphia Inquirer</td>
</tr>
<tr>
<td>Phoenix (AZ)</td>
<td>Arizona Republic/Phoenix Gazette</td>
</tr>
<tr>
<td>Pittsburgh (PA)</td>
<td>Pittsburgh Press-Post-Gazette</td>
</tr>
<tr>
<td>Providence (RI)</td>
<td>Providence Bulletin-Journal</td>
</tr>
<tr>
<td>Richmond (VA)</td>
<td>Richmond News-Leader</td>
</tr>
<tr>
<td>Rochester (NY)</td>
<td>Rochester Democrat &amp; Chronicle</td>
</tr>
<tr>
<td>Sacramento (CA)</td>
<td>Sacramento Bee</td>
</tr>
<tr>
<td>St. Louis (MO)</td>
<td>St. Louis Post-Dispatch</td>
</tr>
<tr>
<td>Salt Lake City (UT)</td>
<td>Salt Lake Tribune-Deseret News</td>
</tr>
<tr>
<td>San Antonio (TX)</td>
<td>San Antonio Express-News</td>
</tr>
<tr>
<td>San Bernadino (CA)</td>
<td>San Bernadino Sun</td>
</tr>
<tr>
<td>San Diego (CA)</td>
<td>San Diego Union-Tribune</td>
</tr>
<tr>
<td>San Francisco (CA)</td>
<td>San Francisco Chronicle-Examiner</td>
</tr>
<tr>
<td>Seattle (WA)</td>
<td>Seattle Times</td>
</tr>
<tr>
<td>Syracuse (NY)</td>
<td>Syracuse Herald-Post-American</td>
</tr>
<tr>
<td>Toledo (OH)</td>
<td>Toledo Blade</td>
</tr>
<tr>
<td>Tulsa (OK)</td>
<td>Tulsa World-Tribune</td>
</tr>
<tr>
<td>Washington (DC)</td>
<td>Washington Post</td>
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</tbody>
</table>

194
<table>
<thead>
<tr>
<th>NEWSPAPER</th>
<th>AVERAGE DAILY ADS</th>
<th>MAX ADS (DAY)</th>
<th>MIN ADS (DAY)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Albany Times-Union/Knickerbocker News</td>
<td>770</td>
<td>1317(S)</td>
<td>647(H)</td>
</tr>
<tr>
<td>Atlanta Constitution-Journal</td>
<td>699</td>
<td>909(S)</td>
<td>571(SA)</td>
</tr>
<tr>
<td>Baltimore Sun</td>
<td>1007</td>
<td>1796(S)</td>
<td>708(SA)</td>
</tr>
<tr>
<td>Birmingham News-Post-Herald</td>
<td>264</td>
<td>464(S)</td>
<td>204(SA)</td>
</tr>
<tr>
<td>Boston Globe</td>
<td>665</td>
<td>1619(S)</td>
<td>202(SA)</td>
</tr>
<tr>
<td>Charlotte News-Observer</td>
<td>464</td>
<td>714(S)</td>
<td>362(SA)</td>
</tr>
<tr>
<td>Chicago Tribune</td>
<td>1230</td>
<td>3277(S)</td>
<td>688(SA)</td>
</tr>
<tr>
<td>Cincinnati Enquirer</td>
<td>561</td>
<td>759(S)</td>
<td>512(F)</td>
</tr>
<tr>
<td>Cleveland Plain Dealer</td>
<td>1012</td>
<td>1587(S)</td>
<td>751(SA)</td>
</tr>
<tr>
<td>Columbus Dispatch-Citizen-Journal</td>
<td>495</td>
<td>647(S)</td>
<td>423(SA)</td>
</tr>
<tr>
<td>Dallas News</td>
<td>727</td>
<td>877(S)</td>
<td>664(SA)</td>
</tr>
<tr>
<td>Dayton News-Journal-Herald</td>
<td>425</td>
<td>476(S)</td>
<td>358(M)</td>
</tr>
<tr>
<td>Denver Post</td>
<td>452</td>
<td>662(S)</td>
<td>392(SA)</td>
</tr>
<tr>
<td>Detroit News</td>
<td>1238</td>
<td>2000(S)</td>
<td>1038(SA)</td>
</tr>
<tr>
<td>Hartford Courant</td>
<td>564</td>
<td>889(S)</td>
<td>409(SA)</td>
</tr>
<tr>
<td>Houston Chronicle</td>
<td>1043</td>
<td>1393(S)</td>
<td>841(F)</td>
</tr>
<tr>
<td>Indianapolis Star-News</td>
<td>637</td>
<td>900(S)</td>
<td>473(SA)</td>
</tr>
<tr>
<td>Jacksonville Times-Union</td>
<td>443</td>
<td>623(S)</td>
<td>242(SA)</td>
</tr>
<tr>
<td>Kansas City Star-Times</td>
<td>472</td>
<td>947(S)</td>
<td>297(SA)</td>
</tr>
<tr>
<td>Knoxville News-Sentinel</td>
<td>174</td>
<td>436(S)</td>
<td>115(SA)</td>
</tr>
<tr>
<td>Los Angeles Times</td>
<td>3129</td>
<td>4463(S)</td>
<td>2368(SA)</td>
</tr>
<tr>
<td>Louisville Courier-Journal</td>
<td>409</td>
<td>576(S)</td>
<td>324(F)</td>
</tr>
<tr>
<td>Memphis Commercial Appeal-Press-Scimitar</td>
<td>374</td>
<td>621(S)</td>
<td>236(SA)</td>
</tr>
<tr>
<td>Miami News-Herald</td>
<td>1057</td>
<td>1306(S)</td>
<td>982(SA)</td>
</tr>
<tr>
<td>Milwaukee Journal-Sentinel</td>
<td>893</td>
<td>1353(S)</td>
<td>682(SA)</td>
</tr>
<tr>
<td>Minneapolis Star-Tribune</td>
<td>1150</td>
<td>1822(S)</td>
<td>924(SA)</td>
</tr>
<tr>
<td>Nashville Banner-Tennessean</td>
<td>273</td>
<td>388(S)</td>
<td>206(SA)</td>
</tr>
<tr>
<td>New Orleans Times-Picayune</td>
<td>526</td>
<td>630(S)</td>
<td>472(F)</td>
</tr>
<tr>
<td>New York Times</td>
<td>3571</td>
<td>12245(S)</td>
<td>443(SA)</td>
</tr>
<tr>
<td>Oklahoma City Oklahoman-Times</td>
<td>399</td>
<td>640(S)</td>
<td>238(SA)</td>
</tr>
<tr>
<td>Omaha World-Herald</td>
<td>314</td>
<td>542(S)</td>
<td>264(SA)</td>
</tr>
<tr>
<td>Philadelphia Inquirer</td>
<td>1780</td>
<td>3340(S)</td>
<td>1187(SA)</td>
</tr>
<tr>
<td>Arizona Republic/Phoenix Gazette</td>
<td>376</td>
<td>556(S)</td>
<td>317(TU)</td>
</tr>
<tr>
<td>Pittsburgh Press-Post-Gazette</td>
<td>604</td>
<td>1108(S)</td>
<td>440(SA)</td>
</tr>
<tr>
<td>Providence Bulletin-Journal</td>
<td>675</td>
<td>803(S)</td>
<td>556(FR)</td>
</tr>
<tr>
<td>Richmond News-Leader</td>
<td>529</td>
<td>790(S)</td>
<td>347(SA)</td>
</tr>
<tr>
<td>Rochester Democrat &amp; Chronicle</td>
<td>698</td>
<td>846(S)</td>
<td>618(TH)</td>
</tr>
<tr>
<td>Sacramento Bee</td>
<td>428</td>
<td>602(S)</td>
<td>346(SA)</td>
</tr>
<tr>
<td>St. Louis Post-Dispatch</td>
<td>1049</td>
<td>1577(S)</td>
<td>890(SA)</td>
</tr>
<tr>
<td>Salt Lake Tribune-Deseret News</td>
<td>168</td>
<td>216(S)</td>
<td>144(W)</td>
</tr>
<tr>
<td>San Antonio Express-News</td>
<td>343</td>
<td>377(S)</td>
<td>272(FR)</td>
</tr>
<tr>
<td>San Diego Union-Tribune</td>
<td>345</td>
<td>516(S)</td>
<td>280(SA)</td>
</tr>
<tr>
<td>San Francisco Chronicle-Examiner</td>
<td>511</td>
<td>730(S)</td>
<td>439(F)</td>
</tr>
<tr>
<td>Seattle Times</td>
<td>570</td>
<td>936(S)</td>
<td>487(SA)</td>
</tr>
<tr>
<td>Syracuse Herald-Post-American</td>
<td>303</td>
<td>497(S)</td>
<td>216(SA)</td>
</tr>
<tr>
<td>Toledo Blade</td>
<td>258</td>
<td>312(S)</td>
<td>214(SA)</td>
</tr>
<tr>
<td>Tulsa World-Tribune</td>
<td>243</td>
<td>360(S)</td>
<td>198(SA)</td>
</tr>
<tr>
<td>Washington Post</td>
<td>1353</td>
<td>2202(S)</td>
<td>898(SA)</td>
</tr>
</tbody>
</table>

Notes for Table 2-2 follow Table 2-3.
<table>
<thead>
<tr>
<th>DAY</th>
<th>MEAN</th>
<th>STD. DEV.</th>
<th>MAXIMUM</th>
<th>MINIMUM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Monday</td>
<td>728</td>
<td>554</td>
<td>3180 (Los Angeles)</td>
<td>145 Knoxville</td>
</tr>
<tr>
<td>Tuesday</td>
<td>718</td>
<td>602</td>
<td>3446 (Los Angeles)</td>
<td>138 Knoxville</td>
</tr>
<tr>
<td>Wednesday</td>
<td>722</td>
<td>698</td>
<td>3870 (Los Angeles)</td>
<td>138 Knoxville</td>
</tr>
<tr>
<td>Thursday</td>
<td>638</td>
<td>475</td>
<td>2490 (New York)</td>
<td>131 Knoxville</td>
</tr>
<tr>
<td>Friday</td>
<td>569</td>
<td>407</td>
<td>2494 (Los Angeles)</td>
<td>115 Knoxville</td>
</tr>
<tr>
<td>Saturday</td>
<td>524</td>
<td>377</td>
<td>2368 (Los Angeles)</td>
<td>115 Knoxville</td>
</tr>
<tr>
<td>Sunday</td>
<td>1303</td>
<td>1819</td>
<td>12245 (Los Angeles)</td>
<td>216 (Salt Lake)</td>
</tr>
</tbody>
</table>

Notes: Tables 2-2 and 2-3

All figures from author's counts of help-wanted advertisements listed in the classified sections of each paper during the week of October 9-15, 1967. Four newspapers' ads were counted in different weeks: Sacramento Bee, October 13-19, 1975; Albany Times-Union, October 10-16, 1988; Knoxville News-Sentinel, October 14-20, 1985; and Houston Chronicle, October 12-18, 1970. The letter in parentheses following maximum and minimum entries in Table 2-2 represents the day of the week that this count corresponds to. The summary statistics presented in Table 2-3 are for the sample of all forty-eight newspapers. The newspapers running the minimum and maximum number of ads on each of the days is given in parentheses under the reported count.
### TABLE 2-4: HELP-WANTED AND VACANCY RATES IN 1980

<table>
<thead>
<tr>
<th>MSA</th>
<th>Help-Wanted Rate</th>
<th>Vacancy Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Birmingham (AL)</td>
<td>3.38</td>
<td>0.8</td>
</tr>
<tr>
<td>Cincinnati (OH)</td>
<td>3.55</td>
<td>2.8</td>
</tr>
<tr>
<td>Columbus (OH)</td>
<td>3.03</td>
<td>1.6</td>
</tr>
<tr>
<td>Dayton (OH)</td>
<td>2.42</td>
<td>0.5</td>
</tr>
<tr>
<td>New Orleans (LA)</td>
<td>6.12</td>
<td>2.0</td>
</tr>
<tr>
<td>San Antonio (TX)</td>
<td>4.33</td>
<td>1.9</td>
</tr>
<tr>
<td>Toledo (OH)</td>
<td>3.16</td>
<td>0.6</td>
</tr>
</tbody>
</table>

Sources: Vacancy rates are taken from Holzer (1989), Table 3-2, pg. 32. Help-wanted rates are calculated as the annual average of monthly help-wanted counts divided by the annual average of monthly non-agricultural employment in millions, and then multiplied by 100. MSA-level non-agricultural employment figures were obtained from DRI's USREG database, as described in Endnote 1 to Appendix 2-E.
### TABLE 2-5: ESTIMATED $\delta$ WITH ALTERNATIVE $\gamma$ ASSUMPTIONS

<table>
<thead>
<tr>
<th>Competing Newspapers in MSA</th>
<th>$\gamma^*$</th>
<th>$\gamma^{2*}$</th>
<th>$\gamma^{4*}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>TWO</td>
<td>0.57</td>
<td>0.29</td>
<td>0.15</td>
</tr>
<tr>
<td>THREE</td>
<td>0.39</td>
<td>0.20</td>
<td>0.10</td>
</tr>
<tr>
<td>FOUR OR MORE</td>
<td>0.43</td>
<td>0.23</td>
<td>0.13</td>
</tr>
</tbody>
</table>

Sources: Various issues of *Media Records, Editor and Publisher*, Standard Rate and Data Service’s *Newspaper Circulation Analysis* and *Newspaper Rates and Data*, American Newspaper Markets’ *Circulation*, and author’s calculations as described in Appendix 2-D.

Each entry represents the average value of $\delta$, as given in Equation (2D-8) in Appendix 2-D, for different assumptions regarding the value of $\gamma$, and for MSAs with different numbers of competing newspapers. $\delta$ represents the proportion of ads appearing in secondary help-wanted advertisers in an MSA that are not duplicates of ads appearing in the leading advertiser.
TABLE 2-6: RELATIVE PROBABILITY THAT A VACANCY IS ADVERTISED

<table>
<thead>
<tr>
<th>Occupational Category</th>
<th>Myers and Creamer (1967) Estimates</th>
<th>Walsh, Sugarman, and Johnson (1975) Estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Feb. 1965</td>
<td>May 1965</td>
</tr>
<tr>
<td>Professional-Technical</td>
<td>0.57</td>
<td>0.50</td>
</tr>
<tr>
<td>Managerial</td>
<td>4.19</td>
<td>2.70</td>
</tr>
<tr>
<td>Clerical</td>
<td>4.81</td>
<td>1.63</td>
</tr>
<tr>
<td>Sales</td>
<td>7.32</td>
<td>2.59</td>
</tr>
<tr>
<td>Blue-Collar</td>
<td>1.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Service</td>
<td>4.85</td>
<td>3.14</td>
</tr>
</tbody>
</table>

Source: Abraham (1987), Table 3, pg. 218.
The entries represent the probability a job vacancy in each occupational category will be advertised relative to the probability that a blue-collar vacancy is advertised. This normalization implies that all blue-collar entries equal 1.00.
TABLE 2-7: ADVERTISING PROBABILITIES FROM RECRUITING PRACTICES SURVEYS

<table>
<thead>
<tr>
<th>Occupational Category</th>
<th>1968</th>
<th>1979</th>
<th>1987</th>
</tr>
</thead>
<tbody>
<tr>
<td>Professional-Technical</td>
<td>0.72</td>
<td>0.89</td>
<td>0.94</td>
</tr>
<tr>
<td>Managerial</td>
<td>0.66</td>
<td>0.82</td>
<td>0.85</td>
</tr>
<tr>
<td>Clerical</td>
<td>0.87</td>
<td>0.68</td>
<td>0.84</td>
</tr>
<tr>
<td>Sales</td>
<td>0.62</td>
<td>0.75</td>
<td>0.84</td>
</tr>
<tr>
<td>Blue-Collar/Service</td>
<td>0.94</td>
<td>0.88</td>
<td>0.77</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>MSA</th>
<th>Prof-Tech</th>
<th>Managerial</th>
<th>Clerical</th>
<th>Sales</th>
<th>Blue-Collar</th>
<th>Service</th>
</tr>
</thead>
<tbody>
<tr>
<td>Albany (NY)</td>
<td>0.18</td>
<td>0.08</td>
<td>0.23</td>
<td>0.07</td>
<td>0.32</td>
<td>0.12</td>
</tr>
<tr>
<td>Atlanta (GA)</td>
<td>0.16</td>
<td>0.10</td>
<td>0.23</td>
<td>0.09</td>
<td>0.30</td>
<td>0.12</td>
</tr>
<tr>
<td>Baltimore (MD)</td>
<td>0.16</td>
<td>0.08</td>
<td>0.21</td>
<td>0.07</td>
<td>0.35</td>
<td>0.13</td>
</tr>
<tr>
<td>Birmingham (AL)</td>
<td>0.13</td>
<td>0.09</td>
<td>0.18</td>
<td>0.08</td>
<td>0.39</td>
<td>0.14</td>
</tr>
<tr>
<td>Boston (MA)</td>
<td>0.20</td>
<td>0.09</td>
<td>0.23</td>
<td>0.08</td>
<td>0.28</td>
<td>0.13</td>
</tr>
<tr>
<td>Charlotte (NC)</td>
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<td>0.10</td>
<td>0.21</td>
<td>0.10</td>
<td>0.35</td>
<td>0.11</td>
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<tr>
<td>Chicago (IL)</td>
<td>0.15</td>
<td>0.08</td>
<td>0.22</td>
<td>0.08</td>
<td>0.36</td>
<td>0.11</td>
</tr>
<tr>
<td>Cincinnati (OH)</td>
<td>0.15</td>
<td>0.08</td>
<td>0.19</td>
<td>0.08</td>
<td>0.37</td>
<td>0.13</td>
</tr>
<tr>
<td>Cleveland (OH)</td>
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<td>0.08</td>
<td>0.20</td>
<td>0.08</td>
<td>0.38</td>
<td>0.12</td>
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<tr>
<td>Columbus (OH)</td>
<td>0.18</td>
<td>0.09</td>
<td>0.22</td>
<td>0.08</td>
<td>0.32</td>
<td>0.12</td>
</tr>
<tr>
<td>Dallas (TX)</td>
<td>0.16</td>
<td>0.10</td>
<td>0.22</td>
<td>0.09</td>
<td>0.32</td>
<td>0.12</td>
</tr>
<tr>
<td>Dayton (OH)</td>
<td>0.16</td>
<td>0.07</td>
<td>0.19</td>
<td>0.07</td>
<td>0.40</td>
<td>0.11</td>
</tr>
<tr>
<td>Denver (CO)</td>
<td>0.20</td>
<td>0.10</td>
<td>0.21</td>
<td>0.08</td>
<td>0.27</td>
<td>0.13</td>
</tr>
<tr>
<td>Detroit (MI)</td>
<td>0.15</td>
<td>0.07</td>
<td>0.19</td>
<td>0.07</td>
<td>0.40</td>
<td>0.12</td>
</tr>
<tr>
<td>Hartford (CT)</td>
<td>0.19</td>
<td>0.09</td>
<td>0.23</td>
<td>0.08</td>
<td>0.31</td>
<td>0.10</td>
</tr>
<tr>
<td>Houston (TX)</td>
<td>0.17</td>
<td>0.09</td>
<td>0.19</td>
<td>0.08</td>
<td>0.35</td>
<td>0.13</td>
</tr>
<tr>
<td>Indianapolis (IN)</td>
<td>0.14</td>
<td>0.08</td>
<td>0.20</td>
<td>0.08</td>
<td>0.37</td>
<td>0.12</td>
</tr>
<tr>
<td>Jacksonville (FL)</td>
<td>0.13</td>
<td>0.09</td>
<td>0.23</td>
<td>0.09</td>
<td>0.32</td>
<td>0.14</td>
</tr>
<tr>
<td>Kansas City (MO)</td>
<td>0.15</td>
<td>0.09</td>
<td>0.22</td>
<td>0.08</td>
<td>0.34</td>
<td>0.12</td>
</tr>
<tr>
<td>Knoxville (TN)</td>
<td>0.17</td>
<td>0.09</td>
<td>0.16</td>
<td>0.08</td>
<td>0.37</td>
<td>0.14</td>
</tr>
<tr>
<td>Los Angeles (CA)</td>
<td>0.17</td>
<td>0.09</td>
<td>0.21</td>
<td>0.08</td>
<td>0.33</td>
<td>0.12</td>
</tr>
<tr>
<td>Louisville (KY)</td>
<td>0.13</td>
<td>0.07</td>
<td>0.19</td>
<td>0.08</td>
<td>0.41</td>
<td>0.12</td>
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Sources: 1970 Census of Population, General Social and Economic Characteristics, Table 86; and author's calculations as described in endnote 28.

Each entry represents the proportion of total non-agricultural employment in the MSA belonging to that occupational category. Entries may not sum to one for a given MSA due to rounding errors.
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Sources: 1980 Census of Population, General Social and Economic Characteristics, Table 121; and author's calculations as described in endnote 28.

Each entry represents the proportion of total non-agricultural employment in the MSA belonging to that occupational category. Entries may not sum to one for a given MSA due to rounding errors.
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Sources: Author's calculations using data from Tables 2-6, 2-7, 2-8, and 2-9, as described in the text. New York City in 1970 is the baseline city and period for these calculations. All figures are rounded.

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Each entry is the percentage of total FICA employment accounted for by SIC 736 in the county in which the central city of the MSA is located. All figures are rounded.
REFERENCES FOR CHAPTER 2


Editor and Publisher, May issues from 1970.


Marketing and Media Decisions, Fall 1984 and August 1989 issues.


Media Records, annual issues since 1970.


Newspaper Circulation Analysis, Standard Rate and Data Service, annual issues from 1970.

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I. INTRODUCTION AND PREVIEW OF THE EMPIRICAL RESULTS

This chapter presents results from a detailed study of aggregate and regional Beveridge curves in the U.S. since 1970. Each section of the chapter is organized around a different question.

Section II poses the following question: Has the aggregate Beveridge curve shifted significantly in any periods since 1970, indicating fluctuations in structural mismatch? Confirming earlier results from Abraham (1987) and Blanchard and Diamond (1989), I find a significant outward shift of this curve in the 1970s and early 1980s, followed by an inward shift since 1983-84 of equal or slightly greater magnitude. My baseline estimates suggest that the aggregate unemployment rate for any given help-wanted rate increased by 1.37 percentage points from 1970 to 1983, and decreased by 1.80 percentage points from 1983 to 1989. These figures imply an increase in structural unemployment of approximately 0.5 percentage point from 1970 to 1983, followed by a decrease of about the same amount since 1983.

Section III addresses the following question: Why has the aggregate Beveridge curve shifted? In particular, are these shifts explained by regional Beveridge curve shifts, fluctuations in geographic mismatch, or both? I use two different approaches in this section. First, I compute weighted averages of shifts in regional Beveridge curves, and compare these averages to aggregate curve shifts. Second, I estimate the bivariate geographic mismatch indices developed in Chapter 1. Both approaches lead to the same conclusion: aggregate Beveridge curve shifts since 1970 have been driven primarily by changes in within-region matching efficiency. Geographic mismatch
has not been a major determinant of either the level of, or fluctuations in, the structural component of aggregate unemployment since 1970.

In Section IV, I use these bivariate mismatch indices to address the following question: What is the relationship between job-matching function parameters estimated at the aggregate and regional levels? I estimate an aggregate matching function as in Blanchard and Diamond (1989), and use the techniques described in Section IV of Chapter 1 to recover estimates of unobserved regional matching function parameters. These estimates suggest that both regional and aggregate matching functions exhibit constant, or slightly increasing, returns to scale. Given the results in Section III, I argue that it is not surprising that I find little difference between regional and aggregate matching function estimates. These estimates are substantially different only when geographic mismatch fluctuations are strongly negatively or positively correlated with movements in aggregate unemployment and vacancies. Since geographic mismatch has been virtually constant, playing very little role in aggregate unemployment and vacancy fluctuations since 1970, the aggregate matching function provides accurate estimates of regional matching function parameters.

The final section poses the following question: What are possible explanations for the limited role of geographic mismatch in the economy, and do these explanations suggest important extensions to the current analysis? I offer two possible explanations for the minor role of geographic mismatch in the U.S. economy: (1) Labor demand shocks tend to be aggregate in nature; (2) Sectoral labor demand shocks are important, but within-region wage and price flexibility,
along with across-region labor mobility, prevent these shocks from having widely divergent effects on regional vacancy and unemployment rates. To determine the empirical relevance of these alternative explanations requires detailed analyses of unemployment, vacancy, wage, price, and labor force dynamics both within and across regional labor markets. I argue that dynamic regional analyses may also provide valuable insights into the sources of aggregate business cycle fluctuations, in that such analyses allow for more accurate identification of cyclical versus sectoral shocks. This final section offers a preliminary research agenda based on regional labor market analyses that should ultimately provide unique information on aggregate U.S. labor market dynamics.

II. SHIFTS IN THE AGGREGATE BEVERIDGE CURVE

Figure 3-1 illustrates the aggregate Beveridge curve for the 48 sample MSAs from 1970 to 1989, using my "preferred" help-wanted rate series. The curve appears to shift out both in the early and mid 1970s, while shifting back in during the late 1980s.²,³

As a convenient way of summarizing observed shifts in the aggregate Beveridge curve, I estimate the following equation using annual data from 1970 through 1989:⁴

\[
(3-1) \quad HWR = \alpha_0 + \alpha_1 UR + \alpha_2 UR^2 + \alpha_3 TREN\, + \alpha_4 TREN^2 + \alpha_5 D74 + \alpha_6 D84 + \epsilon
\]

where: \( HWR \) = aggregate help-wanted rate
\( UR \) = aggregate unemployment rate
\( TREN\) = time trend
\( D74 \) = dummy for years 1970-74
\( D84 \) = dummy for years 1984-89

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Table 3-1 presents estimates of this equation using my preferred help-wanted rate series. The second column shows estimates of Equation (3-1) with UR replacing HWR as the dependent variable, and HWR and HWR$^2$ replacing UR and UR$^2$ as independent variables. Positive coefficients on UR$^2$ in the first column, and HWR$^2$ in the second column, suggest that the aggregate Beveridge curve is convex to the origin.

I use estimated time trend and dummy variable coefficients to quantify the magnitude of shifts in the aggregate Beveridge curve. Column one coefficients identify vertical shifts in the Beveridge curve. The help-wanted rate associated with any given unemployment rate increased by 0.87 percentage point between 1970 and 1983, and decreased by 1.19 percentage points from 1983 to 1989. Column two estimates identify horizontal shifts in the Beveridge curve. The unemployment rate for any given help-wanted rate increased by 1.37 percentage points from 1970 to 1983, and decreased by 1.80 percentage points from 1983 to 1989.

I re-estimate Equation 3-1 using twelve different help-wanted rate series. I construct each series using alternative assumptions regarding want-ad duplication in competitive newspaper markets, occupational vacancy-advertising probabilities, and the ratio of white-collar to blue-collar vacancy rates. I estimate a significant outward shift of the aggregate Beveridge curve from 1970 to 1983, followed by an even greater inward shift since 1983, for all alternative help-wanted rate series. I also re-estimate Equation (3-1) using quarterly data from 1970 through the first quarter of 1989. Quarterly estimates using my preferred help-wanted rate series
suggest that the unemployment rate for any given help-wanted rate increased by 1.83 percentage points from 1970 to 1983, and decreased by 1.84 percentage points from 1983 to 1989.  

The significant outward shift of the aggregate Beveridge curve from 1970 to 1983, along with its inward shift since 1983, suggest that changes in the amount of structural unemployment in the U.S. economy may be important determinants of observed unemployment rate trends. The unemployment rate in the forty-eight sample MSAs increased from 4.88 to 8.93 percent from 1970 to 1983, and decreased to 4.76 percent by 1989. A simple "back of the envelope" calculation, using estimates from Table 3-1, suggests that structural unemployment increased by approximately 0.5 percentage point from 1970 to 1983, and decreased by about the same amount from 1983 to 1989. Changes in structural unemployment account for approximately twelve percent of both the increase in the unemployment rate from 1970 to 1983 and its subsequent decrease since 1983.

Zagorsky (1990) challenges this interpretation of observed shifts in the relationship between help-wanted and unemployment rates. He presents empirical evidence that the relationship between job vacancies and help-wanted advertising counts has shifted over time. He argues that structural changes in the help-wanted advertising market, and not structural changes in the labor market, are responsible for observed Beveridge curve shifts.

In Appendix 2-A, I argue that Zagorsky (1990) uses a potentially flawed conceptual framework in his empirical analysis, implying that his conclusions are questionable at best. At the same time, I provide strong evidence in Chapter 2 that adjusted help-wanted rate series
accurately track cross-sectional and time-series variation in vacancy rates. I conclude that shifts in the relationship between aggregate adjusted help-wanted and unemployment rates indicate underlying structural changes in the labor market that warrant careful study.

In the next section, I present evidence on the relative importance of changes in regional mismatch and within-region job-matching efficiency in explaining these aggregate Beveridge curve shifts. This evidence helps to identify the sources of structural mismatch in the U.S. aggregate labor market since 1970.

III. WHY HAS THE AGGREGATE BEVERIDGE CURVE SHIFTED?

SHIFTS IN REGIONAL BEVERIDGE CURVES

To what extent do regional Beveridge curve shifts explain aggregate Beveridge curve shifts since 1970? I use the following procedure to address this question: First, I re-estimate Equation (3-1) for each of the forty-eight sample MSAs, using annual data from 1970 to 1989.¹⁰ I use estimated time trend and dummy variable coefficients from each of these regressions to calculate the implied 1970-1983 and 1983-1989 horizontal and vertical shifts of each regional curve. I compute weighted averages of these regional curve shifts, and then compare these weighted averages to 1970-1983 and 1983-1989 shifts in the aggregate Beveridge curve.¹¹

Using my preferred help-wanted rate series, I find that the weighted average horizontal shift of regional Beveridge curves from 1970 and 1983 is 1.01 percentage points. Regional Beveridge curve
shifts account for 74 percent (1.01/1.37) of the increase in the aggregate unemployment rate for any given aggregate help-wanted rate from 1970 to 1983. The weighted average vertical shift of regional curves from 1970 to 1983 is 0.39 percentage point, accounting for 45 percent (0.39/0.87) of the estimated vertical shift of the aggregate Beveridge curve over this time period.

Regional Beveridge curve shifts play an even greater role in explaining the inward shift of the aggregate curve since 1983. The weighted average horizontal shift of regional curves from 1983 to 1989 is -1.86 percentage points, while the vertical shift over the same period is -0.88 percentage point. Regional curve shifts account for 74 percent (0.88/1.19) of estimated vertical shifts, and 104 percent (1.86/1.80) of estimated horizontal shifts in the aggregate Beveridge curve from 1983 to 1989.

Changes in the efficiency of within-region job-matching processes, leading to shifts in regional Beveridge curves, explain a large proportion of observed shifts in the aggregate Beveridge curve, particularly from 1983 to 1989. Decreased geographic mismatch appears to explain little, if any, of the post-1983 inward shift of the aggregate curve. Increased geographic mismatch appears to be an important, but not primary, determinant of the outward shift during the 1970s and early 1980s.

I repeat this accounting exercise using different help-wanted rate series and quarterly data. Results from these alternative specifications are invariably consistent with the conclusions reached above.  

This section implies a limited role for geographic mismatch in
explaining aggregate Beveridge curve shifts since 1970. In the next section, I use a more direct approach to identify the importance of geographic mismatch in determining the position of the aggregate Beveridge curve. I compute geographic mismatch indices developed in Chapter 1, and compare time-series movements in these indices to observed aggregate Beveridge curve shifts.

**GEOGRAPHIC MISMATCH: BIVARIATE MISMATCH INDICES**

Equations (3-2) and (3-3) describe the bivariate mismatch index developed in Chapter 1:13

\[(3-2) \quad gmm^* = \sum_{i=1}^{N} \left( \frac{U_i^b v_i^b}{U_i^* v_i^*} \right) \]

\[(3-3) \quad u/u_{\min} = \left[ \frac{gmm^*}{gmm_{\max}} \right]^{1/a^*} \]

Computation of this mismatch index requires estimates of regional job-matching function parameters \((a_i \text{ and } b_i)\). These parameters cannot be identified through econometric estimation of regional matching functions, however, since MSA hires data are unavailable.

In this section, I identify \(a_i \text{ and } b_i\) using regional Beveridge curve estimates and an assumption on returns to scale in regional matching functions. I use these parameter estimates to compute time series for the bivariate mismatch index under alternative assumptions regarding returns to scale and regional heterogeneity in matching functions.

The model presented in Chapter 1 suggests that ratios of regional
matching function parameters \((b_i/a_i)\) can be identified by estimating log-linear regional Beveridge curves. The model predicts that regional Beveridge curves are given by Equation (3-4):

\[
(3-4) \quad s L_i = U_i^{a_i} v_i^{b_i}
\]

Suppose job reallocation rate, matching-efficiency parameter, and labor force fluctuations for each MSA follow a quadratic trend. Under these assumptions, the MSA "Beveridge curve" regression given by Equation (3-5) provides an unbiased estimate for \(b_i/a_i\):

\[
(3-5) \quad \log(UR_i) = \alpha_0 + \alpha_1 \text{TREND} + \alpha_2 \text{TREND}^2 + \alpha_3 \log(HWR_i) + \epsilon
\]

where \(UR_i\) = unemployment rate in MSA \(i\)

\(HWR_i\) = help-wanted rate in MSA \(i\)

\(\epsilon\) = residual

The absolute value of the OLS estimate of \(\alpha_3\) (\(\hat{\alpha}_3\)) is an unbiased estimate of \(b_i/a_i\) under these assumptions. Alternatively, if help-wanted and unemployment rates trade places in this specification, the absolute value of \(1/\hat{\alpha}_3\) provides an unbiased estimate of \(b_i/a_i\).

If variables that affect the position of any given regional Beveridge curve do not follow a quadratic trend, however, the \(\hat{\alpha}_3\) from OLS regressions provide biased estimates of \(b_i/a_i\). Unobserved variables that shift regional curves, and thus move unemployment and help-wanted rates in the same direction, are omitted from the regression. The absolute value of \(\hat{\alpha}_3\) should underestimate \(b_i/a_i\) with \(\log(UR_i)\) as the dependent variable, while the absolute value of \(1/\hat{\alpha}_3\) should overestimate \(b_i/a_i\) with \(\log(HWR)\) as the dependent variable.
I identify lower- and upper-bound estimates of $b_i/s_i$ by running two OLS regressions of Equation (3.5) for each MSA, one with $\log(UR)_{i1}$ as the dependent variable, and one with $\log(HWR)_{i1}$ as the dependent variable. This allows me to compute mismatch indices for the range of parameter values given by these lower- and upper-bound estimates.\textsuperscript{15}

Table 3-2 presents $\hat{\alpha}_3$ from OLS regressions of Equation (3.5) for each MSA, using annual data from 1970 to 1989. It shows $\hat{\alpha}_3$ from equations fitted with either the log of the unemployment rate, or the log of my preferred help-wanted rate series, as the dependent variable. The last row presents $\hat{\alpha}_3$ from models that pool data from all MSAs and enforce equality of $\alpha_3$, while allowing $\alpha_0, \alpha_1, \text{ and } \alpha_2$ to vary across MSAs.

The estimates support the prediction that factors omitted from Equation (3.5) tend to move $\log(UR)_{i1}$ and $\log(HWR)_{i1}$ in the same direction. The absolute value of $\hat{\alpha}_3$ with $\log(UR)_{i1}$ as the dependent variable is less than the absolute value of $1/\hat{\alpha}_3$ with $\log(HWR)_{i1}$ as the dependent variable in all forty-eight MSAs.\textsuperscript{16}

The estimates suggest substantial cross-sectional variation in the slopes of regional log-linear Beveridge curves. With $\log(UR)_{i1}$ as the dependent variable, the average slope across the forty-eight MSAs is -0.829, with a standard deviation of 0.236, and a range from -1.215 to -0.294. With $\log(HWR)_{i1}$ as the dependent variable, the average slope is -0.877, with a standard deviation of 0.215, and a range from -1.313 to -0.160. The pooled models estimate a slope of -0.812 with $\log(UR)_{i1}$ as the dependent variable, and -0.879 with $\log(HWR)_{i1}$ as the dependent variable. The null hypothesis of equality of slopes across MSAs is soundly rejected in both specifications, with p-values of less
than 0.001. These estimates support the theoretical discussion in Chapter 1, suggesting that cross-sectional variation in industrial and occupational employment composition across MSAs might result in significant diversity in regional matching function parameters.¹⁷

These slope estimates imply matching function parameters consistent with parameters estimated from econometric models of the job-matching process. Jackman, Layard, and Savouri (1990) identify several studies suggesting that job-matching functions exhibit constant returns to scale, with \( a_i \neq 0.5 \).¹⁸ Assuming constant returns to scale in regional matching functions, the pooled slope estimates imply a lower-bound estimate for \( a_i \) of 0.47, and an upper-bound estimate of 0.55.

Regional Beveridge curve slope estimates are extremely robust to the use of alternative help-wanted rate series and quarterly data. For example, pooled estimates, assuming constant returns to scale, imply lower-bound estimates of \( a_i \) which range between 0.458 and 0.471 in alternative specifications, while upper-bound estimates range from 0.550 to 0.566. I also reject the null hypothesis that slope coefficients are equal across MSAs in every specification.

Imposing an assumption on returns to scale \( (a_i + b_i) \) in regional matching functions, estimates of \( b_i/a_i \) in Table 3-2 identify upper- and lower-bound estimates of \( a_i \) and \( b_i \). I consider returns-to-scale assumptions ranging from \( a_i + b_i = 0.8 \), to \( a_i + b_i = 1.6 \), while maintaining equality in the degree of returns to scale in each of the regional job-matching functions (i.e., \( a_i + b_i = a_j + b_j = a + b \), \( \forall \ i,j \) MSAs).¹⁸ I then compute geographic mismatch indices using lower- and upper-bound estimates for \( a_i \) and \( b_i \) for each alternative
returns-to-scale assumption.

First, I consider the Jackman, Layard, and Savouri (1987, 1990) mismatch index, which assumes all regional Beveridge curve slopes are equal. Since I assume regional matching functions also exhibit the same degree of returns to scale, this implies $a_i = a_j = a$, and $b_i = b_j = b$, $\forall i, j$ MSAs. I compute lower- and upper-bound estimates for $a$ and $b$ using the pooled model estimates of $b/a$ from Table 3-2.20

Estimates of $u/u_{\min}$, as given by Equation (3-3), are independent of returns-to-scale assumptions when regional Beveridge curve slopes are equal. I prove this result in Appendix 3-B. This allows me to focus on the simple constant-returns-to-scale case with $a^* = a$, and $b^* = 1-a$.

Table 3-3 shows estimates of the Jackman, Layard, and Savouri (1987, 1990) geographic mismatch index for the U.S. from 1970 to 1989. The estimates in columns 2-4 are quite similar to those in columns 5-7; upper- and lower-bound estimates of $b_i/a_i$ imply geographic mismatch of approximately the same magnitude. Figure 3-3 demonstrates that time-series fluctuations in the mismatch index are particularly insensitive to the use of upper- or lower-bound estimates of $b_i/a_i$. In this figure, UUMIN1 is $u/u_{\min}$ using slope estimates from column one in Table 3-2, while UUMIN2 is $u/u_{\min}$ using slope estimates from the second column in this table. The correlation of the growth rates of UUMIN1 and UUMIN2 over the sample period is 0.99.21

Columns two, three, five, and six suggest that geographic mismatch plays a relatively minor role in determining the position of the aggregate Beveridge curve since 1970. Geographic mismatch accounts for no more than fourteen percent of aggregate unemployment
in any sample year. This proportion also fluctuates within a fairly narrow band, with a minimum value of approximately five percent in 1970.

Changes in geographic mismatch certainly have had some impact on the position of the aggregate Beveridge curve during the 1970s and late 1980s. For example, there is a slight increase in geographic mismatch in the early 1970s, and a much larger increase in the late 1970s and early 1980s. The mismatch index also declines slightly after 1983.

However, these mismatch shifts are too small to be primary determinants of observed aggregate Beveridge curve shifts. Fluctuations in \( u_{\text{min}} \) have driven aggregate Beveridge curve movements since 1970. Increases in \( u_{\text{min}} \) account for approximately 83 percent of the increase in the aggregate unemployment rate from 1970 to 1983, while decreases in \( u_{\text{min}} \) account for 82 percent of the post-1983 decrease in the aggregate unemployment rate.

These results are clearly consistent with the analysis of regional Beveridge curve shifts presented earlier in this section. Within-region fluctuations in the efficiency of the job-matching process are the primary determinants of aggregate Beveridge curve shifts.\(^{22}\)

To determine if movements in \( u/u_{\text{min}} \) are primarily associated with cyclical conditions in the labor market, I regress the alternative \( u/u_{\text{min}} \) series on \( u \) and a constant, and present the residuals in columns four and seven of Table 3-3 and Figure 3-4. While the mismatch indices are slightly countercyclical, correction for their cyclical tendencies does not significantly affect their observed
time-series behavior. The indices still identify the early 1970s and 1980s as periods of relatively high geographic mismatch, and the mid 1970s and late 1980s as periods with declining geographic mismatch. However, these differences are not great enough to imply wide-swing in the aggregate Beveridge curve.²³

I now consider mismatch indices that allow for regional variation in Beveridge curve slopes. Table 3-2 estimates suggest that regional matching function parameters are not identical. Chapter 1 simulation exercises show that indices computed assuming that regional matching functions are identical, when in fact they are not, may do a poor job of tracking time-series fluctuations in mismatch.

I encounter several technical problems when constructing mismatch indices that allow for regional diversity in job-matching function parameters. I discuss many of these issues in Chapter 1. In Appendix 3-C, I present complete documentation for the procedures I use to compute mismatch indices under these more general assumptions.

Table 3-4 presents mismatch index series assuming all MSA matching functions exhibit constant returns to scale, while allowing for regional diversity in matching-function parameters. Indices computed under alternative returns-to-scale assumptions suggest mismatch levels and growth rates that are nearly equivalent to these.²⁴

It is immediately apparent that the figures in Tables 3-3 and 3-4 are quite similar. While estimated levels of mismatch unemployment are slightly different in the two tables, they do not imply significant differences in the proportion of aggregate unemployment accounted for by geographic mismatch. Time-series fluctuations in series from the two tables are virtually identical. The correlation
of growth rates between any two of the four \( u/u_{\text{min}} \) series in Tables 3-3 and 3-4 is 0.99. The tables suggest that geographic mismatch has had little effect on both aggregate unemployment levels and fluctuations in the United States since 1970.\(^{25,26}\)

Appendix 3-D presents an alternative approach to measuring geographic mismatch in the United States since 1970. I compute Lilien (1982) univariate regional dispersion measures for unemployment, help-wanted, and non-agricultural employment growth rates from 1970 to 1989. These measures are not directly comparable with the bivariate mismatch indices presented in this section. Nonetheless, they demonstrate time-series fluctuations that are broadly consistent with the bivariate indices. With the exception of a sharp decline in regional employment growth rate dispersion in the late 1980s, none of the univariate measures show strong upward trends from 1970 to 1983, or downward trends since 1983. This once again suggests a limited role for geographic mismatch in explaining observed shifts in the aggregate U.S. Beveridge curve.\(^{27}\)

The results presented in this section suggest three strong conclusions:\(^{28}\) (1) The level of geographic mismatch unemployment in the U.S. since 1970 has been quite modest, and has not had a large impact on the structural component of aggregate unemployment. (2) Geographic mismatch fluctuations over this time period have also been minimal. There is some evidence that shifts in geographic mismatch, particularly in the late 1970s, early 1980s, and late 1980s, were partially responsible for observed aggregate Beveridge curve movements. However, the magnitude of these shifts was so small that regional Beveridge curve shifts must have been the driving force

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behind aggregate fluctuations in structural unemployment. In other words, within-region industrial, occupational, or skill mismatch, that changed matching efficiency within MSA labor markets, appear to be primarily responsible for aggregate Beveridge curve shifts since 1970. (3) The Jackman, Layard and Savouri (1987, 1990) mismatch index does an excellent job of tracking the more complex indices developed in Chapter 1. This may be considered encouraging news for those who have been using this index to quantify mismatch in European labor markets.²⁹

I postpone further interpretation of the results of this section until the last section of this chapter. I now turn to an analysis of possible biases in returns-to-scale estimates from aggregate matching functions estimated with data from the 1970-89 sample period.

IV. RETURNS-TO-SCALE BIAS IN AGGREGATE MATCHING FUNCTION ESTIMATES

The literature on labor market search behavior, in particular Diamond (1982), predicts that job-matching functions in "island" economies should exhibit increasing returns to scale. In Section IV of Chapter 1, I argue that labor markets with impermeable short-run boundaries, such as regional markets, may be considered "island" economies, while the aggregate labor market may not. In order to conduct readily interpretable empirical tests of the Diamond (1982) prediction, it is important to identify regional job-matching function parameters, and not necessarily aggregate matching function parameters.

This discussion suggests an obvious empirical agenda: collect data on hiring activity in more disaggregated labor markets, and
estimate matching function parameters within these markets. Unfortunately, disaggregated hires data are currently unavailable.\textsuperscript{30} However, I demonstrate in Chapter 1 that sample relationships between geographic mismatch indices, aggregate unemployment, and aggregate vacancies can be used to generate estimates of unobserved regional matching function parameters from observed aggregate matching function parameters.

I follow the procedures outlined in Chapter 1 to identify sample relationships between aggregate and regional matching function parameters. First, I use new hires series from Blanchard and Diamond (1989) to estimate the following aggregate matching function by OLS, using quarterly data from 1970:2 through 1981:4:\textsuperscript{31}

\[
(3-6) \quad \log(H_t) = \alpha_0 + \alpha_1 TRENDS_t + \alpha_2 \log(HW_{t-1}) + \alpha_3 \log(U_{t-1}) + \epsilon_t
\]

where \( t \) = time subscript
- \( HW \) = total help-wanted ads in the 48 sample MSAs
- \( U \) = total unemployment in the 48 sample MSAs
- \( H \) = new hires as constructed by Blanchard and Diamond (1989)

Using my preferred help-wanted series, I estimate \( \hat{\alpha}_2 \) to be 0.60, with a standard error of 0.108, and \( \hat{\alpha}_3 \) to be 0.41, with a standard error of 0.124. These estimates are quite consistent with those reported in Blanchard and Diamond (1989), and suggest constant returns to scale in the aggregate job-matching process. The results appear to be robust to the use of alternative help-wanted rate series as well.

The next step is to generate estimates of gmm\textsuperscript{*} under alternative returns-to-scale and regional matching function heterogeneity assumptions.\textsuperscript{32} I estimate Equation (3-7) by OLS for each of these alternative gmm\textsuperscript{*} series, using quarterly data from 1970:1-1981:3:
\( (3-7) \quad \log(gmm_t^*) = \beta_0 + \beta_1 \text{TREND}_{t+1} + \beta_2 \log(HW_t) + \beta_3 \log(U_t) + \epsilon_t \)

In Chapter 1, I show that \( \hat{\beta}_2 (\hat{\beta}_3) \) is the difference between \( \hat{\alpha}_2 \) (\( \hat{\alpha}_3 \)) from the aggregate matching function, and the coefficient estimate that would be obtained if regional matching functions could be estimated. \( \hat{\beta}_2 + \hat{\beta}_3 \) is a measure of returns-to-scale "bias" in the aggregate matching function; it represents the difference between returns to scale as estimated in aggregate matching functions, and returns to scale in regional matching functions.

However, \( \hat{\beta}_2 \) and \( \hat{\beta}_3 \) obviously depend upon the assumed regional matching function parameters used to construct \( gmm^* \). In order to recover the underlying regional function parameters, Equation (3-7) must be re-estimated with \( gmm^* \) series constructed using alternative assumptions regarding \( \alpha^* \) and \( \beta^* \), until \( \hat{\beta}_2 + \hat{\beta}_3 + \alpha^* + \beta^* = \hat{\alpha}_2 + \hat{\alpha}_3 \). The \( \alpha^* \) and \( \beta^* \) that satisfy this condition identify the underlying regional matching function parameters.\(^{33}\)

Table 3-6 presents \( \hat{\beta}_2 \) and \( \hat{\beta}_3 \) using \( gmm^* \) series constructed assuming that regional matching functions are identical. Each row shows estimates under a different returns-to-scale assumption, ranging from 0.8 in the first row, to 1.6 in the last row.

These estimates suggest two main results. First, as returns to scale increases at the regional level, it becomes more likely that the aggregate matching function will overestimate regional returns to scale (\( \hat{\beta}_2 + \hat{\beta}_3 \) increases). The intuition behind this result is clear. Since this table assumes identical regional matching functions, I calculate \( gmm^* \) assuming \( \alpha_i = \bar{\alpha} - \beta_i \) and \( \beta_i = \bar{\beta} - \beta_i \), for all \( i \) MSAs.
If $\sigma + \varepsilon > (>) 1$, as hires (and thus unemployment and vacancies given the steady-state Beveridge curve relationship) become concentrated in particular regions, $gmm^*$ rises (falls) for any given distribution of unemployment rate/vacancy rate ratios across regions. The positive correlation between $\hat{\beta}_2 + \hat{\beta}_3$ and returns to scale reflects the fact that hires, unemployment, and vacancies tend to become more concentrated in particular regional markets during periods with high aggregate unemployment and vacancies.

Regional dispersion in unemployment rate/vacancy rate ratios decreases $gmm^*$ for any value of $\sigma + \varepsilon$. The fact that returns-to-scale bias is so positive for certain returns-to-scale assumptions, and near zero when assuming constant returns to scale, suggests that geographic mismatch is not a major determinant of aggregate Beveridge curve shifts. Geographic mismatch lowers $gmm^*$, while increasing aggregate unemployment and vacancies, and should result in negative returns-to-scale bias.

Table 3-6 also suggests that regional matching functions exhibit constant, or very slightly increasing, returns to scale. The estimates in the second row imply that if regional functions exhibit constant returns to scale, then aggregate curve estimates of returns to scale will be either 0.952 or 0.957. These figures are quite close to the 1.01 estimated in the aggregate specification in Equation (3-6). At the same time, since the table shows that returns-to-scale bias increases as returns to scale in the regional functions increases, it suggests that upper-bound estimates of regional returns to scale are either 1.048 or 1.043.

Table 3-7 presents $\hat{\beta}_2$ and $\hat{\beta}_3$ estimates using $gmm^*$ series that
allow for regional heterogeneity in Beveridge curve slopes. Returns-to-scale bias is still positively correlated with returns to scale at the regional level. Estimates using slope coefficients from column one in Table 3-2 suggest constant returns to scale in regional matching functions. These estimates imply that if regional curves exhibit constant returns to scale, aggregate specifications will estimate returns to scale of approximately 1.01, which is in fact the returns-to-scale estimate from Equation (3-6). Estimates using slope coefficients from column two in Table 3-2 suggest that 1.075 is an upper-bound estimate of returns to scale in regional matching functions.34

Given the results of the earlier sections, it is not surprising that I find little evidence of negative returns-to-scale bias in the aggregate matching function. Only when geographic mismatch is a major determinant of aggregate Beveridge curve shifts will large negative correlations exist between \( g_m^* \) and aggregate unemployment and vacancies. Over the 1970-81 sample period, mismatch estimates are well-approximated by a constant with a slight upward trend, so that Equation (3-6) does not provide significantly biased estimates of regional matching function parameters.

It is not clear whether these results provide strong evidence against the Diamond (1982) increasing-returns-to-scale prediction. MSA labor markets are certainly more representative of "island" economies than aggregate labor markets are. However, it is likely that true island economies correspond to labor markets at even finer levels of disaggregation. For example, labor markets for fast-food workers are probably defined by regional and occupational boundaries.
On the other hand, the labor market for academic economists is defined primarily by occupational boundaries, and perhaps secondarily by regional boundaries. Further tests of the Diamond (1982) prediction thus require careful delineation of the relevant employer and worker pools that define separate island economies.

V. POSSIBLE INTERPRETATIONS AND SUGGESTIONS FOR FURTHER RESEARCH

The previous two sections provide strong evidence that geographic mismatch has not been a major determinant of either the level of, or fluctuations in, the structural component of aggregate unemployment in the U.S. since 1970. Observed fluctuations in the aggregate Beveridge curve are driven by within-region changes in job-matching efficiency and mismatch, leading to shifts in regional Beveridge curves. The results suggest two related questions: Why has geographic mismatch played such a minor role in the U.S. economy, and what accounts for such major inward and outward shifts of regional Beveridge curves since 1970? In this section, I discuss each of these questions in turn. I identify a research agenda based on detailed regional labor market analyses that is designed to answer these questions. I then conclude by summarizing the lessons from the previous three chapters that may prove useful in this new agenda.

WHY HAS GEOGRAPHIC MISMATCH PLAYED SUCH A MINOR ROLE IN THE U.S. ECONOMY SINCE 1970?

There seem to be two possible interpretations for the limited
role of geographic mismatch in determining aggregate unemployment in the U.S. The first is that labor demand shocks in the U.S. macroeconomy tend to be "aggregate" in nature. Aggregate shocks are not concentrated in particular industries and regions, and affect regional labor markets in roughly the same manner. These shocks move regional labor markets along their Beveridge curves in the same direction, and thus have little impact on geographic mismatch. Aggregate Beveridge curve shifts are then driven by changes in search behavior that affect regional matching-efficiency parameters, or within-region changes in occupational or industrial mismatch.

An alternative interpretation, however, is that sectoral labor demand shocks concentrated in particular industrial and regional sectors of the economy are an important determinant of fluctuations in the U.S. economy. However, either within-region wage and price flexibility, or across-region labor mobility, prevent these shocks from having greatly divergent effects on regional unemployment and vacancy rates.\textsuperscript{35}

To determine if either of these explanations account for the limited role of geographic mismatch in the U.S. economy requires detailed analyses of regional unemployment, vacancy, price, wage, and labor force dynamics. Of primary importance in these analyses is the proper identification of aggregate (or cyclical) and sectoral labor demand shocks.

A typical approach for identifying aggregate shocks involves isolating those components of fluctuations in industry employment that are common to all industries. Sectoral shocks are fluctuations in industry employment not accounted for by these aggregate shocks. If
demand spillover effects are very strong across industrial labor markets, economists using this approach may improperly identify shocks which originate in particular industrial sectors as aggregate shocks. If industrial employment is not uniformly distributed across regions, however, regional labor market data can be used to more accurately identify aggregate and sectoral shocks.

As an example, suppose there are two regions and two industries in an economy. One industry produces on a competitive world market, while the other is a non-traded good sector which produces for consumption only within the region it is produced. Suppose employment in the first region is concentrated in the traded goods sector, while employment in the second region is concentrated in the non-traded sector. Suppose there is a negative terms of trade shock which decreases demand for traded goods produced in this economy. If there are strong demand spillover effects, employment in both the traded and non-traded goods sectors may show marked declines. Traditional identification procedures may label this an aggregate shock, when a sectoral terms of trade shock is in fact the impulse driving the economy. However, the regional economies may respond quite differently to this shock. The first region, with a higher original proportion of employment in the traded goods sector, may show a much greater decline in employment than the second region. This additional information allows researchers to identify the source of this aggregate employment fluctuation as a sectoral, and not aggregate, shock. Since industry employment is not uniformly distributed across geographic regions, regional labor market outcomes provide additional information on the role of industry sectoral shocks in driving
macroeconomic fluctuations, particularly if demand spillover effects across industries are important in the economy. A combination of regional and industrial analyses results in more accurate identification of the underlying impulses driving the macroeconomy.

The dynamic responses of regional labor market variables to such impulses may also help explain the limited role of geographic mismatch in the economy. Wage, price, and labor force dynamic responses to sectoral shocks concentrated in particular regions of the economy identify the relative importance of within-region wage and price flexibility, and across-region labor mobility, in mitigating geographic mismatch.

WHAT ACCOUNTS FOR MAJOR REGIONAL BEVERIDGE CURVE SHIFTS SINCE 1970?

I have studied in some detail the estimated shifts in the forty-eight MSA Beveridge curves since 1970. In general, MSAs with high proportions of blue-collar employment, in particular employment in the steel, auto, and oil industries, exhibit the greatest outward Beveridge curve shifts in the 1970-83 period.36 On the other hand, Beveridge curves in MSAs such as Hartford and Minneapolis actually shift inward from 1970-83. These MSAs tend to have much lower proportions of blue-collar employment.37

Why would job-matching processes become more efficient in MSAs with high proportions of white-collar employment, while at the same time becoming less efficient in MSAs dominated by blue-collar employment? As discussed in Chapter 2, and demonstrated in Table 2-11, the role of intermediaries in the job-matching process, such as
employment agencies, temporary help services, or "head hunters," appears to have increased substantially over the sample period. These intermediaries, however, tend to specialize in the matching of firms and workers in clerical and white-collar occupations, and much less so in blue-collar occupations. If these intermediaries improve the efficiency of the job-matching process, then Beveridge curves in MSAs dominated by white-collar employment should shift inward. They may have little effect on Beveridge curves in MSAs with higher levels of blue-collar employment.

Job-matching intermediaries may explain the inward shifts of the "white-collar MSA" curves. However, what explains the outward shifts of so many "blue-collar MSA" Beveridge curves? In the late 1970s and early 1980s, the extent of worker displacement from blue-collar employment, in particular operatives in the manufacturing sector, increased considerably.\(^{38}\) Workers laid-off from high-wage, union-sector jobs may exhibit different job-search behavior than the average unemployed worker. In particular, such workers may postpone any job-search effort for quite a while after layoff, as they queue for their old jobs. At the same time, even when these workers begin an active job search, they may be less likely to find an acceptable match in any given period of time. They are often leaving well-paying jobs with substantial specific human capital requirements, and may have difficulty finding employment comparable to their old jobs.\(^{39}\) If displaced workers accounted for a higher proportion of unemployment in blue-collar MSAs from 1970-83, then job-matching efficiency parameters in those MSAs should have fallen, leading to outward shifts of their Beveridge curves.\(^{40}\)
From 1983 to 1989, virtually all MSAs exhibit substantial increases in within-region job-matching efficiency, resulting in inward Beveridge curve shifts. MSAs showing the largest inward shifts include those same blue-collar MSAs that shifted out in the earlier period (Detroit, Toledo, Houston, and Cleveland), as well as MSAs with high proportions of white-collar, financial services employment (Boston and New York). A decrease in the proportion of unemployment accounted for by displaced workers in the blue-collar MSAs is a plausible explanation for these shifts. The proportion of unemployment accounted for by such workers decreased as the manufacturing sector rebounded from the 1982-83 recession. The substantial inward shifts in cities such as Boston and New York, on the other hand, may very well reflect the increasingly important role of job-matching intermediaries in filling clerical and white-collar job vacancies.

The discussion in the preceding paragraphs is obviously nothing more than informed conjecture at this point. Once again, detailed cross-sectional analyses of regional labor markets are required to identify the sources of movements in regional Beveridge curves since 1970. Cross-sectional variation in regional Beveridge curve shifts can be related to cross-sectional variation in demographic, institutional, and economic characteristics, so that the importance of these characteristics in the job-matching process can be identified.\footnote{Cross-sectional analysis of matching functions across national boundaries may also prove useful in determining the role of demographic, and particularly institutional, factors in job-matching functions.}
CONCLUSION

In summary, it is apparent that further analyses of regional labor markets may provide insights into some of the most controversial issues in macroeconomics. The data series, theoretical constructs, and empirical results presented in this dissertation should prove useful to the profession as it begins to focus increasing attention on the role of regional markets in explaining aggregate labor market outcomes.

Chapter 1 provides a general framework for identifying the importance of sectoral mismatch in the economy, and should prove useful to economists studying the causes of structural unemployment. The vacancy rate proxies developed in Chapter 2 are also valuable additions to this research agenda, as they are necessary inputs for any study attempting to characterize local labor market dynamics. Finally, the empirical results presented in this chapter are important not only for the insights they provide on geographic mismatch in the U.S., but also because they serve to identify alternative hypotheses about regional labor market dynamics in the U.S. Careful tests of these hypotheses using detailed regional data should provide evidence on the sources of impulses driving aggregate economic fluctuations, wage and price flexibility within regional markets, and labor mobility, all of which are important issues in the current macroeconomic research agenda.
I calculate regional and aggregate unemployment and help-wanted rates as described in Endnote 43 to Chapter 2, and Endnote 1 to Appendix 2-E. The 1989 figure represents only the seasonally-adjusted first quarter observation.

This aggregate Beveridge curve is very similar to those presented in Abraham (1987) and Blanchard and Diamond (1989). These two studies use aggregate help-wanted rate series constructed in Abraham (1987). The help-wanted rate series I construct in Chapter 2, when aggregated, track time-series variation in the Abraham (1987) series quite closely. This result is not surprising. I develop correction factors that adjust help-wanted indices for possible sample variation in ad-count/vacancy ratios using techniques similar to those in Abraham (1987). The primary difference between our approaches is the level of aggregation at which we develop these correction factors. I develop correction factors at the MSA level and then aggregate to compute aggregate correction factors. Abraham (1987) computes aggregate correction factors without explicitly estimating regional factors. Figure 3-1 suggests that this Abraham (1987) "short-cut" does not significantly affect estimates of movements in the aggregate Beveridge curve since 1970.

The magnitude of observed shifts depends somewhat on the assumptions I make when constructing help-wanted rate series in Chapter 2. However, the basic pattern of an outward shift of the aggregate Beveridge curve in the 1970s, followed by an inward shift in the mid to late 1980s, is independent of correction factor assumptions.

I estimate several alternative specifications with different time-period dummy variables. The specification in Equation (3-1) returns the highest $R^2$. Results on the magnitude of aggregate Beveridge curve shifts do not change significantly when alternative time-period dummies are included.
In Appendix 2-D, I construct vacancy rate proxy series using five different assumptions for want-ad duplication in competitive newspaper markets: no duplication, full duplication, duplication with $\gamma = \gamma'$, duplication with $\gamma = \gamma_2'$, and duplication with $\gamma = \gamma'$. I also construct proxy series using three alternative estimates for occupational vacancy-advertising probabilities: the February, 1965, Myers and Creamer (1967) estimates, the May, 1965, Myers and Creamer (1967) estimates, and the Walsh, Sugarman, and Johnson (1975) estimates. Finally, I construct proxy series assuming the white-collar/blue-collar vacancy rate ratio is either 0.5, 0.67, 1, 1.5, or 2.

I use the following assumptions to construct my preferred help-wanted rate series: want-ad duplication with $\gamma = \gamma'$, vacancy advertising probabilities from Walsh, Sugarman, and Johnson (1975) are correct, and the white-collar/blue-collar vacancy rate ratio is equal to one. I repeat all empirical exercises in this chapter using eleven series that are variants of this preferred series. I construct four series by varying the ad duplication assumption while maintaining the preferred assumptions regarding advertising probabilities and vacancy rate ratios. Four more series are constructed by varying the vacancy rate ratio assumption while maintaining preferred assumptions for ad duplication and advertising probabilities. I construct two more series by varying the advertising probability assumption while maintaining baseline assumptions for ad duplication and vacancy rate ratios. I also construct a series assuming that the raw help-wanted count series do not require adjustment for any of the correction factors in Section III of Chapter 2.
Estimates of the horizontal shift of the aggregate Beveridge curve from 1970 to 1983 from these twelve specifications average 1.38 percentage points, with a standard deviation of 0.24, and a range from 0.88 to 1.97. Estimates of the vertical shift of the curve over this time period average 0.89 percentage point, with a standard deviation of only 0.08, and a range from 0.84 to 1.14. Estimates of the horizontal shift of the curve from 1983 to 1989 average -1.76 percentage points, with a standard deviation of 0.11, while estimates of the vertical shift over these six years average -1.20 percentage points, with a standard deviation of 0.10. While the range of these estimates is rather broad, it is nonetheless apparent that I identify significant shifts in the aggregate Beveridge curve no matter what correction factor assumptions I use in building help-wanted rate proxy series.

Most of the variation in Beveridge curve shift estimates is accounted for by series with different assumptions regarding want-ad duplication. For example, series I construct assuming no duplication generally demonstrate the smallest inward and outward shifts of the curve, while series assuming full duplication exhibit much greater shifts. Increasing volatility in MSA newspaper market structures from 1970 to 1989 may explain these results. Abraham (1987) and Simpson (1989) document significant changes in the level of advertising competition observed in MSA newspaper markets since 1970. If one assumes no want-ad duplication, changes in advertising concentration ratios across newspapers in an MSA do not affect estimated ad counts. However, changes in these concentration ratios do have an impact on ad counts under a full-duplication assumption. For example, suppose in one period ten total help-wanted ads are placed in newspapers in an MSA, six of which appear in the leading advertiser. Suppose that in the next period ten separate ads are again placed, but that the leader now captures a larger share of the advertising market, running eight of these ads. Assuming full duplication of want-ads, one would estimate a thirty-three percent increase in ad counts between the two periods, while one would estimate no change in ad counts under a no-duplication assumption. Periods with marked changes in advertising concentration ratios, for any given number of separate advertisements, are associated with wider fluctuations in ad count series assuming high levels of want-ad duplication, than in those assuming less duplication.
I have annual data for MSA unemployment rate and labor force series from 1970 to 1975, and quarterly data from 1976 to 1989. I have quarterly data for state unemployment rate and labor force series from 1970 to 1989. I use these quarterly state data to construct proxies for quarterly MSA unemployment rate and labor force figures from 1970 to 1975. I make the following assumption: The ratio of the unobserved quarterly MSA unemployment rate (labor force) to its observed annual value is equal to the observed ratio of its state quarterly unemployment rate (labor force) to its state annual value. I conduct an informal test to check the validity of this assumption. First, I use this assumption to construct quarterly proxy series from 1976 to 1989 for MSA unemployment rates and labor forces. I then regress each quarterly proxy series from 1976 to 1989 on the observed quarterly series it is proxying for and a constant. For each regression, I test the joint null hypothesis that the constant term is zero and the slope coefficient is one. I accept this null hypothesis at the five-percent significance level for all forty-eight MSA unemployment rate proxy series, and for forty-five of the forty-eight MSA labor force proxies. I conclude that quarterly proxy series built using this assumption accurately track fluctuations in the observed quarterly series from 1976 to 1989. It is reasonable to assume that proxies built under this same assumption also accurately track fluctuations in the unobserved quarterly series from 1970 to 1975.

Estimates of the outward shift of the Beveridge curve from 1970 to 1983 are slightly larger in these quarterly specifications than they are in the annual specifications. Estimates of the inward shift of this curve since 1983 are almost identical in annual and quarterly models. The magnitudes of estimated Beveridge curve shifts using quarterly models are affected by assumptions used in constructing help-wanted rate proxy series, but in all cases there is substantial evidence of both shifts.

I assume factors affecting structural unemployment in the economy move unemployment and help-wanted rates along a 45-degree line in the Beveridge curve space when making this calculation. See Chapter 1 for details on using the Beveridge curve to decompose unemployment fluctuations into structural and cyclical components.

I also estimate this equation with the unemployment rate replacing the help-wanted rate as the dependent variable.

I use MSA labor force figures to weight horizontal shifts of the curves, since I use these weights to construct the aggregate unemployment rate from its regional counterparts. MSA non-agricultural employment numbers serve as the weights for vertical shifts of the curves, since I use these weights to construct the aggregate help-wanted rate. See Endnote 43 in Chapter 2, and Endnote 1 in Appendix 2-E, for details on the construction of help-wanted and unemployment rates.
I repeat this exercise using annual and quarterly time series for the twelve alternative help-wanted rate series identified in Endnote 5. Using annual data, I find that regional Beveridge curve shifts from these twelve alternative specifications account for on average: (a) 69 percent of the 1970-1983 outward horizontal shift of the aggregate Beveridge curve; (b) 103 percent of the 1983-1989 inward horizontal shift of the aggregate Beveridge curve; (c) 44 percent of the 1970-1983 outward vertical shift of the aggregate Beveridge curve; and (d) 74 percent of the 1983-1989 inward vertical shift of the aggregate Beveridge curve. Standard deviations of these estimated percentages across the twelve alternative specifications are: (a) 0.16 for the outward horizontal shift; (b) 0.02 for the inward horizontal shift; (c) 0.08 for the outward vertical shift; and (d) 0.01 for the inward vertical shift. Estimates constructed using quarterly data suggest regional Beveridge curve shifts of approximately the same magnitude.

The notation is as given in Chapter 1. The functional forms that determine \( a^* \) and \( b^* \) depend upon assumptions regarding returns to scale and regional disparities in job-matching functions. See Chapter 1 for details.

I am also assuming that HWR is a good proxy for vacancy rates in MSA 1, so that I can ignore measurement error biases in these regressions.

An alternative method is to identify proper instruments for regional help-wanted rates, and to estimate \( b_1/a_1 \) through instrumental variables estimation of Equation (3-5). I prefer the OLS approach since I have found it difficult to identify appropriate instruments for help-wanted rates. In practice, the OLS approach, identifying upper- and lower-bound parameter values, appears suitable for the purposes of this study. Estimates of the geographic mismatch index presented in this section are not sensitive to alternative values of \( b_1/a_1 \) between these upper- and lower-bound estimates.

As an indirect "specification test" of Equation (3-5), I test the null hypothesis for each MSA that \( a_3 \) from the specification with \( \log(UR) \) as the dependent variable is equal to \( 1/a_3 \) with \( \log(HWR) \) as the dependent variable. I accept this null hypothesis at the five percent significance level for twenty-seven of the forty-eight MSAs.

In future research, I hope to use the cross-sectional variance in these parameters to generate a better understanding of how occupational, industrial, institutional, and demographic factors within MSAs affect the job-matching process. I discuss this research agenda in more detail in the concluding section of this chapter.

These studies include Pissarides (1986), Jackman, Layard, and Savouré (1987), and Blanchard and Diamond (1989). In Chapter 1, I argue that, under certain circumstances, the Blanchard and Diamond (1989) parameter estimates for the U.S. aggregate matching function may differ substantially from U.S. regional matching function parameters. In the next section, however, I show that U.S. aggregate and regional matching function parameters are not significantly different.
I present arguments in Chapter 1 that suggest matching-efficiency parameters, and the relative roles of unemployment and vacancies in the job-matching process, may vary across regions because of substantial cross-sectional variance in institutional, demographic, and economic factors. However, it is less clear if this variation also leads to differences in returns to scale in regional job-matching functions. I am thus hesitant to impose an arbitrary distribution of returns-to-scale parameters across MSAs.

This is obviously not the "correct" mismatch index, since the null hypothesis of equality of slopes across MSAs is soundly rejected. Nonetheless, it still provides information on some important issues. Jackman, Layard, and Savouri (1987,1990) use this index to quantify U.K. mismatch unemployment. Computation of this same index for the U.S. allows a direct comparison of U.S. and U.K. mismatch unemployment since 1970, at least as implied by this imperfect measure. Comparisons of this index with U.S. indices that relax the equal Beveridge curve slopes assumption also provide some indirect evidence on the validity of the Jackman, Layard, and Savouri (1987,1990) claims regarding U.K. mismatch unemployment. For example, if there are no significant differences between indices assuming homogeneous and heterogeneous regional matching function parameters, then confidence in the ability of the Jackman, Layard, and Savouri (1987,1990) index to accurately measure mismatch may be increased.

Mismatch estimates are also extremely robust to the use of alternative help-wanted rate series and quarterly data.

Jackman, Layard, and Savouri (1987,1990) and others have found very similar results for shifts in the U.K. aggregate Beveridge curve.

If regional Beveridge curves have identical slopes, regional mismatch unemployment reaches its minimum value when vacancy/unemployment rate ratios are equal in all regions. As an alternative bivariate "mismatch" index, I compute Lilien's (1982) σ measure for MSA help-wanted/unemployment rate ratios. Time-series fluctuations in this index generally match the u/u_min index quite closely. There is evidence of a slight increase in mismatch in the early 1970s and 1980s, and weaker evidence of a decline in mismatch since 1983.

If MSA Beveridge curve slopes are not equal, u/u_min is not independent of returns-to-scale assumptions. Therefore, I compute mismatch indices under decreasing, constant, and increasing returns-to-scale assumptions for regional matching functions.

I repeat all calculations using alternative help-wanted rate series and data frequencies, and these conclusions are invariably supported.

Geographic mismatch unemployment reaches its minimum value when v_i/u_i ratios are equated across MSAs. As an alternative "mismatch" index, I compute Lilien's (1982) σ measure for this ratio across the forty-eight MSAs. This measure shows a significant upward trend since 1983, suggesting a greater degree of geographic mismatch since 1983. This provides even further evidence that regional Beveridge curve shifts must be responsible for the inward shift of the aggregate Beveridge curve since 1983.
See Appendix 3-D for details.

Cross-sectional variation in regional help-wanted rates is a major determinant of the mismatch measures considered in this section. Conclusions based on these mismatch indices are questionable if regional help-wanted rates do not exhibit the same cross-sectional variation as regional vacancy rates. Table 2-4 presents my preferred help-wanted rates, and vacancy rates from Holzer (1989), for seven MSAs in 1980. The mean of the help-wanted rates is 3.72, with a standard deviation of 1.118, while the mean of the vacancy rates is 1.46, with a standard deviation of 0.793. The help-wanted rate figures exhibit greater variability around a higher mean value. Using this information, I construct two more help-wanted rate series that may more accurately reflect cross-sectional variation in vacancy rates. For the first series, I adjust help-wanted rate levels, while holding their ratios across MSAs constant, so that the 1980 standard deviation of help-wanted rates for the seven MSAs in Table 2-4 is 0.793 (the Holzer (1989) estimate). For the second series, I multiply all help-wanted rate series by 1.46/3.72, so that 1980 mean help-wanted and vacancy rates from these seven MSAs are equal. I then repeat the exercises described in this, and all previous sections, using these new series. I find no significant differences in the results.

This is merely a tentative conclusion. A re-examination of European mismatch using the techniques developed in this dissertation would certainly be a valuable addition to the literature.

The BLS labor turnover series provide hires data for disaggregated manufacturing sectors. However, these series were discontinued in 1981.

Equation (3-6) is the baseline specification from Blanchard and Diamond (1989). Consult their paper for a discussion of timing issues that arise when estimating this function. The new hires series I use is also their baseline series. This regression corresponds to their Equation (1) in Table 1, estimated over a slightly different time period, with quarterly, instead of monthly, data.

When allowing for heterogeneity in regional matching functions, I argue in Chapter 1 that researchers would be interested in obtaining hires-weighted averages of $a_i$ and $b_i$ as summary measures of regional parameters. Therefore, it appears that regional hires data are required to construct $a^*$ and $b^*$ estimates when computing $gmm$. I show in Appendix 3-C, however, that the steady-state regional Beveridge curve relationship suggests that regional hires are given by Equation (3C-1), which can be calculated given regional unemployment rates, help-wanted rates, and labor forces. I use this equation to generate estimates of regional hires, and then calculate $a^*$, $b^*$ and $gmm$. When assuming identical regional matching functions ($a_i = a$ and $b_i = b$, $\forall i$), the researcher wants to recover $a$ and $b$. I set $a^* = a$, and $b^* = b$ when computing $gmm$ under these assumptions.

See Section IV in Chapter 1 and Appendix 1-E for details of this procedure.
Estimates using all twelve alternative help-wanted rate series support the conclusion that regional Beveridge curves exhibit constant or slightly increasing returns to scale.

For example, suppose there are two regions in an economy, one which produces guns and one which produces butter in competitive world markets. Suppose an era of international goodwill begins, so that there is a worldwide shift in demand away from guns and toward butter, lowering the relative price of guns. If nominal wages are rigid, and there is no labor mobility across regions, then labor demand falls in the guns region, lowering the vacancy/unemployment ratio, while labor demand rises in the butter region, increasing the vacancy/unemployment ratio. Rigid nominal wages and limited labor mobility imply that such a shock increases geographic mismatch. Now suppose wages are not rigid, but there still is no labor mobility. The increase in labor demand in the butter region should increase nominal wages, and thus choke off some of the increase in the vacancy/unemployment rate. The decrease in labor demand in the guns region is mitigated by lower nominal wages, preventing the vacancy/unemployment rate from declining by a large amount. Therefore, nominal wage flexibility results in the measurement of less geographic mismatch. Finally, labor mobility from the guns region to the butter region, with constant nominal wages, tends to lower the vacancy/unemployment ratio in the butter region, while increasing this ratio in the guns region. Once again, geographic mismatch is mitigated.

Birmingham and Chicago (steel), Detroit and Toledo (auto), and Houston (oil) are among the MSAs with the largest outward Beveridge curve shifts in this period.

See Tables 2-8 and 2-9 for the occupational composition of employment in the sample MSAs in 1970 and 1980.


See Hamermesh (1987) for a review of the literature on worker displacement effects on unemployment durations and subsequent wages once re-employed.

Another way of expressing this is that occupational and industrial mismatch within blue-collar MSAs rose severely as the pace of job displacement in the manufacturing sector increased. This mismatch resulted in large outward shifts of these MSA Beveridge curves.

The clearest way to identify the determinants of job-matching processes in regional labor markets is to estimate regional matching functions. I plan to explore the possibility that the CPS data from which the Abowd and Zellner (1985) aggregate gross flows series are estimated can be used to generate regional hires series.
APPENDIX 3-A: Do shifts in the relationship between help-wanted advertising and the unemployment rate indicate underlying changes in the unobserved vacancy-unemployment Beveridge curve?

In this appendix, I discuss the possibility that shifts in the relationship between help-wanted advertising and the unemployment rate merely reflect structural changes in the help-wanted advertising market, and thus do not indicate structural changes in the labor market. For example, Zagorsky (1990) argues that shifts in the aggregate Beveridge curve identified by Abraham (1987), Blanchard and Diamond (1989), and others, are driven only by changes in the quantity of help-wanted ads demanded per job vacancy. I argue that Zagorsky (1990) uses a potentially flawed conceptual framework in his empirical analysis, so that his conclusions are not convincing. I conclude there is little evidence to support the claim that changes in the help-wanted advertising market explain most shifts in the aggregate U.S. Beveridge curve.

Zagorsky (1990) considers an informal model of the determinants of help-wanted advertising that is quite similar to the ad duplication model in Appendix 2-D. His model predicts that increases in help-wanted readership by the unemployed, along with decreases in advertising rates, should increase ad-count/vacancy ratios. He collects help-wanted advertising numbers from nine major metropolitan daily newspapers, help-wanted ad readership figures from the CPS, and advertising rates from Newspaper Rates and Data. He then estimates an econometric model which shows that the quantity of help-wanted advertising increases with want-ad readership, and decreases with ad rates. He uses these econometric estimates to argue that increased
readership of help-wanted ads by the unemployed in the 1970s led to substantial increases in ad-count/vacancy ratios. Since a greater proportion of unemployed workers were reading want-ads, recruitment advertisements became a more cost-effective means of filling job vacancies, and ad-count/vacancy ratios rose. Zagorsky (1990) argues that this increase in the ad-count/vacancy ratio is responsible for the observed outward shift of the aggregate Beveridge curve in the 1970s. He also claims that the observed inward shift of the Beveridge curve in the late 1980s is attributable to higher real advertising rates which resulted in lower ad-count/vacancy ratios.

There may be some serious problems with Zagorsky's (1990) empirical methods. He implicitly assumes that increases in readership of help-wanted ads by the unemployed are exogenous to any underlying structural changes in the labor market. However, in periods of structural mismatch, as workers begin to move across industrial, occupational, or regional labor market boundaries, they may rely upon more formal job-search techniques, such as reading want-ads. Workers moving across these labor market boundaries may not be as familiar with the informal job-search techniques, such as employee referrals, that workers already established in an industry, occupation, or region may use. This suggests there should be a strong positive correlation between structural mismatch shocks and help-wanted readership.

Zagorsky (1990) argues that exogenous increases in want-ad readership increased ad-count/vacancy ratios in the 1970s, resulting in an outward shift of the observable want-ad-unemployment Beveridge curve, while leaving the unobservable vacancy-unemployment Beveridge curve unchanged. A feasible alternative interpretation, however, is
that structural mismatch increased during the 1970s, which shifted out the unobserved vacancy-unemployment Beveridge curve. This structural mismatch also increased help-wanted readership, increasing help-wanted advertising demand, and resulting in an outward shift of the observed want-ad-unemployment Beveridge curve. Without further research on the exogeneity of help-wanted readership, Zagorsky's (1990) results can be interpreted as providing evidence either for or against increased structural unemployment in the U.S. during the 1970s.

I also believe that Zagorsky's (1990) measures of real want-ad rates are incorrect. He deflects nominal advertising rates by the CPI when computing real want-ad rates. However, ad-count/vacancy ratios should depend on the price of ads relative to alternative recruitment strategies, and not necessarily relative to a market consumption basket. The "correct" deflator is a measure of the average cost of alternative forms of employee recruitment.

I construct real want-ad milline rates in Chapter 2 using the "media cost per thousand index" as my deflator. This index measures the cost per thousand consumers reached of advertising through television, radio, magazines, trade journals, newspapers, and billboards. One alternative to recruiting through newspaper want-ads is to solicit applications through advertisements in trade journals, on local radio stations, or even on television. It is certainly true that this advertising cost index (ACI) is not the "correct" deflator either. However, since it does reflect cost movements in at least some alternative recruitment strategies, it may be preferable to the CPI.

Figure 3-2 illustrates Zagorsky's (1990) help-wanted price index
from 1969 to 1988 deflated by either the CPI or the ACI. Real want-ad rates rise by over 40 percent from 1982 to 1988 when deflated by the CPI, but by less than 20 percent when deflated by the ACI. If Zagorsky (1990) had used the ACI as his deflator instead of the CPI, he would have estimated a much smaller decrease in the ad-count/vacancy ratio in the late 1980s. A small decrease in the ad-count/vacancy ratio cannot explain the significant inward shift of the Beveridge curve in the late 1980s. This example illustrates the importance of the deflator in interpreting Zagorsky’s (1990) results, and suggests that his conclusions about the stability of the aggregate Beveridge curve over the last twenty years may be overstated.

There are factors besides increasing costs of help-wanted advertising, however, that may have decreased ad-count/vacancy ratios in the late 1980s. For example, sources in the newspaper industry have noted increased competition for employment advertisements from specialized recruitment tabloids in the last few years. Some employers may now choose to advertise vacancies in these tabloids instead of newspaper classified sections. As recruitment tabloids grew, ad-count/vacancy ratios may have fallen, resulting in an inward shift of the observed Beveridge curve.

I have been unable to identify research documenting the extent of the shift of want-ad demand from newspapers to recruitment tabloids. However, BNA surveys of employee recruiting practices suggest that firms have become more reliant on newspaper help-wanted ads as a recruitment strategy throughout the 1980s (see Table 2-7). If BNA survey firms are a representative sample, then it appears that
recruitment tabloids have not decreased ad-count/vacancy ratios, and thus are not solely responsible for inward shifts of the observed Beveridge curve. ¹

In sum, I find arguments suggesting that observed shifts in the aggregate Beveridge curve are driven merely by changes in help-wanted advertising practices to be less than convincing. At the same time, I am confident that the proxy series I develop in Chapter 2 accurately track time-series and cross-sectional variation in vacancy rates. I conclude that observed shifts in the aggregate Beveridge curve indicate underlying structural changes in the labor market.
NOTES FOR APPENDIX 3-A

1See Endnote 3 in Appendix 2-D for more information on this index.

2For example, the McDonald's restaurant chain has used television advertisements to solicit employment applications from senior citizens and teenagers.

3See Horovitz's (1990) Los Angeles Times article for a discussion of the recent proliferation of these specialized recruitment publications. I thank Katharine Abraham for providing this citation.

4Wachter (1987) notes that the BNA samples have a disproportionate number of large, manufacturing sector employers, and thus may not be reflective of the economy as a whole.
APPENDIX 3-B: A proof that $u/u_{\min}$ is independent of returns-to-scale assumptions when regional Beveridge curves have identical slopes.

In Chapter 1, I show that $g_{\max}^{\ast}$ is equal to one when regional Beveridge curves have identical slopes. Therefore, $u/u_{\min}$ is given by Equation (3B-1):

$$
(3B-1) \quad \frac{u}{u_{\min}} = \left[ g_{\max}^{\ast} \right] (-1/a^{\ast}) = \left[ \frac{L^{s_{\ast}+b_{\ast}} u_{\ast}^{b_{\ast}}}{\sum_{i=1}^{N} (L_{1}^{a_{i}+b_{i}} u_{1}^{a_{i} b_{i}})} \right]^{(1/a^{\ast})}
$$

If $u/u_{\min}$ is independent of returns-to-scale assumptions, it must be the case that for given $L$, $u$, $v$, $L_{1}$, $u_{1}$, and $v_{1}$, the expression on the right-hand side of Equation (3B-1) is independent of $a_{i} + b_{i}$, and thus $a^{\ast} + b^{\ast}$. The numerator of this expression raised to the $(1/a^{\ast})$ power is constant given $L$, $u$, and $v$. This follows from the fact that the slope of the pooled log-linear Beveridge curve determines $b^{\ast}/a^{\ast} = b_{1}/a_{1}$, and is thus some constant $k^{\ast}$.

Is the denominator raised to the $(1/a^{\ast})$ power also constant given $L_{1}$, $u_{1}$, and $v_{1}$? Equation (1-20) gives the formula for $a^{\ast} + b^{\ast}$ under an equal-slopes assumption. Rearranging this expression, I solve for $1/a^{\ast}$:

$$
(3B-2) \quad \frac{1}{a^{\ast}} = (1+k^{\ast}) \log(\Sigma((s_{i} L_{1}))^{1/(a_{i}+b_{i}))})/\log(\sum_{i=1}^{N} (s_{i} L_{1}))
$$

I use the steady-state Beveridge curve relationship in Equation (3-4) to rewrite this as:
\[ \frac{1}{a^*} = (1+k^*) \log \left( \frac{(1+k^*)}{\sum_{i=1}^{N} \left( \frac{L_i^1}{v_i^1} \right)} \right) / \log \left( \frac{1+k^*}{\sum_{i=1}^{N} s_i L_i} \right) \]

\[ = k^{**} / \log \left( \frac{1}{\sum_{i=1}^{N} s_i L_i} \right) \]

where \( k^{**} \) is a constant for given \( L_i^1, v_i^1, \) and \( u_i^1 \).

Let the denominator in Equation (3B-3) be \( d^* \). The steady-state Beveridge curve relationship implies that \( d^* \) is the log of the denominator in Equation (3B-1). It follows that the denominator of Equation (3B-1) risen to the \((1/a^*)\) power can be expressed as:

\[ \exp(d^*) \left( \frac{k^{**}}{d^*} \right) = \exp(k^{**}) \]

This term is also a constant, proving that \( u/u_{\text{min}} \) is independent of returns-to-scale assumptions when Beveridge curve slopes are identical across regions.
APPENDIX 3-C: Computing mismatch indices when allowing for diversity in regional matching function parameters.

The first issue that arises when computing mismatch indices that allow for regional diversity in matching function parameters is how to determine $a^*$ and $b^*$. I demonstrate in Chapter 1 that closed-form solutions for these parameters do not exist under general assumptions. Identification of these parameters requires implementation of a multi-step, data-intensive algorithm. However, Chapter 1 simulations suggest that if $a^*$ and $b^*$ are assumed to be determined by simple hires-weighted averages of regional $a_i$ and $b_i$, the resulting mismatch index tracks time-series variation in the true mismatch index quite closely. Therefore, I calculate $a^*$ and $b^*$ as these hires-weighted averages.

Unfortunately, new hires data at the MSA level are unavailable. However, the steady-state regional Beveridge curve relationship suggests that estimates of regional new hires can be calculated using regional unemployment, vacancy, and labor force data. Normalizing regional matching-efficiency parameters to one, the steady-state regional Beveridge curve suggests that new hires are given by:

\[(3C-1) \text{ Hires in MSA } i = s_i L_i \sum_{1}^{s_i} v_{i} L_{i} \]

Given an assumption on returns to scale in regional matching functions, and estimates of $b_i/a_i$ from log-linear Beveridge curve regressions, I compute MSA hires estimates by plugging MSA unemployment rates, help-wanted rates, and labor force figures into Equation (3C-1). However, before calculating $a^*$ and $b^*$ as
estimated-hires-weighted averages of \( a_i \) and \( b_i \), I must address another conceptual problem. If \( a^* \) and \( b^* \) are calculated in this manner, then \( gmm_{max}^* \) is equal to one only if regional matching functions exhibit constant returns to scale. For all other degrees of returns to scale, \( gmm_{max}^* \) is greater than or less than one. Therefore, \( u/u_{min} \) calculations that assume \( gmm_{max}^* \) is equal to one may be incorrect. The following paragraphs examine this issue in greater detail.

The mismatch index is determined by the following two equations:

\[
(3C-2) \quad gmm^* = \sum_{i=1}^{N} \left( \frac{U_i^{a_i} V_i^{b_i}}{U^{a^*} V^{b^*}} \right)
\]

\[
(3C-3) \quad \frac{u}{u_{min}} = \left( \frac{gmm_{max}^*}{gmm^*} \right)^{1/a^*}
\]

In practice, I calculate \( u/u_{min} \) assuming that \( gmm_{max}^* \) is equal to one, so that \( u/u_{min} \) is given by \( (gmm^*)^{-1/a^*} \). When using the correct \( a^* \) and \( b^* \) parameters, this method provides the correct mismatch index, since \( gmm_{max}^* \) is equal to one in this case. However, if hires-weighted averages of \( a_i \) and \( b_i \) are used as the \( a^* \) and \( b^* \) parameters, then \( gmm_{max}^* \) may not be equal to one, and incorrect estimates of \( u/u_{min} \) may be obtained.

As an example, suppose regional matching function parameters are actually identical. Taking hires-weighted averages of \( a_i \) and \( b_i \) in this case, \( a^* = a_i = a \), and \( b^* = b_i = b \). Maximization of \( gmm^* \) requires \( U_i / V_i = U/V \) for all \( i \) under these assumptions, so that \( gmm_{max}^* \) is given by Equation (3C-4):

\[
(3C-4) \quad gmm_{max}^* = \sum_{i=1}^{N} (V_i / V)^{a^* b^*}
\]
\( g_{\text{max}}^* \) is greater than, less than, or equal to one as \( a + b \) is less than, greater than, or equal to one.

Suppose one assumes \( g_{\text{max}}^* \) is equal to one, and computes mismatch indices that use hires-weighted averages of \( a_i \) and \( b_i \) as estimates of \( a^* \) and \( b^* \). This example shows that in this case mismatch is underestimated when matching functions exhibit decreasing returns to scale, and is overestimated when they exhibit increasing returns to scale.

\( a^* \) and \( b^* \) can be rescaled, however, while maintaining their ratio constant, so that \( g_{\text{max}}^* \) equals one, and the index no longer systematically under- or overestimates mismatch. Continue to assume that regional matching functions have identical parameters. Equation (1-20) presents an expression for \( a^* + b^* \) which ensures that \( g_{\text{max}}^* \) is equal to one when regional matching function parameters are identical. I rewrite that equation here as Equation (3C-5):

\[
(3C-5) \quad a^* + b^* = \log(\Sigma(s L_i))/\log(\Sigma((s L_i)^{1/a_i+b_i}))
\]

Equation (3C-5) is strictly correct only under the assumption that regional matching functions are positive monotonic transformations of one another. Simulation exercises, however, suggest that it closely approximates the true \( a^* + b^* \) when there is more general heterogeneity in regional matching functions.

In light of these conceptual problems, I use the following procedure to identify \( a^* \) and \( b^* \), and then calculate mismatch indices, under general assumptions on regional matching function parameter
heterogeneity. First, I use Equation (3C-5) to calculate $a^* + b^*$. I use Equation (3C-1) to generate estimates of $s_{L^i}$ for this calculation. This scales $a^*$ and $b^*$ so that $g_{\text{mm max}}^*$ is approximately equal to one. I identify $a^*$ and $b^*$ assuming that their ratio is given by the ratio of hires-weighted averages of $a_i$ and $b_i$. Mismatch indices computed assuming this ratio accurately track indices computed with true $a^*$ and $b^*$ values in simulation exercises. I then compute $g_{\text{mm max}}^*$ using these values of $a^*$ and $b^*$. I assume that the scaling of $a^*$ and $b^*$ implicit in Equation (3C-5) ensures that $g_{\text{mm max}}^*$ is equal to one. Therefore, I compute $u/u_{\text{min}}$ as $(g_{\text{mm}}^*)^{(-1/a^*)}$.

The procedure outlined above is strictly correct only if there isn't any heterogeneity in regional matching function parameters. However, simulation exercises suggest that mismatch indices constructed under these assumptions closely track "true" mismatch index levels and growth rates, even when there is substantial heterogeneity in regional matching function parameters.
APPENDIX 3-D: Univariate dispersion measures and geographic mismatch.

An accepted approach to measuring sectoral mismatch is to compute the cross-sectional variation of a measure of labor market activity, such as the unemployment rate or employment growth rate (for example, see Lilien (1982) and Abraham (1987)). I argue in Chapter 1 that these univariate dispersion measures may be misleading, and are not directly comparable with the bivariate indices presented in the text.\(^1\) Nonetheless, I present univariate dispersion measures in this appendix so that a subset of results from this study may be compared directly to previous research on sectoral mismatch in the United States. I compute univariate regional dispersion measures for unemployment rates, help-wanted rates, and non-agricultural employment growth rates.

Dispersion in sectoral unemployment or help-wanted rates causes outward shifts in the aggregate Beveridge curve only if sectoral Beveridge curves exhibit significant non-linearities. Estimates of Equation (3-1) for the forty-eight sample MSAs generally suggest that regional Beveridge curves are convex.\(^2\)

On the other hand, Abraham and Katz (1986) and Abraham (1987) argue that dispersion in desired employment growth rates across sectors creates outward shifts in the aggregate Beveridge curve, even if sectoral curves are not convex. I present evidence on regional dispersion in non-agricultural employment growth rates, as a proxy for unobserved desired employment growth rates.

I use variants of Lilien's (1982) \(a\) statistic as my measure of sectoral dispersion. The formula for this statistic is given in

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Equation (3D-1):

\[
(3D-1) \quad \sigma = \sqrt{\sum_{i=1}^{48} \frac{1}{W_{it}} \sum_{t} (x_{it} - \bar{x}_{it})^2}
\]

where
- \(X_{it}\) = MSA i unemployment, help-wanted, or employment growth rate at time t.
- \(X_{t}\) = average MSA unemployment, help-wanted, or employment growth rate at time t.
- \(W_{it}\) = non-agricultural employment in MSA i at time t.
  if \(X_{it}\) is the help-wanted or employment growth rate; if \(X_{it}\) is the unemployment rate, it is the labor force in MSA i at time t.
- \(W_{t}\) = total non-agricultural employment in the 48 MSAs at time t.
  if \(X_{it}\) is the help-wanted or employment growth rate; if \(X_{it}\) is the unemployment rate, it is the total labor force in the 48 MSAs at time t.

The \(\sigma\) statistic is a weighted average of individual MSA divergences from mean indicators of MSA labor market performance.³

The first two columns of Table 3-5, and Figure 3-5, show values of \(\sigma\) from 1970 to 1989 for the unemployment rate (URDISPER in Figure 3-5) and my preferred help-wanted rate series (HWRDSPER in Figure 3-5). Unemployment and help-wanted rate dispersion measures rise as mean unemployment and help-wanted rates rise, respectively, so that UREDISPER moves countercyclically and HWRDSPER procyclically.⁴

To determine if there have been any trend movements in these variables after controlling for cyclical conditions, I regress UREDISPER and HWRDSPER on constant terms and MSA mean levels of the unemployment and help-wanted rates, respectively. Columns four and five of Table 3-5, and Figure 3-6, present the residuals from these regressions. Non-cyclical regional dispersion rises in the early 1970s and 1980s, and may have contributed to shifts in the aggregate
Beveridge curve during these periods. However, these dispersion measures are relatively low in the mid 1970s, and thus do not explain the outward shift of the aggregate curve observed at this time. These measures also offer mixed signals on the role of geographic mismatch in explaining inward Beveridge curve shifts in the late 1980s. Non-cyclical unemployment rate dispersion has fallen considerably since 1983, but non-cyclical help-wanted rate dispersion has risen. In sum, there does not appear to be any clear trend in these series over the sample period.\(^5\)

Columns three and six of Table 3-5, and Figure 3-7, show values of \( \sigma \) for non-agricultural employment growth rates. Column three presents the raw \( \sigma \) measure, plotted as EGDISP\( \text{R} \) in Figure 3-7. Column six shows residuals from a regression of column three figures on a constant and the MSA mean value of the non-agricultural employment growth rate in that year. I plot these residuals as AEGDSP\( \text{R} \) in Figure 3-5. The figures suggest two main results. First, MSA employment growth rate dispersion measures have not shown a strong cyclical tendency since 1970, so that EGDISP\( \text{R} \) and AEGDSP\( \text{R} \) display similar time-series fluctuations. This is in stark contrast to the strong countercyclical nature of industry employment growth rate dispersion demonstrated in Lilien (1982), among others. Second, there has been a large decline in MSA employment growth rate dispersion since 1983, a trend that was originally identified by Abraham (1987).\(^5\)

Contrary to the analysis in the text, these figures suggest a strong role for decreasing geographic mismatch in explaining the inward shift of the aggregate Beveridge curve in the late 1980s.

These univariate measures thus do not provide a wholly consistent
view of geographic mismatch in the U.S. from 1970 to 1989. There is some evidence of increasing mismatch in all three measures in the early 1970s and 1980s, which may have accounted for outward aggregate Beveridge curve shifts at these times. Cyclically-adjusted employment growth rate dispersion also peaks in 1975, a year in which the aggregate Beveridge curve appears to have shifted out. In the late 1980s, however, unemployment and employment growth rate measures suggest decreasing mismatch, while the help-wanted rate measure shows increasing mismatch.

The figures appear to be broadly consistent with the bivariate indices presented in the text. With the exception of the sharp decline in employment growth rate dispersion in the late 1980s, the dispersion series do not demonstrate strong upward trends from 1970 to 1983, or downward trends since 1983. This suggests that fluctuations in geographic mismatch are not primarily responsible for aggregate U.S. Beveridge curve shifts since 1970.
NOTES FOR APPENDIX 3-D

1 Univariate dispersion measures are strictly comparable to the bivariate indices only if sectors are identical in all aspects affecting the slopes and positions of sectoral Beveridge curves, including job reallocation rates and job-matching efficiency parameters.

2 Using annual data with the unemployment rate as the dependent variable, forty-five of the forty-eight MSAs have positive coefficients on the HWR term, and twenty-two of these coefficients have t-statistics greater than two. With quarterly data, thirty-seven of these positive coefficients have t-statistics greater than two. These results are robust to changes in the twelve alternative help-wanted rates series.

3 I continue to weight unemployment rate measures by the labor force, and help-wanted rate measures by non-agricultural employment.

4 The cyclical nature of URDISPER is discussed by Baily (1984) and Abraham (1987), among others.

5 These conclusions for the help-wanted rate hold for all twelve series considered, with one exception. The dispersion series constructed assuming no help-wanted ad duplication across competing newspapers in an MSA trends upward after controlling for the MSA mean rate. Dispersion measures under this assumption seem highly suspect, however, since they are quite sensitive to changes in help-wanted advertising practices in all competing newspapers in an MSA, and thus are probably the "noisiest" series I have constructed. Conclusions for both the unemployment and help-wanted rates hold for quarterly dispersion measures as well.

6 The extremely low employment growth rate dispersion figure for 1989 is questionable. All 1989 figures are based only on seasonally adjusted data from the first quarter. If regional labor demand shocks are persistent, it is likely that regional dispersion in employment growth rates over any given year is greater than the dispersion exhibited in any quarter during that year. However, note that the decline in employment growth rate dispersion began well prior to 1989. Therefore, one can safely conclude that there has been a real downward shift of this variable in the late 1980s.
FIGURES AND TABLES: CHAPTER 3
FIGURE 3-1: U.S. BEVERIDGE CURVE
FIGURE 3-4: U.S. ADJUSTED GEOGRAPHIC MISMATCH INDEX, 1970-89

Cyclically Adjusted U/S Mismatch Ratio

UUMINA1

UUMINA2
TABLE 3-1: SHIFTS IN THE AGGREGATE BEVERIDGE CURVE

<table>
<thead>
<tr>
<th>Independent Variable</th>
<th>HWR</th>
<th>UR</th>
</tr>
</thead>
<tbody>
<tr>
<td>CONSTANT</td>
<td>8.54</td>
<td>17.29</td>
</tr>
<tr>
<td></td>
<td>(1.57)</td>
<td>(2.24)</td>
</tr>
<tr>
<td>UR</td>
<td>-1.31</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.47)</td>
<td></td>
</tr>
<tr>
<td>UR^2</td>
<td>0.057</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.033)</td>
<td></td>
</tr>
<tr>
<td>HWR</td>
<td></td>
<td>-5.35</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(1.25)</td>
</tr>
<tr>
<td>HWR^2</td>
<td></td>
<td>0.519</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.181)</td>
</tr>
<tr>
<td>TREND</td>
<td>0.290</td>
<td>0.421</td>
</tr>
<tr>
<td></td>
<td>(0.050)</td>
<td>(0.075)</td>
</tr>
<tr>
<td>TREND^2</td>
<td>-0.016</td>
<td>-0.023</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>D74</td>
<td>-0.174</td>
<td>-0.369</td>
</tr>
<tr>
<td></td>
<td>(0.188)</td>
<td>(0.292)</td>
</tr>
<tr>
<td>D84</td>
<td>0.290</td>
<td>0.362</td>
</tr>
<tr>
<td></td>
<td>(0.228)</td>
<td>(0.306)</td>
</tr>
<tr>
<td>Estimated increase in HWR given UR, 1970-83</td>
<td>0.866</td>
<td></td>
</tr>
<tr>
<td>Estimated increase in HWR given UR, 1983-89</td>
<td>-1.190</td>
<td></td>
</tr>
<tr>
<td>Estimated Increase in UR given HWR, 1970-83</td>
<td>1.366</td>
<td></td>
</tr>
<tr>
<td>Estimated increase in UR given HWR, 1983-89</td>
<td>-1.795</td>
<td></td>
</tr>
<tr>
<td>Summary Statistics</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Durbin-Watson</td>
<td>1.97</td>
<td>2.06</td>
</tr>
<tr>
<td>R^2</td>
<td>0.922</td>
<td>0.965</td>
</tr>
</tbody>
</table>

Source: Author's calculations with annual data from 1970 to 1989, as described in Chapter 2. Standard errors are in parentheses. Both equations are fit using OLS.
<table>
<thead>
<tr>
<th>MSA</th>
<th>log(HMR)</th>
<th>log(UR)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Albany (NY)</td>
<td>-0.944 (0.289)</td>
<td>-0.522 (0.160)</td>
</tr>
<tr>
<td>Atlanta (GA)</td>
<td>-0.717 (0.178)</td>
<td>-0.749 (0.186)</td>
</tr>
<tr>
<td>Baltimore (MD)</td>
<td>-1.049 (0.286)</td>
<td>-0.467 (0.127)</td>
</tr>
<tr>
<td>Birmingham (AL)</td>
<td>-0.818 (0.059)</td>
<td>-1.139 (0.082)</td>
</tr>
<tr>
<td>Boston (MA)</td>
<td>-0.912 (0.094)</td>
<td>-0.956 (0.098)</td>
</tr>
<tr>
<td>Charlotte (NC)</td>
<td>-0.768 (0.084)</td>
<td>-1.114 (0.122)</td>
</tr>
<tr>
<td>Chicago (IL)</td>
<td>-1.140 (0.135)</td>
<td>-0.733 (0.087)</td>
</tr>
<tr>
<td>Cincinnati (OH)</td>
<td>-1.106 (0.116)</td>
<td>-0.784 (0.082)</td>
</tr>
<tr>
<td>Cleveland (OH)</td>
<td>-1.035 (0.044)</td>
<td>-0.942 (0.040)</td>
</tr>
<tr>
<td>Columbus (OH)</td>
<td>-1.045 (0.120)</td>
<td>-0.808 (0.093)</td>
</tr>
<tr>
<td>Dallas (TX)</td>
<td>-0.940 (0.228)</td>
<td>-0.582 (0.141)</td>
</tr>
<tr>
<td>Dayton (OH)</td>
<td>-0.922 (0.088)</td>
<td>-0.963 (0.092)</td>
</tr>
<tr>
<td>Denver (CO)</td>
<td>-0.787 (0.265)</td>
<td>-0.482 (0.165)</td>
</tr>
<tr>
<td>Detroit (MI)</td>
<td>-1.076 (0.037)</td>
<td>-0.834 (0.075)</td>
</tr>
<tr>
<td>Hartford (CT)</td>
<td>-0.995 (0.182)</td>
<td>-0.717 (0.131)</td>
</tr>
<tr>
<td>Houston (TX)</td>
<td>-0.593 (0.102)</td>
<td>-1.191 (0.205)</td>
</tr>
<tr>
<td>Indianapolis (IN)</td>
<td>-1.270 (0.142)</td>
<td>-0.670 (0.075)</td>
</tr>
<tr>
<td>Jacksonville (FL)</td>
<td>-0.160 (0.193)</td>
<td>-0.294 (0.353)</td>
</tr>
<tr>
<td>Kansas City (MO)</td>
<td>-1.046 (0.225)</td>
<td>-0.579 (0.125)</td>
</tr>
<tr>
<td>Knoxville (TN)</td>
<td>-0.727 (0.073)</td>
<td>-1.203 (0.122)</td>
</tr>
<tr>
<td>Los Angeles (CA)</td>
<td>-0.892 (0.088)</td>
<td>-0.987 (0.097)</td>
</tr>
<tr>
<td>Louisville (KY)</td>
<td>-0.900 (0.083)</td>
<td>-0.992 (0.092)</td>
</tr>
<tr>
<td>Memphis (TN)</td>
<td>-0.685 (0.089)</td>
<td>-1.178 (0.154)</td>
</tr>
<tr>
<td>Miami (FL)</td>
<td>-1.046 (0.257)</td>
<td>-0.450 (0.128)</td>
</tr>
<tr>
<td>Milwaukee (WI)</td>
<td>-1.056 (0.130)</td>
<td>-0.782 (0.096)</td>
</tr>
<tr>
<td>Minneapolis (MN)</td>
<td>-1.313 (0.195)</td>
<td>-0.581 (0.087)</td>
</tr>
<tr>
<td>Nashville (TN)</td>
<td>-0.881 (0.122)</td>
<td>-0.895 (0.124)</td>
</tr>
<tr>
<td>New Orleans (LA)</td>
<td>-1.003 (0.172)</td>
<td>-0.707 (0.121)</td>
</tr>
<tr>
<td>New York (NY)</td>
<td>-0.917 (0.153)</td>
<td>-0.785 (0.131)</td>
</tr>
<tr>
<td>Oklahoma City (OK)</td>
<td>-0.713 (0.075)</td>
<td>-1.215 (0.128)</td>
</tr>
<tr>
<td>Omaha (NE)</td>
<td>-0.774 (0.171)</td>
<td>-0.768 (0.170)</td>
</tr>
<tr>
<td>Philadelphia (PA)</td>
<td>-0.572 (0.257)</td>
<td>-0.456 (0.205)</td>
</tr>
<tr>
<td>Phoenix (AZ)</td>
<td>-0.502 (0.130)</td>
<td>-1.024 (0.266)</td>
</tr>
<tr>
<td>Pittsburgh (PA)</td>
<td>-0.574 (0.104)</td>
<td>-1.193 (0.216)</td>
</tr>
<tr>
<td>Providence (RI)</td>
<td>-0.928 (0.165)</td>
<td>-0.747 (0.133)</td>
</tr>
<tr>
<td>Richmond (VA)</td>
<td>-1.042 (0.223)</td>
<td>-0.586 (0.125)</td>
</tr>
<tr>
<td>Rochester (NY)</td>
<td>-0.702 (0.098)</td>
<td>-1.175 (0.163)</td>
</tr>
<tr>
<td>Sacramento (CA)</td>
<td>-0.853 (0.096)</td>
<td>-0.986 (0.112)</td>
</tr>
<tr>
<td>St. Louis (MO)</td>
<td>-1.096 (0.110)</td>
<td>-0.789 (0.081)</td>
</tr>
<tr>
<td>Salt Lake City (UT)</td>
<td>-1.025 (0.126)</td>
<td>-0.806 (0.099)</td>
</tr>
<tr>
<td>San Antonio (TX)</td>
<td>-0.932 (0.139)</td>
<td>-0.819 (0.122)</td>
</tr>
<tr>
<td>San Diego (CA)</td>
<td>-0.990 (0.149)</td>
<td>-0.767 (0.115)</td>
</tr>
<tr>
<td>San Francisco (CA)</td>
<td>-0.739 (0.110)</td>
<td>-1.031 (0.154)</td>
</tr>
<tr>
<td>Seattle (WA)</td>
<td>-0.657 (0.132)</td>
<td>-0.973 (0.195)</td>
</tr>
<tr>
<td>Syracuse (NY)</td>
<td>-0.534 (0.184)</td>
<td>-0.813 (0.280)</td>
</tr>
<tr>
<td>Toledo (OH)</td>
<td>-1.077 (0.161)</td>
<td>-0.827 (0.077)</td>
</tr>
<tr>
<td>Tulsa (OK)</td>
<td>-0.738 (0.087)</td>
<td>-1.133 (0.134)</td>
</tr>
<tr>
<td>Washington (DC)</td>
<td>-0.895 (0.253)</td>
<td>-0.548 (0.155)</td>
</tr>
</tbody>
</table>

**************

All 48 MSAs pooled  
-0.879 (0.021)    -0.812 (0.019)

Source: Author's calculations using annual data from 1970 to 1989, as described in Chapter 2. Each entry represents the OLS estimate of $\alpha_3$ from Equation (3-5). Standard errors are in parentheses.
### Table 3-3: Geographic Mismatch Unemployment with Identical Regional Matching Function Parameters

<table>
<thead>
<tr>
<th>Year</th>
<th>$u$</th>
<th>$u_{\text{min}}$</th>
<th>log(HWR)</th>
<th>% of $u$ accounted for by mismatch</th>
<th>adj. $u_{\text{min}}$</th>
<th>log(UR)</th>
<th>% of $u$ accounted for by mismatch</th>
<th>adj. $u_{\text{min}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1970</td>
<td>4.88</td>
<td>1.06</td>
<td>5.53</td>
<td>-0.029</td>
<td>1.05</td>
<td>4.92</td>
<td>-0.024</td>
<td></td>
</tr>
<tr>
<td>1971</td>
<td>6.04</td>
<td>1.09</td>
<td>8.28</td>
<td>-0.010</td>
<td>1.08</td>
<td>7.12</td>
<td>-0.008</td>
<td></td>
</tr>
<tr>
<td>1972</td>
<td>5.59</td>
<td>1.10</td>
<td>9.30</td>
<td>0.007</td>
<td>1.09</td>
<td>8.05</td>
<td>0.007</td>
<td></td>
</tr>
<tr>
<td>1973</td>
<td>5.01</td>
<td>1.10</td>
<td>9.18</td>
<td>0.010</td>
<td>1.09</td>
<td>7.98</td>
<td>0.009</td>
<td></td>
</tr>
<tr>
<td>1974</td>
<td>5.46</td>
<td>1.08</td>
<td>7.69</td>
<td>-0.011</td>
<td>1.07</td>
<td>6.59</td>
<td>-0.008</td>
<td></td>
</tr>
<tr>
<td>1975</td>
<td>8.33</td>
<td>1.08</td>
<td>7.68</td>
<td>-0.038</td>
<td>1.07</td>
<td>6.60</td>
<td>-0.030</td>
<td></td>
</tr>
<tr>
<td>1976</td>
<td>7.65</td>
<td>1.08</td>
<td>7.32</td>
<td>-0.035</td>
<td>1.07</td>
<td>6.27</td>
<td>-0.028</td>
<td></td>
</tr>
<tr>
<td>1977</td>
<td>6.88</td>
<td>1.09</td>
<td>7.84</td>
<td>-0.022</td>
<td>1.07</td>
<td>6.69</td>
<td>-0.018</td>
<td></td>
</tr>
<tr>
<td>1978</td>
<td>5.83</td>
<td>1.11</td>
<td>9.78</td>
<td>0.011</td>
<td>1.09</td>
<td>8.40</td>
<td>0.009</td>
<td></td>
</tr>
<tr>
<td>1979</td>
<td>5.52</td>
<td>1.12</td>
<td>10.51</td>
<td>0.023</td>
<td>1.10</td>
<td>9.06</td>
<td>0.019</td>
<td></td>
</tr>
<tr>
<td>1980</td>
<td>6.70</td>
<td>1.14</td>
<td>11.94</td>
<td>0.030</td>
<td>1.11</td>
<td>10.15</td>
<td>0.024</td>
<td></td>
</tr>
<tr>
<td>1981</td>
<td>7.20</td>
<td>1.16</td>
<td>13.89</td>
<td>0.051</td>
<td>1.13</td>
<td>11.67</td>
<td>0.039</td>
<td></td>
</tr>
<tr>
<td>1982</td>
<td>8.97</td>
<td>1.25</td>
<td>12.71</td>
<td>0.018</td>
<td>1.12</td>
<td>10.70</td>
<td>0.014</td>
<td></td>
</tr>
<tr>
<td>1983</td>
<td>8.93</td>
<td>1.12</td>
<td>10.86</td>
<td>-0.005</td>
<td>1.10</td>
<td>9.29</td>
<td>-0.004</td>
<td></td>
</tr>
<tr>
<td>1984</td>
<td>6.92</td>
<td>1.13</td>
<td>11.71</td>
<td>0.025</td>
<td>1.11</td>
<td>9.97</td>
<td>0.020</td>
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<tr>
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<td>1.10</td>
<td>8.69</td>
<td>-0.000</td>
<td>1.08</td>
<td>7.45</td>
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<tr>
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<td>5.02</td>
<td>1.09</td>
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<td>-0.003</td>
<td>1.07</td>
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<tr>
<td>1989</td>
<td>4.76</td>
<td>1.08</td>
<td>7.35</td>
<td>-0.009</td>
<td>1.07</td>
<td>6.30</td>
<td>-0.007</td>
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</tr>
</tbody>
</table>

**Source:** Author's calculations with annual data, as described in Chapter 2. The first column is the unemployment rate in the forty-eight MSAs. Columns 2-4 (5-7) present mismatch measures assuming that the slopes of all regional Beveridge curves are given by the slope coefficient from the pooled regression with log(HWR) (log (UR)) as the dependent variable, as reported in Table 3-2. Columns 2 and 5 present $u_{\text{min}}$ as given by Equation (3-3), while columns 4 and 7 show this measure adjusted for cyclical conditions. Columns 3 and 6 present the percentage of total unemployment that is accounted for by geographic mismatch unemployment.
<table>
<thead>
<tr>
<th>Year</th>
<th>u</th>
<th>w/u_{min}</th>
<th>log(HMR)</th>
<th>% of u accounted for by mismatch</th>
<th>adj. w/u_{min}</th>
<th>w/u_{min}</th>
<th>log(UR)</th>
<th>% of u accounted for by mismatch</th>
<th>adj. w/u_{min}</th>
</tr>
</thead>
<tbody>
<tr>
<td>1970</td>
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<td>1.04</td>
<td>4.10</td>
<td>-0.031</td>
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<td>1.10</td>
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<td>1972</td>
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<td>1.11</td>
<td>9.84</td>
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<td></td>
<td></td>
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<tr>
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<td>1.09</td>
<td>8.88</td>
<td>0.013</td>
<td>1.10</td>
<td>9.18</td>
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<tr>
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<td>7.27</td>
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<td>1.06</td>
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<tr>
<td>1978</td>
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<td>9.09</td>
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<td>1979</td>
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<tr>
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<tr>
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<td>1.07</td>
<td>6.30</td>
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</table>

Source: Author's calculations with annual data, as described in Chapter 2. The first column is the unemployment rate in the forty-eight MSAs. Columns 2-4 (5-7) present mismatch measures assuming that slopes of all regional Beveridge curves are given by their OLS estimates of $a_3$ from Equation (3-5) with log(HMR) (log(UR)) as the dependent variable, as reported in Table 3-2. Columns 2 and 5 present $w/u_{min}$ as given by Equation (3-3), while columns 4 and 7 show this measure adjusted for cyclical conditions. Columns 3 and 6 present the percentage of total unemployment that is accounted for by geographic mismatch unemployment.
<table>
<thead>
<tr>
<th>Year</th>
<th>UR</th>
<th>HMR</th>
<th>Employment Growth Rate</th>
<th>UR</th>
<th>HMR</th>
<th>Employment Growth Rate</th>
</tr>
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<td>NA</td>
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<td>0.849</td>
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<td>-1.299</td>
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</table>

Source: Author's calculations with data described in Chapter 2. All figures represent Lilien's (1982) $\sigma$ measure, as described in Equation (3D-1), for the variable of interest, using data from the forty-eight sample MSAs. The unadjusted columns show the raw $\sigma$ measures, while the cyclically adjusted columns show these measures after correcting for any effects cyclical changes in the economy may have on these statistics. This correction procedure is described in Appendix 3-D.


<table>
<thead>
<tr>
<th>Returns to scale assumption</th>
<th>Independent Variable</th>
<th>Independent Variable</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>U</td>
<td>HW</td>
</tr>
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<td>-0.063</td>
<td>-0.059</td>
</tr>
<tr>
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<td>(0.009)</td>
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<tr>
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<td>-0.028</td>
</tr>
<tr>
<td></td>
<td>(0.013)</td>
<td>(0.009)</td>
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<tr>
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<tr>
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<td>(0.037)</td>
<td>(0.024)</td>
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</table>

Source: Author's calculations with data described in Chapter 2. Figures represent OLS estimates of Equation (3-7) parameters, with standard errors in parentheses, using quarterly data from 1970:1-1981:3. The first and second (fourth and fifth) columns give estimates of $\beta_3$ and $\beta_2$ using gmm series constructed assuming that all regional Beveridge curve slopes are given by the pooled estimate in the first (second) column of Table 3-2. The third and sixth columns present the sums of these coefficients. The gmm series are constructed with the returns to scale assumption identified by the row heading.
TABLE 3-7: RETURNS TO SCALE BIAS WITH GEOGRAPHIC MISMATCH ASSUMING NON-IDENTICAL REGIONAL MATCHING FUNCTION PARAMETERS

Column in Table 3-2 from which slope coefficients are taken

<table>
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<tr>
<th>Returns to scale assumption</th>
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<th></th>
<th></th>
<th></th>
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<td>U</td>
<td>HW</td>
<td>sum</td>
<td></td>
</tr>
<tr>
<td>a+b = 0.8</td>
<td>-0.034</td>
<td>-0.040</td>
<td>-0.074</td>
<td>-0.071</td>
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<tr>
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<td>(0.011)</td>
<td>(0.007)</td>
<td></td>
<td>(0.017)</td>
</tr>
<tr>
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<td>-0.036</td>
</tr>
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<td>(0.006)</td>
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<td>(0.017)</td>
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<td>0.112</td>
<td>0.002</td>
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<tr>
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<td>(0.010)</td>
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<tr>
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<td>(0.024)</td>
<td>(0.016)</td>
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<td>(0.030)</td>
</tr>
<tr>
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<td>0.342</td>
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<tr>
<td></td>
<td>(0.037)</td>
<td>(0.024)</td>
<td></td>
<td>(0.041)</td>
</tr>
</tbody>
</table>

Source: Author's calculations with data described in Chapter 2. Figures represent OLS estimates of Equation (3-7) parameters, with standard errors in parentheses, using quarterly data from 1970:1-1981:3. The first and second (fourth and fifth) columns give estimates of $\beta_3$ and $\beta_2$ using gmm series constructed assuming that regional Beveridge curve slopes are given by the their estimates in the first (second) column of Table 3-2. The third and sixth columns present the sums of these coefficients. The gmm series are constructed with the returns to scale assumption identified by the row heading.
REFERENCES FOR CHAPTER 3


CHAPTER 4: OKUN'S LAW AND THE BUSINESS CYCLE
I. INTRODUCTION

Okun's Law, like the Beveridge curve, is an empirical relationship that macroeconomists often use to organize their thoughts about fluctuations in the aggregate unemployment rate. As currently defined, Okun's Law is an empirical regularity that suggests a linear relationship between changes in the aggregate unemployment rate and GNP growth. For example, Dornbusch and Fischer (1990) claim that post-war U.S. data suggest the following definition for Okun's Law: On average, every percentage point of annual U.S. real GNP growth above the trend growth rate decreases the aggregate unemployment rate by 0.4 percentage point.¹

In this chapter, I argue that Okun's Law, as it is currently defined, is in fact not a very good "law" at all. My argument is not based on the usual caveat that Okun's Law is merely an empirical regularity, so that the relationship between real GNP growth and unemployment rate changes in any given period deviates randomly from that implied by the Okun's Law coefficient. Rather, I argue that the Okun's Law coefficient demonstrates systematic, and not random, fluctuations. In particular, I show that these fluctuations are dependent on the state of the business cycle. Using post-war U.S. data, I estimate economically and statistically significant differences in the relationship between real GNP growth and unemployment rate changes in growth cycle expansions and contractions (real GNP growth either above or below trend), as well as in "boom" and "bust" periods (real GNP levels either above or below trend). The data suggest a discontinuous, nonlinear relationship between U.S. GNP growth and changes in the unemployment rate. Therefore, economists
using "Okun's Law" to forecast unemployment rate fluctuations for hypothetical GNP growth rate targets are likely to make systematic errors.

I am not the first author to argue that the Okun's Law coefficient is dependent on the state of the business cycle. Researchers studying business cycle asymmetries have documented trends in U.S. data that suggest such state dependence. For example, DeLong and Summers (1986) find that detrended U.S. real GNP growth rates are distributed symmetrically around their mean level, while the empirical distribution for aggregate unemployment rate changes is significantly skewed. DeLong and Summers (1986) note that these distributions suggest that the Okun's Law coefficient is different in economic expansions and contractions.

The empirical work in this chapter moves beyond the DeLong and Summers (1986) approach by explicitly identifying and quantifying business cycle state dependence in the Okun's Law coefficient. The chapter also develops a simple growth-accounting framework that identifies empirical tests that are implemented to determine the sources of such state dependence. Finally, the chapter explains how business cycle state dependence in Okun's Law, or the aggregate production relationship in general, may provide new evidence on the validity of alternative models of business cycle fluctuations.

The empirical strategy implemented in this chapter is motivated by the traditional Burns and Mitchell (1946) approach to the study of business cycles. Burns and Mitchell (1946) stress the importance of breaking the cycle into different phases, focusing analysis on the movement of economic variables both within and between different
phases of the cycle. In Section II, I identify four separate phases of the business cycle, and estimate the relationship between output growth, employment growth, and unemployment rate changes in each of these phases. The results uniformly suggest that Okun's Law is dependent on the state of the cycle, and that ignoring this state dependence can lead to very poor forecasting performance.

For example, the estimates suggest that in growth cycle contractions, if output growth is 2.50 percentage points below trend for a quarter, the unemployment rate increases by one percentage point. On the other hand, it takes 4.76 percentage points of growth above trend, sustained for a quarter, to decrease the unemployment rate by one percentage point. I show that asymmetric movements in production worker and non-agricultural employment, in response to output growth in growth cycle contractions and expansions, are responsible for this result. Production employment decreases by one percentage point for every 1.27 percentage points of growth below trend within the quarter, while a symmetric increase in output growth above trend increases this employment by only 0.44 percentage point.

I also demonstrate that the level of the cycle is an important determinant of the Okun's Law coefficient. During growth cycle expansions, movements in output at low output levels decrease unemployment and increase aggregate employment by a greater amount than they do as the economy nears a growth peak.

In Section III, I present a growth-accounting framework that identifies the possible sources of state dependence in Okun's Law. I argue that any fluctuations in the relationship between employment and output growth throughout the cycle must be associated with
fluctuations in the relationship between the growth of other factors of production and output growth, and/or fluctuations in the relationship between multi-factor productivity growth and output growth. Loosely, Okun's Law coefficients may fluctuate because of factor substitution in production processes, or because multi-factor productivity growth moves asymmetrically through the cycle. Section III argues that it is not surprising that state dependence is observed, since there are strong theoretical arguments suggesting that firms may substitute factors of production through the business cycle, and productivity growth may depend on the state of the economy.

Section IV analyzes the statistical properties of the state dependence tests presented in Section II. I demonstrate that the tests are indeed interpretable as tests for a non-constant Okun's Law coefficient through the cycle. I also use simulations from Appendix 4-A's model of employment and hours determination to determine the alternative specifications' abilities to identify and quantify any state dependence in the data.

The main contribution of Section IV, however, is that it offers two simple tests for identifying the sources of business cycle asymmetries in Okun's Law. If factor substitution is not responsible for asymmetries in Okun's Law, all inputs in production must either move symmetrically with output through the cycle, or exhibit asymmetries of the same sign as those estimated for employment. Since employment growth responds more to output growth in contractions than expansions, if other factors of production respond more to output growth in expansions than contractions, then the null hypothesis of "no factor substitution" can be rejected. Alternatively, if
multi-factor productivity fluctuations are not responsible for estimated asymmetries, then at least one input must exhibit asymmetries in the opposite direction of employment.

The analysis in Section IV suggests that studying the cyclical behavior of alternative factors of production might allow identification of the sources of fluctuations in the Okun's Law coefficient. Therefore, in Section V, I estimate the relationship between hours per employee growth, manhours growth, and output growth in different phases of the cycle. These estimates provide little support for a factor-substitution based explanation of employment growth asymmetries. However, I argue that unobserved labor hoarding, which involves factor substitution between employee hours and employee effort, may be an important determinant of state dependence in Okun's Law.

Section VI serves two purposes. First, I summarize conclusions from this study, and offer some natural limited extensions to the current analysis. Second, I discuss a more ambitious research agenda, designed to identify the consistency of estimated state dependence in Okun's Law, and the aggregate production relationship in general, with alternative business cycle models. I argue that existing models may generate very different predictions about state dependence in production relationships, so that evidence of such dependence may enable tests with substantial power to discriminate between alternative business cycle theories.
II. OKUN'S LAW AND THE BUSINESS CYCLE: EMPIRICAL RESULTS

Recent evidence on business cycle asymmetries (DeLong and Summers (1986), Falk (1986)) suggests that employment growth and changes in the unemployment rate exhibit significant temporal asymmetries, while output and production growth do not. Employment growth rates are characterized by sharper, more severe, contractions than expansions, while output and production growth rates move relatively symmetrically through upturns and downturns. These results indicate that the relationship between output growth and unemployment rate changes is not constant over time; Okun's Law must vary systematically throughout the business cycle.

In this section, I attempt to identify and quantify any changes in Okun's Law as the economy moves through different phases of the business cycle. The empirical strategy is motivated by the traditional Burns and Mitchell (1946) approach to the study of business cycles. Their approach stresses the importance of breaking the cycle into different phases, focusing analysis on the movement of economic variables both within and between different phases of the cycle. In this section, I break the cycle into either two or four phases, and estimate the relationship between output growth, employment growth, and unemployment rate changes in each of these phases.

Figure 4-1 illustrates a symmetric business cycle in the detrended natural logarithm of output. In NBER terminology, Figure 4-1 assumes a symmetric "growth cycle" for the log of output. Figure 4-1 identifies the separate regions of the business cycle I focus on in this section. I define phases of the business cycle by whether
detrended output growth rates and levels are greater or less than zero. Tests of the null hypothesis that Okun's Law (or alternatively the relationship between employment and output growth) is constant over the different phases of the cycle are easy to implement in this framework. I estimate equations relating employment or unemployment changes to detrended output growth, allowing for different coefficients in different phases of the cycle, and compute test statistics for the restrictions that the coefficients are equal across phases.

In order to implement these tests, I must first assign each data point to one of the four business cycle phases. This requires that I detrend a measure of aggregate output for the U.S. economy. I use the natural logarithm of seasonally adjusted real GNP, measured in 1982 dollars, as my output measure. I detrend this series using the cubic-spline detrending method suggested by Prescott (1986), and utilized recently in a related study of business cycle asymmetries by Sichel (1987). I experiment with a variety of piecewise log-linear detrending methods, and the results of this section are insensitive to the procedure chosen.

The first test I consider is whether Okun's Law is the same in growth cycle expansions and contractions. Does output growth above trend levels decrease the unemployment rate by the same amount that output growth below trend levels increases this rate? I implement this test by estimating a slightly modified version of the traditional Okun's Law equation that relates changes in the unemployment rate to changes in output growth above and below trend. I define $I(t)$ to be an indicator variable that equals one when output growth is above
trend levels in period $t$. In terms of the growth cycle illustrated in Figure 4-1, $I(t)$ is one in regions C and D of the cycle, and is zero in regions A and B. I define PGROW($t$) to be the deviation of output growth from trend when $I(t) = 1$, and NGROW($t$) to be this deviation when $I(t) = 0$. I estimate the following equation:

\[(4-1) \quad \Delta UR(t) = \alpha + \beta_0 PGROW(t) + \gamma_0 NGROW(t) + \epsilon(t)\]

$\Delta UR(t)$ is the first difference of the unemployment rate, while $\epsilon(t)$ is the error term from the regression. I test the null hypothesis that $\beta_0 = \gamma_0$ in order to determine if Okun's Law is symmetric in growth cycle expansions and contractions.

The first column of Table 4-1 reports results from the estimation of Equation (4-1) using post-war US data. Okun's Law does not appear to be constant throughout the cycle. $\beta_0$ is statistically different from $\gamma_0$ at the 0.02 significance level. The estimates suggest that in downturns, if output growth is 2.50 percentage points below trend for a quarter, the unemployment rate increases by one percentage point. However, it takes 4.76 percentage points of growth above trend, sustained for a quarter, to decrease the unemployment rate by one percentage point. Constraining $\beta_0$ to be equal to $\gamma_0$, I find that the coefficient on detrended output growth is -0.31; imposing symmetry in the Okun's Law regression leads to serious underestimates of unemployment rate increases in contractions, and overestimates of decreases in the unemployment rate during expansions.

I re-estimate Equation (4-1) using the growth rate of various employment measures as the dependent variable. The next three
columns of Table 4-1 demonstrate that asymmetric movements in production worker and non-agricultural employment, in response to output growth above and below trend, are responsible for the estimated asymmetries in Okun's Law. Fluctuations in the Okun's Law coefficient are not driven merely by cyclical changes in labor force participation rates. Employment in non-agricultural establishments decreases by 0.65 percentage point for every percentage point of GNP growth below trend, but only increases by 0.35 percentage point for a symmetric increase in output above trend. The magnitude of the estimated asymmetry is even greater for the class of production workers; production worker employment decreases by one percentage point for every 1.27 percentage points of growth below trend sustained for a quarter, while output growth of 1.27 percentage points above trend for a quarter increases employment by only 0.44 percentage point. Non-production worker employment is relatively unaffected by fluctuations in output above and below trend, suggesting that such workers may be hoarded during contractions, while production workers account for most of the observed cyclical fluctuations in employment.

Table 4-2 reports results from estimation of the following equation:

\[
\Delta UR(t) = \alpha + \sum_{i=0}^{2} \beta_i \text{PGROW}(t-i) + \sum_{i=0}^{2} \gamma_i \text{NGROW}(t-i) + \epsilon(t)
\]

This equation allows for lagged effects of output growth on the unemployment rate or employment growth. If employment is subject to costs of adjustment that may differ in growth cycle expansions and contractions, asymmetry in the contemporaneous relationship betw...
employment, unemployment, and output changes across the cycle may disappear when lagged responses of employment to output changes are allowed.

However, I find that asymmetries in expansions versus contractions are even more pronounced in this specification. Non-agricultural employment growth eventually declines by more than one percentage point for every one percent decline in output growth below trend, but expands by only 0.50 percentage point for each percentage point of growth above trend. Once again, this asymmetry is particularly strong for production worker employment. Non-production employment remains fairly insensitive to cyclical fluctuations, although less so during growth cycle contractions than expansions. The unemployment rate regression suggests the strong asymmetry in Okun's Law that I find in the specification without lags; output growth above trend decreases the unemployment rate by much less than output growth below trend increases the unemployment rate.⁷

In Tables 4-3 and 4-4, I allow the Okun's Law coefficients to vary across all four regions of the cycle. I define \( J(t) \) to be an indicator variable that equals one when output is above trend in period \( t \). \( J(t) \) equals one in regions A and D, and 0 in regions B and C of the cycle. Multiplying \( \text{NGROW}(t) \) and \( \text{PGROW}(t) \) by \( J(t) \), I split the sample into the four regions of the cycle identified in Figure 4-1. Let \( \text{PGROW}(t) \) be detrended output growth in region D, \( \text{NGROW}(t) \) growth in A, \( \text{PBGROW}(t) \) growth in C, and \( \text{NBGROW}(t) \) growth in B.⁸ Table 4-3 reports regressions of the following form:

\[
(4-3) \quad \Delta \text{UR}(t) - \alpha + \beta_0 \text{PGROW}(t) + \gamma_0 \text{NGROW}(t) + \delta_0 \text{PBGROW}(t) + \phi_0 \text{NBGROW}(t) + \varepsilon(t)
\]
The table also reports significance levels for the following null hypotheses: (a) When output is above trend levels, unemployment and employment responses to output contractions and expansions are symmetric ($\beta_0 = \gamma_0$). (b) When output is below trend levels, unemployment and employment responses to output contractions and expansions are symmetric ($\delta_0 = \phi_0$). (c) During growth cycle expansions, unemployment and employment responses to output growth are independent of the level of detrended output ($\beta_0 = \delta_0$). (d) During growth cycle contractions, unemployment and employment responses to output growth are independent of the level of detrended output ($\gamma_0 = \phi_0$).

Focusing first on the unemployment rate regression, Table 4-3 suggests that the estimated difference between growth cycle expansions and contractions is primarily due to asymmetries when output levels are below trend. $\delta_0$ is significantly less in absolute value than $\phi_0$, while the null hypothesis that $\beta_0 = \gamma_0$ cannot be rejected at conventional significance levels. During growth cycle expansions, the Okun's Law coefficient appears to be independent of the level of detrended output. During contractions, however, a one percentage point decrease in output growth increases unemployment by 0.43 percentage point when output is below trend levels, but when output is above trend, the unemployment rate increases by roughly 0.13 percentage point.

The unemployment rate results appear to be driven by asymmetric responses of non-agricultural and production worker employment to output fluctuations throughout the cycle. There is more firing
associated with a given decrease in output when output is below trend than when output is above trend. On the other hand, the level of the cycle does not significantly affect employment growth rates during expansions. Non-production employment growth rates are largely independent of cyclical fluctuations. However, there does appear to be more hiring of non-production workers at the peak rather than at the beginning of expansions, while firing is concentrated in trough periods of contractions.

Table 4-4 allows for lagged effects of output growth on employment and unemployment. The estimates correspond quite closely to those in Table 4-3, with a few notable exceptions. During growth cycle expansions, movements in output at low output levels decrease unemployment and increase aggregate employment by a greater amount than they do as the economy nears a growth peak. As I discuss in the next section, if it is easier to recruit and train qualified workers in business cycle troughs, one might expect to observe such a pattern.\(^9\) While production employment does not respond contemporaneously to output declines at the beginning of contractions, when lagged effects are accounted for, I estimate significant decreases in employment. Firms may be reluctant to fire at the beginning of contractions if they are uncertain as to whether or not the economy will reverse itself in the near future.

The asymmetries in Okun's Law suggested by Table 4-4 are quite economically significant. It would take nine percentage points of growth above trend at peak levels of expansions to decrease the unemployment rate by one percentage point, but only 1.43 percentage points of growth below trend in trough periods of contractions to
increase the unemployment rate by one percentage point.

Tables 4-1 through 4-4 strongly suggest that Okun's Law varies systematically throughout the business cycle, and that this variance can be attributed to a non-constant relationship between output and employment growth. At this point, however, it is difficult to interpret these results. One would like to know, for example, what models of firm behavior might lead to relationships between output and employment growth that are contingent on the state of the business cycle. Furthermore, one would like to calibrate and simulate such models to determine whether they can replicate the sometimes stark asymmetries that are evident in post-war US data. The results are also difficult to interpret in that it is not clear in what sense, if any, the tests presented in this section are tests for asymmetry in the relationship between employment and output growth rates throughout the cycle. A closer examination of the statistical properties of the tests for asymmetry presented here is required so that a more precise understanding of these estimates as "data descriptors" is allowed. In particular, one would like to know under what circumstances these estimates provide a good description of asymmetries present in the data, and under what circumstances alternative specifications would be preferable. In the next two sections, I address these theoretical and methodological concerns. These sections provide a clearer analytical framework to interpret the significant asymmetries reported in Tables 4-1 through 4-4.
III. ACCOUNTING FOR STATE DEPENDENCE IN OKUN'S LAW

In a growth-accounting sense, fluctuations in the relationship between employment and output growth throughout the cycle must be associated with fluctuations in the relationship between the growth of other inputs of production and output growth, and/or fluctuations in the relationship between multi-factor productivity growth and output growth.\(^\text{10}\) Consider a simplified aggregate production function in which employment \((E)\), the capital stock \((K)\), and hours per employee \((H)\), are combined in a Cobb-Douglas function to produce a value-added measure of output \((Y)\):

\[
(4-4) \quad Y = G K^\alpha E^\beta H^\gamma
\]

\(G\) is a measure of multi-factor productivity. I allow \(E\) and \(H\) to enter the production function with different elasticities, which is consistent with existing empirical evidence.\(^\text{11}\)

Letting lowercase letters represent log first differences (so that "\(e\)" represents the growth rate of employment, for example), employment growth is determined by Equation \((4-5)\):

\[
(4-5) \quad e = [y - g - \alpha k - \gamma h]^*\beta^{-1}
\]

If the relationships between \(g\) and \(y\), \(h\) and \(y\), and \(k\) and \(y\), are all constant throughout the cycle, the relationship between employment and output growth must also be constant. Any fluctuations in Okun’s Law through the cycle, assuming no asymmetries in labor force participation movements, must involve non-constant relationships
between \( h \) and \( y \), \( g \) and \( y \), \( k \) and \( y \), or all three.

Assume for the moment that factor productivity growth is proportional to output growth, so that \( g = ry \). Under this assumption, \( e \) is determined by:

\[
(4-6) \quad e = [(1-r)y - ak - \gamma h] \beta^{-1}
\]

If \( h \) and/or \( k \) are not proportional to \( y \), then a non-constant relationship between \( e \) and \( y \) is observed. What, in economic terms, does it mean to have non-constant relationships between these input and output growth rates throughout the cycle? Non-constant relationships imply factor substitution throughout the cycle; at some points in the cycle, changes in output are associated with large changes in employment and little movement in hours per worker or the capital stock, while at other times, most of output growth is accounted for by fluctuations in the average work week or capital investment.

If the expected cost of using different factors of production varies throughout the cycle, then cost minimization implies that firms substitute factors during the cycle. For example, if hiring and firing costs are not equal, the relationship between employment growth and output growth may be different in expansions and contractions. In the absence of factor productivity fluctuations, this further implies that the relationship between the growth rate of at least one other factor of production and output growth is also different in contractions and expansions. It may also be the case that the level of aggregate economic activity affects hiring and firing costs; this

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seems plausible since tightness in the aggregate labor market affects
the ease with which firms can recruit new employees, as well as the
possibility that any laid-off workers await recall in lieu of seeking
alternative employment. Therefore, the level as well as the direction
of economic activity might affect the relationship observed between
output and employment growth.

Several recent papers have shown that asymmetries in the
adjustment costs of quasi-fixed factors can generate state dependence
in the relationship between output and input growth rates (for
example, see Nickell (1978), Leban and Lesourne (1980), and Caplin and
Krishna (1986)). However, fluctuations in the costs of more flexible
production factors throughout the cycle may also lead to factor
substitution. For example, the cost of increasing the average work
week may be quite high near business cycle peaks, as further increases
in hours may lead to prohibitive overtime wage premiums.

Models that incorporate cyclical labor hoarding also provide
examples of state dependent factor substitution. These models suggest
non-constant relationships between worker effort, employment, and
output growth through the cycle.

Firms' expectations of the permanence of any given demand
stimulus in the economy are also probably state dependent. These
expectations in turn affect firm choices between using quasi-fixed
versus more flexible production inputs in meeting these increases in
demand. For example, after a prolonged economic expansion, firms may
become wary of the economy's ability to continue on its upward trend.
In this case, any further demand stimuli at the end of an expansion
may be met by increasing the hours of existing workers, even if this
means paying overtime wage premiums, to avoid the hiring and training costs involved with new employees. At the end of an economic downturn, on the other hand, firms expecting an impending upturn may be reluctant to fire any more workers, since they expect to increase production in the near future.

In sum, there is a whole class of alternative models of firm behavior that suggests state dependent factor substitution is a plausible explanation for the Okun's Law asymmetries I document in Section II. However, suppose that there is no factor substitution in the sense that \( h \) and \( k \) are proportional to \( e \) throughout the cycle.\(^{12}\) All fluctuations in Okun's Law in this scenario are then attributable to a non-constant relationship between \( z \) and \( y \). By the definition of no factor substitution, fluctuations in the relationship between \( e \) and \( y \) throughout the cycle are matched by proportional fluctuations in the relationships between \( h, k \) and \( y \).

Suppose \( g \) is a positive constant as \( y \) fluctuates through a cycle. The relationship between \( e \) and \( y \) is not constant in this case even without factor substitution; with factor productivity increasing by the same amount in upturns and downturns, firms require fewer new hires to produce increases in output than the amount they can fire in generating a symmetric decrease in output. However, if asymmetry is due only to trend productivity growth as described here, the specification of the Okun's Law regressions I estimate in the previous section captures this trend in the constant term. Constant productivity growth cannot be an explanation for the differences in the relationship between employment and output growth during expansions and contractions.\(^{13}\)
The intuition built by considering constant multi-factor productivity growth rates, however, helps to identify conditions under which changes in productivity throughout the cycle result in estimated asymmetries. Consider an economy where productivity growth is usually, if not always, positive. This assumption seems uncontroversial; negative productivity growth may be the result of fairly unusual economic events, such as natural disasters, while positive growth is associated with more common economic events such as investments in research, development, and technology. If output growth rates respond positively to demand and productivity shocks, under certain conditions on the distribution of demand and productivity shocks, the expected value of the productivity shock is greater in absolute value when output is increasing than when it is decreasing. Increases in output can be met with relatively little hiring, while decreases involve large dismissals of workers; on average, decreases in output are attributable to negative demand shocks, and not decreases in productivity growth.\textsuperscript{14}

The example considered here builds intuition as to why Okun's Law might be non-constant across expansionary and contractionary periods, even without factor substitution. If the relationship between productivity and output growth also depends on the level of the cycle, Okun's Law coefficients may also fluctuate within contractions and expansions. For example, if productivity growth is "endogenous," in the sense that periods with the highest degree of economic activity spur investment in research, development, and technology, then the relationship between $e$ and $y$ depends on the level of the cycle.

Factor substitution and fluctuations in productivity growth
throughout the cycle both appear to be reasonable explanations for fluctuations in Okun's Law. To build a more complete understanding of the business cycle phenomenon, however, it is useful to identify the relative importance of these two explanations in accounting for observed asymmetries. Equation (4-5) suggests a simple test for distinguishing between the two sources of asymmetry. Consider running a regression of $e$ on $y$, but allowing for different coefficients when $y$ is positive and negative. If one also includes $h$ and $k$ in the regression, any asymmetries in $e$'s response to positive and negative movements in $y$ must then be attributable to a non-constant relationship between $g$ and $y$ throughout the cycle. This point is obviously more general: If the aggregate production function is well-approximated by a Cobb-Douglas function of inputs, and if one estimates a non-constant relationship between an input's growth rate and the output growth rate, when the growth rates of all other factors of production have been accounted for, the non-constant relationship may be attributed to fluctuations in multi-factor productivity. Alternatively, suppose one estimates a non-constant relationship between input and output growth rates when the growth rates of other factors haven't been accounted for, but one estimates a constant relationship when these other factor growth rates are included in the regression. In this case, one could conclude that factor substitution is responsible for the observed non-constant relationship between input and output growth rates.

This discussion suggests two simple procedures to identify the sources of asymmetry evident in Tables 4-1 through 4-4. Re-estimate the regressions in Tables 4-1 through 4-4, including growth rates of
all other factors of production as regressors. If the estimated asymmetries disappear when other factors are accounted for, factor substitution is responsible for the asymmetries estimated in Tables 4-1 through 4-4. If asymmetries are still prevalent, they must be attributable to a non-constant relationship between \( g \) and \( y \) through the cycle.

Alternatively, the competing explanations can be tested by estimating the specifications of Section II on other inputs of production. Under the null hypothesis of no factor substitution, inputs move proportionately throughout the cycle. In this case, if employment responds more to negative movements in output, then all other inputs must share this asymmetry. If some inputs demonstrate asymmetries in the opposite direction of employment, it must be the case that factor substitution is at least partially responsible for estimated fluctuations in Okun's Law.\(^{15}\)

Empirical implementation of the first test described above may be difficult. This test requires that all inputs of production are identified and measured accurately. If certain inputs cannot be accurately quantified, asymmetries due to factor substitution may be identified as asymmetries due to productivity growth fluctuations. For example, recent research on labor hoarding suggests that labor effort may fluctuate considerably throughout the cycle.\(^{16}\) Unfortunately, labor effort is an unobservable factor of production. If substitution of effort across the cycle is responsible for estimated asymmetries, this test would attribute asymmetries to fluctuations in productivity growth. Therefore, a study concentrating on the cyclical properties of the Solow residual may provide only
limited insights into the sources of fluctuations in Okun's Law. The second test, however, requires that only one other factor is accurately measured and observed, and is thus easy to implement.\textsuperscript{17}

Section IV formalizes much of the discussion in this section. First, I derive conditions under which the specifications in Section II are reasonable tests for asymmetries in the data. Once I clarify the statistical properties of these estimators, I show that tests of the competing explanations for estimated asymmetries follow quite naturally. This more systematic approach also identifies situations in which the tests described above may not be appropriate.

IV. SPECIFICATION ISSUES IN TESTING FOR STATE DEPENDENCE

Consider points a and d in Figure 4-1, which illustrates a symmetric growth cycle for output. These points are at the same level of output, and output growth at d is the absolute value of output growth at a. If Okun's Law is the same at points a and d, unemployment rate increases at a, equal unemployment rate decreases at d. In fact, if Okun's Law is constant, at all levels of output in the cycle, increases in the unemployment rate during contractions match decreases during expansions. Any deviations from this pattern represent breakdowns in Okun's Law.

An econometric specification designed to identify state dependence in Okun's Law should have the following properties: (1) it should be capable of identifying state dependence in the data; (2) it should be flexible enough to allow for a precise characterization of the form of any state dependence in the data; (3) it should possess
reasonable forecasting properties. In this section, I identify circumstances under which the Section II specifications satisfy these criteria. I propose an alternative specification that has the same interpretation as the Section II specifications, yet allows for a more flexible characterization of state dependence. I also discuss how alternative specifications can be used to differentiate between factor substitution and factor productivity explanations for state dependence in the Okun's Law coefficient.

Throughout the discussion, I assume the log of output follows a symmetric growth cycle, as in Figure 4-1. This assumption eases the interpretation of alternative specifications considerably. Evidence cited previously from DeLong and Summers (1986) and Falk (1986) suggests that expansions and contractions in output growth cycles are symmetric. Figure 4-2 graphs cubic-spline detrended log GNP (DTLGNP82) and a symmetric cycle (CYCLE), with a period of 24 quarters. Since the mid 1960s, the symmetric cycle accurately tracks output fluctuations. Furthermore, if I allow for cycles with a different period prior to 1965, symmetric cycles match the data over the entire sample period quite well.

Appendix 4-A presents, calibrates, and simulates a model of employment and hours determination throughout a symmetric output cycle. I use this model to clarify the discussion of several technical issues in this section. The model is similar in spirit to Nickell (1978) and Leban and Lesourne (1980), in that it imposes an exogenous symmetric output cycle, and then determines the cyclical behavior of alternative factor demands. It is also motivated by the discussion in Section III; it assumes asymmetric hiring and firing

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costs, which result in factor substitution through the cycle, and also allows for fluctuations in productivity growth as another source of non-constant responses of factor demands to deviations in output growth from trend.

The results of the model are driven by two assumptions: (1) linear, asymmetric hiring and firing costs; (2) the wage rate is an increasing function of average hours per employee. The model predicts that all positive output growth is met with hours growth alone, as long as hours remain below some critical point. When hours reach this critical level, any further increases in output are associated with employment growth alone. Similarly, during contractions, output reductions are met with hours reductions until some critical lower level of hours is met, after which further decreases in output are met solely with employment reductions. This model obviously implies a non-constant relationship between employment and output growth through the cycle. At the beginning of contractions, for example, hours are at high levels and all output fluctuations are associated with hours reductions. Alternatively, at the end of expansions, hours have reached their critical level, and all output fluctuations are accounted for by employment growth. During the discussion that follows, I describe in what sense alternative econometric specifications are able to identify and characterize these asymmetries.

Consider the specification given by Equation (4.1), with employment growth as the dependent variable, which I repeat here for convenience:
\[(4-1) \quad \Delta E(t) = \alpha + \beta_0 \text{PGROW}(t) + \gamma_0 \text{NGROW}(t) + \epsilon(t)\]

Let \(\hat{\beta}_0\) and \(\hat{\gamma}_0\) be the OLS estimates of \(\beta_0\) and \(\gamma_0\), respectively. Under the assumption of a symmetric growth cycle for the log of output, the relationship between \(\hat{\beta}_0\) and \(\hat{\gamma}_0\) is:

\[(4-7) \quad \hat{\gamma}_0 - \hat{\beta}_0 = k_1 \sum_t \left[ \Delta E(t) \times (\text{NGROW}(t) - \text{PGROW}(t)) \right] \]

\(k_1\) is a constant which decreases with the variance of \(\text{PGROW}\).

If \(\hat{\gamma}_0 \neq \hat{\beta}_0\), then the relationship between output and employment growth throughout the cycle must be non-constant. If \(\Delta E(t) = \tau \Delta y(t)\), Equation (4-7) can be simplified as follows:

\[(4-8) \quad \hat{\gamma}_0 - \hat{\beta}_0 = k_1 \tau \sum_t \left[ \Delta y(t) \times (\text{NGROW}(t) - \text{PGROW}(t)) \right] \]

\[= k_1 \tau \sum_t \left[ (\text{NGROW}(t) + \text{PGROW}(t)) \times (\text{NGROW}(t) - \text{PGROW}(t)) \right] \]

\[= k_1 \tau \sum_t \left[ (\text{NGROW}(t))^2 - (\text{PGROW}(t))^2 \right] = 0 \]

The last line in (4-8) follows from the assumption of a symmetric growth cycle.

Therefore, in order to estimate \(\hat{\gamma}_0 \neq \hat{\beta}_0\), it is necessary that the relationship between employment and output growth throughout the cycle be non-constant. In this sense, the test is a valid test for state dependence. However, a non-constant relationship between employment and output growth is not a sufficient condition for estimating \(\hat{\gamma}_0 \neq \hat{\beta}_0\). In fact, the model in Appendix 4-A identifies conditions under which \(\hat{\gamma}_0 = \hat{\beta}_0\), even though a non-constant relationship between
employment and output growth exists. This occurs when the pattern of employment growth during expansions is the mirror image of the pattern of employment decline during contractions. This specification does not identify certain forms of asymmetry, and thus alternative specifications may enable more powerful tests of the null hypothesis of no state dependence.

What role does the constant term play in the Equation (4-1) specification? Let \( \hat{\gamma}_{00} \) and \( \hat{\beta}_{00} \) be the OLS estimates of \( \gamma_0 \) and \( \beta_0 \) from a regression identical to Equation (4-1) minus the constant term, and \( \hat{\gamma}_{02} \) and \( \hat{\beta}_{02} \) be these estimates from a regression that allows for a different constant in contractions and expansions. Equation (4-9) summarizes the relationships between these parameter estimates:

\[
(4-9) \quad \hat{\gamma}_0 - \hat{\beta}_0 = \hat{\gamma}_{02} - \hat{\beta}_{02} = k_2 (\hat{\gamma}_{00} - \hat{\beta}_{00})
\]

\( k_2 \) is a constant, so that there is no difference in interpretation between the alternative tests for asymmetries. However, there are other reasons to prefer the specifications with one or two constants.

One desirable feature of any specification is that it provides reasonable forecasts of employment growth over time. Consider the following experiment: An economist estimates the employment growth equation given by Equation (4-1) over one symmetric output cycle. The economist wants to use the estimates from this model to predict what would happen to employment if output were to follow the same symmetric cycle in the future. One desirable property of this forecast is that the predicted total change in employment throughout the forecast cycle
equals the actual change in employment observed over the sample cycle. Including one or two constants in the Equation (4-1) regression guarantees that this property always hold. However, if a constant isn’t included in the specification, this property may not hold. For example, it is possible to estimate $\gamma_{00} > \beta_{00}$ in a cycle with no total employment growth, yet the forecast of employment growth over this cycle from a model estimated with no constant term would predict a decline in employment.

Including a constant is also important in that it controls for trend growth in employment. Since the goal of this empirical exercise is to identify asymmetries that are due either to factor substitution or productivity growth that is non-proportional to output growth, asymmetries due to trend movements must be removed. Under the null hypothesis of no factor substitution and a constant relationship between output and productivity growth, including a constant term removes any estimated asymmetries due solely to trend growth. 22 Therefore, any asymmetry that remains when a constant is included reflects factor substitution or non-proportional productivity fluctuations. 23,24

Can the specification in Equation (4-1) be used to differentiate between competing explanations for asymmetries? Under the null hypothesis of no factor substitution, input growth rates move proportionately through the cycle. For example, suppose employment and hours are the only two factors of production. Re-estimate Equation (4-1) with hours growth as the dependent variable, and let $\gamma_{0h}$ and $\beta_{0h}$ be the OLS estimates of $\beta_0$ and $\gamma_0$ from this regression. Assuming no factor substitution, the following relationship between
estimated parameters holds:

\[(4-10) \quad \gamma_{0h} - \beta_{0h} = c_1 \times [\gamma_0 - \beta_0], \text{ with } c_1 > 0.\]

Assuming the constant of proportionality, \(c_1\), is positive, hours growth must demonstrate an asymmetry of the same sign as employment growth.

On the other hand, under the null hypothesis of a constant relationship between productivity growth and output growth, at least one input must demonstrate an asymmetry in the opposite direction of employment growth. In the two-input example, this implies that:

\[(4-11) \quad \gamma_{0h} - \beta_{0h} = -c_2 \times [\gamma_0 - \beta_0], \text{ with } c_2 > 0.\]

I simulate the model in Appendix 4-A allowing both factor substitution and fluctuations in productivity growth to account for asymmetries in the relationships between input and output growth rates. I find that as factor productivity growth becomes more asymmetric across output expansions and contractions, Equation (4-10) is more likely to hold than Equation (4-11). The stronger productivity growth asymmetries are, the more likely it is that alternative production inputs share the same pattern of asymmetries.

Now consider the specification in Equation (4-3), with employment growth as the dependent variable:

\[(4-3) \quad \Delta E(t) = \alpha + \beta_0 PGGROW(t) + \gamma_0 NGGROW(t) + \delta_0 PBGROW(t) + \phi_0 NBGROW(t) + \epsilon(t)\]
With this specification, I identify four null hypotheses for testing for state dependence in the data. OLS estimates of this equation have the following properties:\textsuperscript{25}

(a) If no constant is included, all four null hypotheses provide readily interpretable tests for asymmetries. \( \hat{\beta}_0 \neq \hat{\gamma}_0 \) if and only if there is a non-constant relationship between employment growth (e) and output growth (y) in periods when output is above trend. \( \hat{\delta}_0 \neq \hat{\phi}_0 \) if and only if there is a non-constant relationship between e and y in periods when output is below trend. \( \hat{\beta}_0 \neq \hat{\delta}_0 \) if and only if there is a non-constant relationship between e and y during growth cycle expansions. \( \hat{\gamma}_0 \neq \hat{\phi}_0 \) if and only if there is a non-constant relationship between e and y in growth cycle contractions. However, a non-proportional relationship between e and y is not a sufficient condition for estimating a difference in the parameters; as in the two-region specifications, certain forms of asymmetry are not identified by this specification. If a constant term is not included, the problems with trend growth and employment forecasts discussed earlier continue to apply in this specification.

(b) If either one or two constants (one for expansions and one for contractions) are included, tests for asymmetries in high output periods and low output periods are difficult to interpret. If there is a non-constant relationship between e and y when output is below trend, one may estimate asymmetries when output is above trend, even if a constant relationship between e and y holds in this region of the cycle. In other words, if Okun's Law breaks down in one region of the cycle, it may affect estimates in the other regions of the cycle.

(c) If four constants are included (one for each region of the cycle), the estimates provide readily interpretable tests for asymmetries in the sense described in part (a) above. I prefer this specification to the specification with no constants, as it ensures reasonable long-term employment forecasts and captures trend growth in the constant terms.
(d) Under the null hypothesis of no factor substitution, all input growth rates demonstrate asymmetries of the same sign as employment growth. Under the null hypothesis of proportional productivity growth and output growth rates, at least one input must demonstrate an asymmetry in the opposite direction of employment growth.

This discussion suggests that I should re-estimate the four-region specification including four constants. In the original specification with one constant, tests for asymmetries in high and low output periods are flawed. An asymmetry in high output periods may lead to the estimation of an asymmetry in low output periods, even if a constant relationship between $e$ and $y$ holds when output is below trend. I report estimates from specifications with four constants in the next section.

The Section II specifications provide reasonable tests for asymmetries. If OLS estimates of employment responses to output movements in different regions of the cycle diverge, it must be the case that there exists a non-constant relationship between $e$ and $y$ through the cycle. Also, the specifications allow for tests of null hypotheses concerning the sources of asymmetry that are easy to implement. However, in certain respects the specifications are lacking. The tests are not powerful in the sense that certain forms of asymmetry are not identified by the parameter estimates. Because the specifications force estimated employment growth derivatives with respect to output growth to change in a discrete manner, they also do not allow for a rich characterization of asymmetries.

Consider the following alternative specification:
\[ \Delta E(t) = \alpha + \beta_0 \text{PGROW}(t) + \gamma_0 \text{NGROW}(t) + \psi_0 \text{PLGROW}(t) + \theta_0 \text{NLGROW}(t) + \varepsilon(t) \]

PLGROW is PGROW multiplied by the level of detrended log output, and NLGROW is NGROW multiplied by the level of detrended log output.

This is a desirable specification for a number of reasons. First, it allows for a richer characterization of asymmetries by allowing the relationship between \( e \) and \( y \) to change continuously within an economic contraction or expansion. At the same time, it allows for discrete changes in this relationship as the economy moves from an expansion to a contraction, and vice-versa. The simulations in Appendix 4-A demonstrate that allowing for this discrete change may be important if factor substitution is driven by asymmetries in hiring and firing costs.

The null hypothesis of no state dependence in this model is the joint hypothesis that \( \beta_0 = \gamma_0 \) and \( \psi_0 = \theta_0 \). If \( \hat{\beta}_0 \neq \hat{\gamma}_0 \) or \( \hat{\psi}_0 \neq \hat{\theta}_0 \), then it must be the case that a non-constant relationship between \( e \) and \( y \) exists. The test for a non-constant relationship during expansions is the \( t \)-statistic on \( \hat{\psi}_0 \); for contractions, it is the \( t \)-statistic on \( \hat{\theta}_0 \). This specification is similar to the Section II specifications in that some forms of asymmetry are not identified by the parameter estimates. However, I report simulations in Appendix 4-A suggesting that this may be less of a problem for this specification than the others.

This specification also allows for simple tests to identify the sources of estimated asymmetries. If \( \hat{\beta}_0 > \hat{\gamma}_0 \) and \( \hat{\psi}_0 > \hat{\theta}_0 \) for one input, under the null hypothesis of no factor substitution, \( \hat{\beta}_0 \geq \hat{\gamma}_0 \) and \( \hat{\psi}_0 \geq \hat{\theta}_0 \) for all other inputs. Under the null hypothesis of
proportional output growth and productivity growth, $\hat{\beta}_0 < \hat{\gamma}_0$ or $\hat{\psi}_0 < \hat{\theta}_0$ for at least one other input.

In the next section, I re-estimate the alternative specifications discussed here for other production inputs, and use the insights of the last two sections to determine if it is possible to identify the sources of state dependence in the Section II estimates.

V. EMPIRICAL RESULTS FOR ALTERNATIVE SPECIFICATIONS AND INPUTS

Tables 4-5 and 4-6 present estimates of Equations (4-1) and (4-2), using alternative production inputs as the dependent variable. If state dependent factor substitution is not prevalent, other inputs of production should either share the employment growth asymmetries estimated in Section II, or should, at the very least, show no signs of asymmetry. Alternatively, if factor substitution is an important source of estimated employment growth asymmetries, at least one other factor of production should exhibit asymmetries in the opposite direction of those for employment.

I examine the cyclical behavior of average weekly hours per employee from the CPS survey, average weekly production worker hours from the BLS Establishment Survey, the Business Conditions Digest's measure of manhours employed, and the Federal Reserve Board's measure of capacity utilization. The reason for studying hours measures is straightforward: hours and employees are likely candidates for substitution across cycles, and multi-factor productivity shocks should affect the productivity of both inputs. Studying manhours offers an alternative method of measuring any factor substitution
between employment and hours; if manhours share asymmetries of the same magnitude as employment, then hours must move symmetrically through the cycle. Finally, the capacity utilization rate may also be thought of as an "input" in production if it accurately measures the intensity of capital utilization in the economy (just as hours are a measure of the utilization rate for labor). 28, 29

Table 4-5 provides little or no evidence of asymmetric responses of hours or production worker hours to output growth in expansions and contractions. Furthermore, while the asymmetry in manhours is not statistically significant, it is of a similar magnitude to that estimated for non-agricultural employment in Table 4-1. The capacity utilization rate is characterized by sharp drops during growth cycle contractions, and more gradual increases during expansions. The capacity utilization rate falls by one percentage point for every 0.58 percentage point in growth below trend, but increases by only 0.46 percentage point for every 0.58 percentage point in growth above trend.

In Table 4-6, there is once again little evidence of asymmetries in hours growth equations. If there is asymmetry in the CPS hours equation, it appears to be in the same direction as that for employment; CPS hours decrease by more when output growth is below trend, than they increase when output growth is above trend. Manhours growth also shows a strong asymmetry of the same magnitude and direction as employment growth. In sum, the evidence in Tables 4-5 and 4-6 suggests that the productivity growth explanation of asymmetries cannot be rejected by the data, while there is no strong evidence of factor substitution.
When I break the sample into the four regions of the cycle, the econometric specifications should include four constant terms in order to provide for more straightforward interpretations of the coefficients. Define PG(t), NG(t), PB(t), and NB(t) to be indicator variables; PG = 1 in region D of the cycle, NG = 1 in A, PB = 1 in C, and NB = 1 in B. I estimate the following equation:

\[
\Delta UR(t) = PG(t) + NG(t) + PB(t) + NB(t) + \sum_{i=0}^{2} \beta_i PGGROW(t-i) \\
+ \sum_{i=0}^{2} \gamma_i NGGROW(t-i) + \sum_{i=0}^{2} \delta_i PBGROW(t-i) + \sum_{i=0}^{2} \phi_i NBGROW(t-i) + \epsilon(t)
\]

Comparing Tables 4-7A and 4-4, note that the additional constant terms do not affect the estimated asymmetries for employment growth and unemployment rate change specifications. Unemployment and employment fluctuations are greatest when output is in trough periods of growth cycle contractions. Output growth does not decrease the unemployment rate or increase aggregate employment by nearly as much, for example, in peak periods of expansions.

Tables 4-7A and 4-7B once again provide little evidence of factor substitution. There are no statistically significant asymmetries in hours or production worker hours equations. The pattern of coefficients in the CPS hours equation also follows the employment equation quite closely; in peak periods of expansions, hours do not respond to output growth, while in trough periods of contractions hours decrease by 0.50 percentage point for every percentage point output growth is below trend. The manhours regression exhibits the same pattern of asymmetries as non-agricultural employment as well.

The last specification I consider is given by Equation (4-12),
which I repeat here for convenience:

\[(4.12) \quad \Delta UR(t) = \alpha + \beta_0 \text{PGROW}(t) + \gamma_0 \text{NGROW}(t) + \psi_0 \text{PLGROW}(t) + \theta_0 \text{NLGROW}(t) + \epsilon(t)\]

This specification allows the derivative of employment growth with respect to output growth to fluctuate continuously throughout the cycle. A test for the null hypothesis of a constant relationship between employment and output growth throughout the cycle constrains \(\beta_0 = \gamma_0\) and \(\psi_0 = \theta_0\). The \(t\)-statistic on \(\hat{\psi}_0\) provides the test statistic for the null hypothesis that there is a constant relationship between employment and output growth in growth cycle expansions. The \(t\)-statistic on \(\hat{\theta}_0\) is the test statistic for the corresponding hypothesis in growth cycle contractions.

Table 4-8A presents strong evidence of asymmetries in employment growth and unemployment rate change responses to output growth throughout the cycle. All employment specifications suggest that near trend levels of output, employment responds symmetrically to contractions and expansions in output. However, in peak periods, output increases are associated with large-scale hiring, while output decreases are met with little firing. Similarly, at the beginning of expansions, very little hiring is associated with increases in output, while at the end of contractions any further output declines lead to large-scale lay-offs.

Table 4-8B shows virtually no signs of asymmetries in hours growth equations through the cycle. The significance level for the null hypothesis that production worker hours growth has a constant relationship with output growth through the cycle is 0.84. Once
again, manhours asymmetries match those of employment, while hours asymmetries are either nonexistent, or in the same direction as employment.

In Appendix 4-B, I present an alternative procedure for identifying the sources of the non-constant relationship between employment and output growth through the cycle. I argue that if the distribution of employment growth rates is negatively skewed, suggesting sharper employment contractions than expansions, then the distribution of growth rates for some other production input must be positively skewed if factor substitution is prevalent. I report tests for skewness in growth rate distributions, as developed by DeLong and Summers (1986) and Sichel (1987), for a variety of output growth and input growth measures. Some evidence of factor substitution is evident in quarterly data, as the distribution of CPS hours growth rates is positively skewed, while the distribution of non-agricultural employment growth rates is negatively skewed. However, this result is not evident in annual data.30

In sum, there is little or no evidence in the cyclical behavior of hours and manhours growth that allows one to reject the null hypothesis of no factor substitution. Under this null hypothesis, asymmetries in one factor are proportional to those in other factors. Furthermore, there is little evidence to accept the null hypothesis that the relationship between productivity growth and output growth is constant throughout the cycle; acceptance of this null requires evidence of an asymmetry in the opposite direction of employment for at least one other production input. Such an asymmetry is not evident in hours or capacity utilization measures. This evidence may lead one
to identify non-proportional output growth and productivity growth as the source of the estimated asymmetries in Okun's Law. While certainly the evidence for factor substitution is weak in this chapter (especially since, a priori, one would expect hours and employment to be among the most easily substitutable inputs in production), I am hesitant to reject such explanations until I obtain a more precise understanding of the power of the statistical tests in this chapter. In particular, I am concerned that unobserved cyclical labor hoarding, which involves the substitution of worker effort and employment, may be a prevalent form of factor substitution that my tests are unable to identify. Therefore, developing a more precise understanding of the power of factor substitution tests in this chapter is obviously a top priority in my current research agenda.

VI. CONCLUSIONS AND EXTENSIONS

I present strong empirical evidence in this chapter suggesting that Okun's Law, and the relationship between employment growth and output growth, vary systematically throughout the business cycle. One possible explanation for this result is factor substitution. A priori, there are strong reasons to believe that adjustment costs of quasi-fixed factors might be contingent on the state of the business cycle, so that cost-minimizing behavior by firms naturally leads to factor substitution. However, the statistical tests I develop in this chapter show little evidence of factor substitution, at least not between employment and average weekly hours. On the other hand, the joint cyclical behavior of employment growth and hours growth suggests
that asymmetries in productivity growth throughout the cycle may be an important source of the state dependence observed in Okun's Law.

There are a number of methodological issues that I must study further. I must address specification issues involved with tests for state dependence in a more systematic fashion. As I argue in Section IV, the specifications I use in this chapter are informative in the sense that, under most circumstances, they are able to identify asymmetries in the data when they are present, and they provide simple tests for the sources of asymmetries. However, it cannot be the case that these specifications are the best "data descriptors" for characterizing the form of asymmetries in the data. The use of nonlinear estimation techniques, as well as spectral analysis, might allow for a better description of the cyclical co-movement of the these production inputs. Another possible approach is multivariate dynamic factor demand estimation as pioneered by Nadiri and Rosen (1973).^31

In order to determine the statistical properties of alternative tests for state dependence, it is also imperative that I develop, calibrate, and simulate more complete models of factor demand determination. These models identify hypothetical time-series paths for production inputs, and thus suggest estimation techniques better suited to characterize any state dependence in the data.^32 I must confront several difficult issues in these modeling exercises, such as how to best characterize the dependence of firm expectations and factor costs (including any adjustment costs of quasi-fixed factors) on the state of the business cycle. Since expectations and costs are likely to exhibit a great deal of state dependence, however, I cannot
avoid these issues when attempting to explain the cyclical characteristics of alternative production inputs.

Another important avenue for research is to examine disaggregated factor demand equations to identify any asymmetries at alternative levels of aggregation. If asymmetries are not evident in more micro-level data, I must consider the importance of aggregation, dealing explicitly with the differential cyclical sensitivity of industries, to explain the aggregate effects. If asymmetries are evident in disaggregated data, this has important implications for aggregate employment and unemployment responses to sectoral and aggregate shocks. In this case, the sectoral distribution of any given output shock is an important determinant of the aggregate employment response to this shock. For example, consider an economy with two sectors of identical size. Assume that in both sectors, employment responds more strongly to negative output movements than positive movements. An aggregate output increase of one percent that is distributed evenly between the sectors has a greater positive impact on employment than one in which output increases by two percent in one industry, and declines by one percent in the other. In general, if sectoral factor demand equations are state dependent, the whole distribution of sectoral growth rates, and not just a summary statistic from that distribution (such as Lilien’s (1982) $\sigma$), affects the relationship observed between aggregate output growth and aggregate employment growth. This suggests that one possible interpretation of business cycle state dependence in the Okun’s Law coefficient is a systematic relationship between the business cycle and the distribution of output growth across sectors.
I re-estimate the same battery of equations reported in Section II for 2-digit manufacturing industries, estimating factor demand responses to changes in the relevant industrial production index. There is substantial evidence of asymmetries in employment fluctuations at this level of aggregation. The next step is to determine if dispersion in output growth rates across these sectors accounts for the state dependence observed in aggregate specifications. As an informal test of this hypothesis, I re-estimate Equation (4-1) including Lilien's (1982) \( \sigma \) measure for industrial production growth in these 2-digit industries as an independent variable. In this specification, I no longer estimate a significant difference between the Okun's Law coefficient in growth cycle contractions and expansions. This preliminary result suggests that the countercyclical nature of sectoral dispersion may play an important role in explaining state dependence in Okun's Law.

Cross-sectional variance in estimated asymmetries across industrial sectors may also provide information that is useful in differentiating between the competing explanations for the source of state dependence. For example, if expansion and contraction asymmetries are strongest in industries characterized by large differences in hiring and firing costs, then the factor substitution explanation is supported. Aggregate cross-sectional studies can also provide such evidence, given the wide dispersion in hiring and firing institutions and costs across countries.\(^{35}\)

Evidence of state dependence in the aggregate production relationship may ultimately help to differentiate between alternative business cycle models. Suppose one estimates an aggregate production
function of the form:

\[(4-14) \quad y = \alpha k + \beta e + \epsilon\]

where \(y\) = growth rate of value-added production  
\(e\) = growth rate of aggregate employment  
\(k\) = growth rate of aggregate capital stock  
\(\epsilon\) = error term, including multi-factor productivity growth

Estimates of \(\beta\) from such a regression tend to be much greater than labor's share in national income (and often greater than one), suggesting short-run increasing returns to labor (SRIRL). Bernanke and Parkinson (1989) argue that the SRIRL phenomenon can be explained by three different classes of business cycle models. Competitive real business cycle theories (e.g., Prescott (1986)) suggest that the true value of \(\beta\) equal labor's share, but OLS estimates of \(\beta\) are biased upward because of a positive correlation between the error term (multi-factor productivity growth) and employment growth. Certain Keynesian models (e.g., Rotemberg and Summers (1988)), on the other hand, suggest that estimates of \(\beta\) are biased upward because of labor hoarding. Growth in labor effort, which should be positively correlated with employment growth, is omitted from this regression and leads to an overestimate of \(\beta\). Finally, models identifying increasing returns to scale, and thus optimal bunching of production, as the source of business cycle fluctuations, suggest that a high estimated \(\beta\) merely reflects true increasing returns to scale in the production process (e.g., Hall (1987)).

Suppose one re-estimates Equation (4-14), but now allows for state dependence in its parameters. For example, suppose one allows estimates of \(\beta\) to depend on whether \(y\) is positive or negative, and
then conducts statistical tests for such state dependence. Can alternative business cycle models explain state dependence if it is identified in the data? State dependent estimates, as interpreted by the real business cycle model, indicate that the correlation of $\epsilon$ and employment growth must change systematically over the business cycle. Alternatively, labor hoarding models explain state dependence by different correlations between effort and employment growth in different phases of the business cycle. Increasing returns to scale models seem less capable of explaining state dependent production parameters, since business cycle fluctuations are supposed to represent movements along a given production function.\textsuperscript{36}

The preceding discussion suggests a unique approach for testing the empirical validity of labor hoarding and real business cycle models. First, calibrate and simulate these models, and identify their predictions about the correlations of employment, effort and multi-factor productivity growth in different phases of the business cycle. These correlations then identify the biases that one should observe in estimates of $\beta$ during different phases of the business cycle, if the data are generated by the model under consideration. The final step is to determine if state dependence in these expected bias terms matches the state dependence observed in coefficients estimated using real data. In essence, the approach entails determining if these models can produce state dependent correlations between multi-factor productivity, employment, and effort growth that can explain state dependent estimates in aggregate production functions.

In summary, the general empirical approach I outline in this
chapter can be applied to provide evidence on some of the major macroeconomic issues of the day. Disaggregated analyses should help identify the importance of sectoral versus aggregate shocks in determining aggregate labor market outcomes, while careful analyses of aggregate production functions that allow for state dependent parameters may provide new evidence on alternative business cycle theories. Therefore, a research agenda focusing on state dependence in aggregate macroeconomic functions, such as Okun's Law, should prove to be quite fruitful.
NOTES FOR CHAPTER 4

1 A sampling of intermediate macroeconomic textbooks suggests that there is some disagreement over what is the best estimate of this Okun's Law coefficient. For example, Hall and Taylor (1991) claim that a percentage point of real GNP growth above trend, that is sustained for a year, decreases the unemployment rate by only 0.33 percentage point.

2 The goal of this asymmetries literature has been to use careful statistical analyses to test the claims of many early business cycle theorists who maintained that the correlation properties of certain macroeconomic variables differ in expansions and contractions. In particular, these theorists often claimed that downturns in economic activity tend to be briefer and more severe than upturns. For example, Keynes (1936, pg. 314) emphasizes the importance of the "crisis" in business cycles. He notes that "the substitution of a downward for an upward tendency often takes place suddenly and violently, whereas there is, as a rule, no such sharp turning point when an upward is substituted for a downward tendency." Burns and Mitchell (1946) also focus particular attention on asymmetries between expansions and contractions.

3 I confirm the DeLong and Summers (1986) results in Appendix 4-3.

4 A cubic spline allows for a flexible trend by splicing together sections of cubic polynomials, while imposing a smoothness constraint on the detrended series so that all fluctuations in a series are not identified as trend. Define \( y(t) \) to be the natural log of GNP in period \( t \). I find trend log GNP in period \( t, r(t) \), by solving the following constrained minimization problem:

\[
\text{Min} \sum_{t=1}^{T} (y(t) - r(t))^2 \\
\text{subject to} \sum_{t=2}^{T-1} [(r(t+1) - r(t)) - (r(t) - r(t-1))]^2 \leq \mu
\]

When \( \mu = 0 \), the difference between \( r(t) \) and \( r(t-1) \) must be constant for all \( t \); the least squares linear time trend results in this case. As \( \mu \) approaches infinity, the smoothness constraint is non-binding, and all fluctuations in output are attributed to trend. Following Prescott (1986) and Sichel (1987), who analyze series of similar frequency and length, I set \( \mu = 1600 \). This assumption allows the procedure to be thought of as a high-pass linear filter which removes oscillations greater than 32 quarters. Once I calculate \( r(t) \), I set detrended log GNP equal to \( y(t) - r(t) \). Therefore, GNP growth is greater than trend in period \( t \) when \( (y(t) - r(t)) - (y(t-1) - r(t-1)) > 0 \).

5 See Okun (1983) for a classic discussion of alternative methods for estimating the relationship between potential output and the unemployment rate.

6 I approximate growth rates by taking first differences of the logs of all variables.
The asymmetry in Okun's Law in expansions versus contractions documented here was first reported by Thuro (1965). Using a specification almost identical to the one used for Table 4-2, and looking at quarterly data from 1948 to 1963, he finds asymmetries similar in magnitude to those reported here. While I have not yet undertaken a thorough study of the sub-sample stability properties of my estimates, his results suggest that at least for the unemployment rate, the estimated asymmetry in Okun's Law is not merely the result of recent changes in labor market conditions.

To keep variable names and their correspondence to the different regions in the cycle in order, use the simple rule that a "P" preceding a variable refers to positive growth, an "N" refers to negative growth, "G" refers to good times (output above trend), and "B" refers to bad times (output below trend). Therefore, PGGROW refers to positive growth in good times, or region D in the cycle.

This explanation suggests that it is the level of the aggregate unemployment rate, and not necessarily the level of output, that affects the Okun's Law coefficient. In an earlier version of this chapter, I presented estimates that broke the cycle into four regions depending on whether the economy was in a growth cycle expansion or contraction, and whether or not the aggregate unemployment rate was above or below trend. These estimates are very similar to those presented in Tables 4-3 and 4-4, as the two procedures cut the data in near identical ways. In this version, I focus on the output level for two reasons: (1) As I demonstrate in Section IV, it allows for a clear interpretation of the estimates presented here as tests for asymmetries in Okun's Law throughout a symmetric output cycle. (2) In the unemployment rate regressions, it avoids the bias resulting from splitting the sample based on the sample properties of the dependent variable.

Davis (1988) provides a brief discussion of this point.

See Shapiro (1986) for evidence on this point.

This is the case when h and k are proportional to (y-g), implying e is also proportional to (y-g). Therefore, I define "no factor substitution" as the case where e, k, and h move in constant proportions to output minus factor productivity growth.

I discuss this point in more detail in the next section when I address specification and methodological concerns. Just as constant trend growth cannot explain asymmetries in the relationship between employment and output growth, constant labor force growth cannot explain the fluctuations in Okun's Law throughout the cycle that I present in Section II.

In an earlier version of this chapter, I derive conditions under which this intuition holds for uniform, independently distributed demand and productivity shocks. This example is available from the author upon request.

This intuition is formalized in the next section when methodological concerns are dealt with more systematically.
See Fay and Medoff (1985) and Shea (1989) for evidence on the cyclicality of labor effort.

However, unless all factors can be properly identified and measured, the procedure is biased towards accepting the null hypothesis of no factor substitution. Even if all factors that can be measured exhibit asymmetries in the same direction as employment, it could be the case that an unobserved factor, such as effort, exhibits asymmetries in the opposite direction.

Evidence in Sichel (1987), however, suggests that growth cycle troughs are further below trend than peaks are above trend.

I ignore the capital stock in this model to consider the simplest case of only two factor inputs.

The wage assumption is supported by consideration of overtime wage premiums that are mandated by law, as in the US manufacturing sector, and by general equilibrium models in which potential workers have increasing marginal disutility from work, and thus must be rewarded for longer hours (see Bils (1987) for a discussion of these issues). See Nickell (1986) for a review of studies on adjustment costs for labor, and a discussion supporting the view that these costs are often well-approximated by linear functions.

See Appendix 4-A for details.

The proof of this assertion is available upon request.

Alternatively, one could detrend the employment data before running the regressions. However, interpretation of the estimates in this case is sensitive to the assumption that the data has been properly detrended. When a constant is included, under the null hypothesis of no asymmetry due to factor substitution or non-proportional productivity fluctuations, a precise interpretation is available.

Because only one constant is necessary to ensure reasonable long-term forecasts and the removal of trend growth, and since the interpretation of the coefficients is the same whether one or two constants are included, I only report regressions with one constant term for this specification.

Proofs of these assertions are available from the author on request.

Once again, a proof of this assertion is available upon request.

In particular, this specification identifies asymmetries in the data when hiring during expansions is the mirror image of firing during contractions.

See Nadiri and Rosen (1974) for a discussion of this point. Some economists have argued that the Federal Reserve's measure of capacity utilization may be a very poor indicator of high-frequency movements in capital utilization. For details, see Shapiro (1989) and the discussion in Appendix 4-B.
I also estimate equations using the growth rate of the aggregate capital stock as the dependent variable. I construct this variable using the Bureau of Economic Analysis' Fixed Reproducible Tangible Wealth annual series, and supplement this series with investment data in order to impute quarterly values. Equations fitted with this series invariably demonstrate very poor fits, as output growth rates explain very little of the variation in capital stock growth rates. As a result, I can never reject the null hypothesis of symmetry in the relationship between capital stock growth and output growth rates in alternative phases of the business cycle.

Consult Appendix 4-B for details of the test procedure and a discussion of its interpretation.

I have also estimated a number of multivariate dynamic factor demand systems that allow for asymmetric responses of inputs to positive and negative shipment shocks. While I would characterize these regressions as merely exploratory at this point, factor demand dynamic responses to shipment shocks show evidence of significant state dependence.

For example, the model in Appendix 4-A suggests that there are two critical points in a business cycle that determine employment and hours responses to increases in output. I identify these two points as the "hiring" and "firing" points in Figure 4A-1. When weekly hours per worker are between these points, only hours respond to output fluctuations. Once hours have reached one of these critical points, however, only employment responds to output fluctuations. This model suggests that the best way to characterize state dependence is to determine if in fact there is evidence of these two critical turning points in the data.

The interpretation of aggregate employment fluctuations in economies characterized by non-convex costs of adjustment for quasi-fixed factors has been studied carefully by Hammermesh (1989) and Bertola and Caballero (1990).

Bertola and Caballero (1990) highlight this intuition on the importance of cross-sectional distributions in making aggregate predictions.

See Bentolila (1988) and Bentolila and Bertola (1990) for thorough discussions of the role of hiring and firing institutions in explaining sustained levels of high unemployment in some European economies.

If a certain level of aggregate production is necessary for increasing returns to scale to be realized, however, the level of aggregate activity may affect estimated production coefficients. However, it is unlikely that these models can explain different coefficients for positive and negative output growth for a given level of aggregate output.
In this appendix, I present, calibrate, and simulate a simple model of employment and hours determination through a symmetric output cycle. The model helps to interpret the tests for state dependence I propose in this chapter, and also suggests patterns of asymmetry that are similar to those evident in US data.¹

In this model, I assume the path for the log of output is given, and study the cost-minimizing behavior of firms given this output path.² I assume the log of output follows a symmetric cycle with period T:

\[(4A-1) \quad y(t) = y_0 - z \cdot \sin(2\pi t / T)\]

I assume two factors of production, employment (E), and hours per employee (H). Output is a Cobb-Douglas function of these inputs:

\[(4A-2) \quad y(t) = \log(G(t)) + a \log(E(t)) + \beta \log(H(t))\]

G(t) is a measure of multi-factor productivity at time t.

I assume the wage rate, W, is an increasing function of H, with the elasticity of W with respect to H, $\epsilon_{wh}$, increasing in H. I also assume the firm faces hiring costs $= a$ for each new hire, and must pay firing costs $= f$ for each employee fired.

I assume firms are myopic in the sense that they do not foresee the symmetric output cycle. This assumption implies that firms solve the following static cost-minimization problem in each period:
\[(4A-3) \min \ W(H(t))H(t)E(t) + aI(E(t)-E(t-1)) + fJ(E(t-1)-E(t)) \]
\[\text{subject to } Y(t) = G(t)H(t)^{\beta}E(t)^{\alpha}\]

I is an indicator variable that is equal to one when the firm is hiring, and J is an indicator variable that is equal to one when the firm is firing.

The solution to this problem takes the following form:

\[(4A-4) \quad \epsilon_{wh} = (\beta - \alpha)/\alpha + \beta a/(aHW(H)), \text{ when the firm hires.}\]

\[(4A-5) \quad \epsilon_{wh} = (\beta - \alpha)/\alpha - \beta f/(aHW(H)), \text{ when the firm fires.}\]

\[(4A-6) \quad (\beta - \alpha)/\alpha - \beta f/(aHW(H)) < \epsilon_{wh} < (\beta - \alpha)/\alpha + \beta a/(aHW(H)), \text{ the firm is neither hiring or firing.}\]

At the beginning of each period, the firm computes the level hours must be in order to meet the output constraint, given the current employment level. If the level of hours is such that the condition in (4A-6) holds, the change in output in that period is met with changes in hours alone, and employment remains constant. If the level of required hours without hiring is such that \(\epsilon_{wh} > (\beta - \alpha)/\alpha + \beta a/(aHW(h))\), the firm sets hours so that (4A-4) holds, and it hires new employees to accommodate increases in output. Similarly, if the level of required hours without firing is such that \(\epsilon_{wh} < (\beta - \alpha)/\alpha - \beta f/(aHW(h))\), the firm sets hours so that (4A-5) holds, and it fires employees to accommodate decreases in output. In the absence of
hiring and firing costs, hours remain constant and all fluctuations are met with employment changes.

Figure 4A-1 illustrates these conditions using the baseline parameters of the model (I discuss these parameters later in this appendix). In this figure, HIRE represents the right-hand side of (4A-4), and FIRE represents the right-hand side of (4A-5). Between points A and B, \( \epsilon_{wh} \) is between HIRE and FIRE, and thus all small fluctuations in output are met with hours fluctuations. When hours reach point A or B, however, the firm meets any further increases or decreases in output with changes in employment alone.

I simulate this model under a variety of alternative assumptions on parameter values. I focus on my preferred specification, which I call the "baseline" simulation. The baseline simulation uses the following assumptions:

(a) \( y(t) = 7 - 0.2 \sin(2\pi t / 32) \); the length of the cycle is 32 periods, and output is approximately twenty percent above and below trend levels in peaks and troughs of the cycle.

(b) \( \beta = 0.54, \alpha = 0.46 \); these estimates are consistent with those in Shapiro (1986).

(c) \( G = 1 \), and is constant; I relax this assumption on zero multi-factor productivity growth later in the appendix.

(d) \( W = 190 + H \); this implies that \( \epsilon_{wh} \) is increasing in \( H \), and along with the technology assumptions in (b), implies that in the absence of hiring and firing costs, hours would always be 40 hours per week.

(e) \( a = 230, f = 170 \); hiring costs are, on average, one week's wages, while firing costs are about 75 percent as large as hiring costs. Evidence on hiring and firing costs surveyed in Nickell (1986)
suggests these are reasonable cost assumptions.

Figure 4A-2 illustrates the behavior of log output (LY), log employment (LL), and log hours (LH) over the cycle. The figure clearly demonstrates the non-constant relationship between employment, hours, and output growth through the cycle.

I estimate the regression equations given in Sections II and V of this chapter, using simulated data for 160 periods, or five complete output cycles, to determine how well these specifications characterize the asymmetries evident in Figure 4A-2. The first two columns of Table 4A-1 present results from the baseline simulation.

When I cut the data according to output expansions and contractions, as in Tables 4-1 and 4-5 in the text, the coefficients on NGROW and PGROW are always equal. A test of the null hypothesis that these coefficients are equal is not a powerful test for asymmetries in the data.3

When I cut the data into the four regions of Figure 4-1, however, these specifications identify and characterize the asymmetries in the data quite well. The estimates suggest that employment responses to output growth are strongest in expansionary peaks and contractionary troughs, and this pattern is readily apparent in Figure 4A-2. The estimated hours equations suggest asymmetries in the opposite direction of those in the employment equation, just as they must when multi-factor productivity growth is proportional to output growth.

The "interaction effect" regressions also do a good job of characterizing the asymmetries in the data. They suggest that employment fluctuations are greatest in expansion peaks and contraction troughs. The level of output has opposite effects on the
derivatives of employment growth and hours growth with respect to output growth; once again, this must be the case if productivity growth is proportional to output growth.

I also simulate the behavior of aggregate employment, output, and hours growth with this model. I assume all firms face the same deterministic output cycle and possess the same technology, but hiring and firing costs differ across firms. For each of 300 firms, I draw hiring and firing cost parameters from a uniform distribution of integers between 0 and 300, simulate its behavior throughout the cycle, and then aggregate over all 300 firms to characterize aggregate fluctuations. In the aggregate, employment and hours growth move more smoothly through the cycle, as discrete changes in behavior at the micro-level are smoothed out in the aggregate.

The first two columns of Table 4A-2 report coefficients from regressions using this simulated aggregate data. The coefficients suggest a "smoother" relationship between employment and hours growth and output growth through the cycle. Except for an overestimate of employment growth in expansionary peaks, the aggregate simulations demonstrate a pattern of coefficients that closely matches the pattern estimated for non-agricultural employment in Table 4-7A.

Asymmetries in employment growth equations are associated with asymmetries in the opposite direction for the hours equation. It can be shown that this does not necessarily have to hold in the aggregate, even when there is no multi-factor productivity growth at the micro level. However, all simulations I have attempted thus far suggest that this is unlikely.

I also run simulations allowing for multi-factor productivity
growth that is not proportional to output growth. I make the
following assumptions:

(a) \( y(t) - y(t-1) = q_d + q_s + \epsilon_s(t) + \epsilon_d(t) \); output growth is determined
by trend demand \( (q_d) \) and productivity \( (q_s) \) growth, and is subject to
demand \( (\epsilon_d) \) and supply \( (\epsilon_s) \) shocks.

(b) \( \epsilon_s(t) = -z\omega*[(\sin(2\pi t/T) - \sin(2\pi(t-1)/T))] \)
\( \epsilon_d(t) = -z(1-\omega)*[(\sin(2\pi t/T) - \sin(2\pi(t-1)/T))] \)
Demand and supply shocks follow symmetric cycles, so that output
exhibits a symmetric growth cycle.

(c) \( g(t) = \text{multi-factor productivity growth} = \gamma q_s + \lambda_1 \epsilon_s \) for \( \epsilon_s > 0 \)
\( = \gamma q_s + \lambda_2 \epsilon_s \) for \( \epsilon_s < 0 \)
\( \lambda_1 > \lambda_2 \)
The assumption that \( \lambda_1 > \lambda_2 \) can be interpreted as follows: Supply
shocks are the result of changes in input costs or productivity.
Positive supply shocks are assumed to be more likely the result of
positive productivity disturbances than decreases in input costs,
while negative supply shocks are more often the result of increases in
input costs than decreases in factor productivity. Therefore,
detrended multi-factor productivity growth is greater in growth cycle
expansions than the absolute value of such growth in contractions.

Assumption (c) implies that \( g(t) \) does not move proportionally
with detrended output growth, so that asymmetries in the simulated
data now reflect factor substitution and fluctuations in productivity
growth.

I assume \( \omega = 0.5, \gamma = 0.5, \lambda_1 = 0.5, \lambda_2 = 0.1, \) and \( q_s = 0.005. \)
Given these parameters, I choose \( q_d \) so that there is no trend in
employment growth throughout the cycle. For all other parameters, I
use the baseline values described earlier.

The third and fourth columns of Tables 4A-1 and 4A-2 report
regression coefficients from simulated samples with these assumptions. Table 4A-2 aggregates 300 firms with identical output and productivity growth, but different hiring and firing costs. The main lesson from these regressions is that estimated asymmetries in the employment growth regression are met with asymmetries in the same direction for hours, even though factor substitution is prevalent. If asymmetries are in the same direction for hours and employment growth, it must be the case that productivity growth is not proportional to output growth, but this does not imply that factor substitution is not an important explanation for asymmetries. In fact, it can be shown that as $(\lambda_1 - \lambda_2)$ increases, it is more likely that hours asymmetries are of the same sign as employment asymmetries, even though factor substitution is also evident in the data.

As a final note, the pattern of estimates for employment growth in the aggregate regressions appears to match the pattern for non-agricultural employment in Table 4-7A fairly well.
1There are aspects of the model that are obviously unsatisfactory, in particular the assumption of myopic behavior of firms. However, the purpose of this exercise is to help clarify circumstances under which the specifications estimated in Section II provide powerful tests for asymmetries; the model is well-suited for this purpose. A separate goal of this research agenda is to characterize optimal factor substitution throughout cycles, but I consider this attempt as merely a first pass at identifying some of the issues involved.  

2This assumption is appropriate if all firms are constrained by demand conditions.  

3This result is easy to interpret by reference to Figure 4A-1. The firm begins each contraction at point A and decreases hours alone until point B is reached, at which time it starts hiring. The firm begins each expansion at point B, increasing hours alone until it reaches point A, at which point hiring is observed. Because output growth in each period from peak to trough is the absolute value of this growth from trough to peak, the firm reaches point A, N periods into the expansion, and point B, N periods into the contraction. The behavior of employment growth in contractions and expansions are mirror images in this model. Cutting the data by expansion and contraction does not allow one to identify this behavior; it is obvious, however, that cutting the data into the four regions of Figure 4-1 would capture this form of asymmetry.  

4I choose trend demand growth so that multi-factor productivity growth is equal to output growth from peak to peak in the cycle. Alternatively, I allow for a positive trend in employment by choosing a larger value for this trend. These simulations are available upon request.
APPENDIX 4-B: Skewness in input and output growth rates.

In this appendix, I report results of tests for asymmetries in growth rates of output and inputs in production using the methods of DeLong and Summers (1986) and Sichel (1987). DeLong and Summers (1986) and Neftci (1984) discuss the long tradition of viewing economic downturns as sharper and shorter in length than expansions. DeLong and Summers (1986) argue that a clear implication of this view of business cycles is that the distribution of growth rates of output should be significantly skewed. If expansions are gradual and contractions severe, the median output growth rate should exceed the mean.

DeLong and Summers (1986) calculate the coefficient of skewness, defined as the third centered moment divided by the cube of the standard deviation, for the distributions of U.S. GDP and industrial production growth rates for several different sample periods. They find little, if any, evidence of significant asymmetries in these output growth rates. However, confirming results obtained by Neftci (1984) using alternative statistical techniques, they find significant asymmetries in changes in the unemployment rate. The unemployment rate rises sharply during contractions, and decreases more gradually during expansions. Furthermore, they find that unemployment rate changes are skewed because employment growth rates exhibit significant skewness; changes in labor force participation rates are not significantly skewed.

In this chapter, I argue that the breakdown in Okun's Law suggested by the DeLong and Summers (1986) results can be explained by
factor substitution across business cycles, and/or by asymmetric movements in multi-factor productivity throughout the cycle. In the text, I propose a test for evaluating the relevance of the two competing explanations; if employment growth responds more to negative output movements than positive movements, then some other factor of production must exhibit an asymmetry in the opposite direction if factor substitution is important, and productivity movements are not. I use this same intuition to propose an alternative, non-parametric test for determining the sources of asymmetry in Okun's Law. If employment growth rates are negatively skewed, suggesting sharper contractions than expansions, then the growth rates of some other input of production must be positively skewed if factor substitution is important. It is apparent then that information on the distribution of output and input growth rates, including, but not limited to, employment growth rates, might be helpful in determining the plausibility of these alternative explanations. If employment is the only skewed factor, or if the distributions of most factor growth rates are skewed in the same direction, then the productivity shock explanations seem more appropriate. Alternatively, evidence of significant skewness in one or more factors in the opposite direction from employment supports the factor substitution models.

Table 4B-1 reports the mean, median, and skewness coefficients for quarterly growth rates in two alternative output measures, the change in the unemployment rate, and the growth rates of several factors of production for aggregate, seasonally adjusted post-war US data. I implement a bootstrap procedure suggested by Sichel (1987) to obtain standard errors for the skewness coefficients under the null.
hypothesis of symmetry. First, I estimate a third-order autoregressive process for each series of growth rates. I then use the estimated AR(3) models to generate three hundred simulations for the sample period, drawing with replacement from the estimated residuals from the original AR(3). I use the standard deviation of the skewnesses from these simulations as the bootstrap standard error for the null hypothesis of no skewness.

Table 4B-1 confirms results from Delong and Summers (1986) and Neftci (1984); growth rates of GNP and the industrial production index are not significantly skewed, while changes in the unemployment rate show marked asymmetry. The positive skewness coefficient for unemployment rates results from negative skewness in employment growth rate distributions. Total and production worker employment in non-agricultural establishments exhibit growth rate distributions suggesting sharper contractions than expansions. Non-production employment, however, shows no signs of asymmetry.

Is there any evidence of asymmetries in inputs of production that might be thought of as substitutes for payroll employment? Changes in capacity utilization rates are negatively skewed. Since the Federal Reserve defines capacity utilization figures as industrial production divided by capacity, this result, combined with symmetry in industrial production growth rates, implies that capacity growth is positively skewed. Utilization rates drop sharply in contractions because capacity responds sluggishly. It is unclear how to interpret this result, especially in light of recent work by Shapiro (1989) that documents conceptual and empirical problems with this capacity utilization series. The Federal Reserve's capacity estimates may in
general be reasonably good measures of production capabilities over long periods of time, but are not accurate indicators of short-term changes. In fact, Shapiro (1989) demonstrates that all the within-year variation in capacity utilization is the result of variation in industrial production. Theoretically, positive skewness in capacity growth rates, coupled with negative skewness in employment growth rates, is consistent with substitution of inputs in production across the cycle. However, Shapiro's (1989) paper suggests it would be unwise to consider this strong evidence in favor of substitution-based explanations for asymmetries in Okun's Law.

Data on hours and manhours growth, however, are somewhat consistent with these explanations. Growth rates of average weekly hours for all workers and industries, as tabulated by the Current Population Survey, are positively skewed; average weekly hours rise more sharply than they contract. The fact that growth rates of production worker hours are not skewed, however, works against this hypothesis, especially in light of the strong evidence of asymmetry in the distribution of production employment growth rates.

The manhours measure displays little asymmetry, which is also suggestive of input substitution. If employment growth rates are skewed, and manhours growth rates are symmetric, then hours growth rates must be skewed in the opposite direction of employment.

The manhours data also call into question the productivity-based explanations for asymmetries. Manhours growth rates should be negatively skewed if output growth rates are symmetric and productivity shocks are usually positive. The manhours results are also consistent with research by Falk (1986), who uses methods
introduced by Neftci (1984) to demonstrate that output per worker hour does not rise and fall asymmetrically over the cycle.

The above conclusions are tempered by evidence from the distributions of annual growth rates for the variables in Table 4B-1. GNP growth remains symmetric, total employment growth remains negatively skewed, and unemployment rate changes remain positively skewed, but hours per worker growth rates become almost completely symmetric. At the same time, annual growth rates in the Business Conditions Digest's measure of total employee hours have a skewness coefficient of -0.70, with an estimated standard error of 0.26. The hours/employment substitution suggested by quarterly data is not evident in annual data; at this frequency, productivity-based explanations appear more compelling.

This evidence might be consistent with a model that includes important roles for both productivity shocks and factor substitution. In higher frequency data, substitution of inputs due to costly adjustment of quasi-fixed factors might lead to short-run breakdowns in Okun's Law. Over time, however, quasi-fixed factors adjust more completely to changes in economic conditions, and substitution may not be as important in explaining unemployment rate asymmetries. In annual data, long-run movements in multi-factor productivity might be the driving force behind the documented asymmetries.
Under the null hypothesis of zero skewness, the estimated skewness of a set of \( n \) independent random normal observations is normally distributed with a standard error of the square root of \( (6/n) \). However, the growth rates considered here are not independent, showing substantial serial correlation, so that this formula is invalid.

I do not report the annual skewness coefficients in this chapter, but they are available from the author upon request.
FIGURES AND TABLES: CHAPTER 4
**REGION A**: Output above trend, output growth below trend.

**REGION B**: Output below trend, output growth below trend.

**REGION C**: Output below trend, output growth above trend.

**REGION D**: Output above trend, output growth above trend.
FIGURE 4-2: DETRENDED REAL GNP AND A SYMMETRIC CYCLE
FIGURE 4A-1: HIRING AND FIRING POINTS

A = HIRING POINT
B = FIRING POINT

WEEKLY HOURS PER WORKER
TABLE 4-1: EXPANSIONS VERSUS CONTRACTIONS, NO LAGS

Note: All regressions are of the form:

\[ \Delta X(t) = \alpha + \beta_0 \text{PGROW}(t) + \gamma_0 \text{NGROW}(t) + \epsilon(t) \]

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Notes: Standard errors in parentheses. All data are seasonally adjusted.

\(^a\)Quarterly data, 48:2-88:1. \(^b\)Quarterly data, 64:2-88:1.
\(^c\)Significance level for null hypothesis that positive and negative growth rates have symmetric effects.
\(^1\)UR: Civilian unemployment rate, ages 16 and over.
\(^2\)Non-Ag. Emp.: Non-agricultural payroll employment (natural log).
\(^3\)Prod. Emp.: Non-agricultural production worker employment (natural log).
\(^4\)Non-Prod. Emp.: Non-agricultural non-production worker employment (natural log).
### Table 4-2: Expansions versus Contractions, Lags

Note: All regressions are of the form:

\[
\Delta X(t) = \alpha + \sum_{1=0}^{2} \beta \cdot \text{PGROW}(t-1) + \sum_{1=0}^{2} \gamma \cdot \text{NGROW}(t-1) + \epsilon(t)
\]

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\[
H_0: \sum_{1=0}^{2} \beta = \sum_{1=0}^{2} \gamma \approx .000 .001 .000 .002
\]

\[
\bar{R}^2\] .74 .72 .77 .14

Notes: Standard errors in parentheses. All data are seasonally adjusted. See Table 4-1 for variable definitions.

\textsuperscript{a}Quarterly data, 48:4-88:1.

\textsuperscript{b}Quarterly data, 64:2-88:1.

\textsuperscript{c}Significance level for null hypothesis that positive and negative growth rates have symmetric effects.
TABLE 4-3: FOUR REGIONS, NO LAGS

Note: All regressions are of the form:
\[ \Delta X(t) = \alpha + \beta_0 \text{PGRGROW}(t) + \gamma_0 \text{NGGROW}(t) + \delta_0 \text{PBGRGROW}(t) + \phi_0 \text{NBGRGROW}(t) + \epsilon(t) \]

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Notes: Standard errors in parentheses. All data are seasonally adjusted. See Table 4-1 for variable definitions.

\(^a\)Quarterly data, 48:2-88:1.  \(^b\)Quarterly data, 64:2-88:1.
\(^c\)Significance level for null hypothesis given by row heading.
### Table 4-4: Four Regions, Lags

Note: All regressions are of the form:

\[
\Delta X(t) = \alpha + \sum_{i=0}^{2} \beta_i \text{PGROW}(t-1) + \sum_{i=0}^{2} \gamma_i \text{NGROW}(t-1) + \sum_{i=0}^{2} \delta_i \text{PBCROW}(t-1) + \sum_{i=0}^{2} \phi_i \text{NBCROW}(t-1) + \epsilon(t)
\]

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Notes: All data are seasonally adjusted. See Table 4-1 for variable definitions.

*aQuarterly data, 48:4-88:1.  
*bQuarterly data, 64:2-88:1.  
*cSignificance level for null hypothesis given by row heading.
TABLE 4-5: EXPANSIONS VERSUS CONTRACTIONS, NO LAGS

Note: All regressions are of the form:
\[ \Delta X(t) = \alpha + \beta_0 \text{PGROW}(t) + \gamma_0 \text{NGROW}(t) + \epsilon(t) \]

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<td>(.10)</td>
<td>(.21)</td>
</tr>
<tr>
<td>(\gamma_0)</td>
<td>.18(^{*})</td>
<td>.21(^{*})</td>
<td>.78(^{*})</td>
<td>1.72(^{*})</td>
</tr>
<tr>
<td></td>
<td>(.08)</td>
<td>(.05)</td>
<td>(.09)</td>
<td>(.20)</td>
</tr>
<tr>
<td>(H_0: \beta_0 = \gamma_0)</td>
<td>.90(^{*})</td>
<td>.82(^{*})</td>
<td>.22(^{*})</td>
<td>.01(^{*})</td>
</tr>
<tr>
<td>(R^2)</td>
<td>.09</td>
<td>.37</td>
<td>.54</td>
<td>.64</td>
</tr>
</tbody>
</table>

Notes: Standard errors in parentheses. All data are seasonally adjusted.

\(^a\)Quarterly data, 48:2-88:1. \(^b\)Quarterly data, 64:2-88:1.
\(^c\)Quarterly data, 67:2-88:1.
\(^d\)Significance level for null hypothesis that positive and negative growth rates have symmetric effects.
\(^1\)HRS: Avg. hours worked weekly, all workers and industries, CPS Survey.
\(^2\)PRODHRS: Avg. hours worked weekly, production workers, private non-agricultural industries, Establishment Survey.
\(^3\)MANHRS: Total employee hours worked in non-agricultural establishments, Business Conditions Digest.
\(^4\)CU: Capacity utilization rate, total industry, Federal Reserve Board.
TABLE 4-6: EXPANSIONS VERSUS CONTRACTIONS, LAGS

Note: All regressions are of the form:

\[
\Delta X(t) = \alpha + \sum_{i=0}^{2} \beta_i \text{PGROW}(t-1) + \sum_{i=0}^{2} \gamma_i \text{NGROW}(t-1) + \epsilon(t)
\]

<table>
<thead>
<tr>
<th></th>
<th>HRS\textsuperscript{a}</th>
<th>PRODHR\textsuperscript{b}</th>
<th>MANHR\textsuperscript{a}</th>
<th>CU\textsuperscript{c}</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\beta_0)</td>
<td>.25</td>
<td>.18</td>
<td>.50</td>
<td>.72</td>
</tr>
<tr>
<td></td>
<td>(.10)</td>
<td>(.05)</td>
<td>(.09)</td>
<td>(.19)</td>
</tr>
<tr>
<td>(\beta_1)</td>
<td>-.18</td>
<td>.03</td>
<td>.14</td>
<td>.07</td>
</tr>
<tr>
<td></td>
<td>(.10)</td>
<td>(.05)</td>
<td>(.09)</td>
<td>(.19)</td>
</tr>
<tr>
<td>(\beta_2)</td>
<td>-.02</td>
<td>-.04</td>
<td>.11</td>
<td>.27</td>
</tr>
<tr>
<td></td>
<td>(.10)</td>
<td>(.05)</td>
<td>(.09)</td>
<td>(.19)</td>
</tr>
<tr>
<td>(\gamma_0)</td>
<td>.17</td>
<td>.26</td>
<td>.64</td>
<td>1.60</td>
</tr>
<tr>
<td></td>
<td>(.09)</td>
<td>(.05)</td>
<td>(.08)</td>
<td>(.18)</td>
</tr>
<tr>
<td>(\gamma_1)</td>
<td>.12</td>
<td>.12</td>
<td>.51</td>
<td>.76</td>
</tr>
<tr>
<td></td>
<td>(.09)</td>
<td>(.05)</td>
<td>(.08)</td>
<td>(.18)</td>
</tr>
<tr>
<td>(\gamma_2)</td>
<td>.06</td>
<td>-.18</td>
<td>.03</td>
<td>-.05</td>
</tr>
<tr>
<td></td>
<td>(.09)</td>
<td>(.05)</td>
<td>(.08)</td>
<td>(.18)</td>
</tr>
</tbody>
</table>

\[H_0 : \sum_{i=0}^{2} \beta_i = \sum_{i=0}^{2} \gamma_i = .21\]

<p>| | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>(H_0)</td>
<td>.81</td>
<td>.04</td>
<td>.02</td>
<td></td>
</tr>
<tr>
<td>(R^2)</td>
<td>.09</td>
<td>.50</td>
<td>.69</td>
<td>.72</td>
</tr>
</tbody>
</table>

Notes: Standard errors in parentheses. All data are seasonally adjusted. See Table 4-5 for variable definitions.

\textsuperscript{a}Quarterly data, 48:4-88:1. \textsuperscript{b}Quarterly data, 64:2-88:1.

\textsuperscript{c}Quarterly data, 67:2-88:1.

\textsuperscript{d}Significance level for null hypothesis that positive and negative growth rates have symmetric effects.
TABLE 4-7A: FOUR REGIONS, LAGS, FOUR CONSTANTS

Note: All regressions are of the form:

\[ \Delta X(t) = PG(t) + NG(t) + PB(t) + NB(t) + \sum_{i=0}^{2} \beta_{i} PGGROW(t-i) + \sum_{i=0}^{2} \gamma_{i} NGGROW(t-i) + \sum_{i=0}^{2} \delta_{i} PBGROW(t-i) + \sum_{i=0}^{2} \phi_{i} NBGROW(t-i) + \epsilon(t) \]

<table>
<thead>
<tr>
<th></th>
<th>UR*</th>
<th>Non-Ag. Emp.*</th>
<th>Prod. Emp. b</th>
<th>Non-Prod. Emp. b</th>
</tr>
</thead>
<tbody>
<tr>
<td>2 \sum_{i=0}^{2} \beta_{i}</td>
<td>-.14</td>
<td>.36</td>
<td>.58</td>
<td>.06</td>
</tr>
<tr>
<td>2 \sum_{i=0}^{2} \gamma_{i}</td>
<td>-.52</td>
<td>.75</td>
<td>.53</td>
<td>-.18</td>
</tr>
<tr>
<td>2 \sum_{i=0}^{2} \delta_{i}</td>
<td>-.45</td>
<td>.89</td>
<td>.62</td>
<td>-.08</td>
</tr>
<tr>
<td>2 \sum_{i=0}^{2} \phi_{i}</td>
<td>-.72</td>
<td>1.20</td>
<td>1.64</td>
<td>.40</td>
</tr>
<tr>
<td>( H_{0}: \sum \beta_{i} = \sum \gamma_{i} )</td>
<td>.03</td>
<td>.21</td>
<td>.90</td>
<td>.65</td>
</tr>
<tr>
<td>( H_{0}: \sum \delta_{i} = \sum \phi_{i} )</td>
<td>.01</td>
<td>.09</td>
<td>.001</td>
<td>.14</td>
</tr>
<tr>
<td>( H_{0}: \sum \beta_{i} = \sum \delta_{i} )</td>
<td>.01</td>
<td>.01</td>
<td>.86</td>
<td>.65</td>
</tr>
<tr>
<td>( H_{0}: \sum \gamma_{i} = \sum \phi_{i} )</td>
<td>.14</td>
<td>.09</td>
<td>.01</td>
<td>.20</td>
</tr>
<tr>
<td>( R^{2} )</td>
<td>.76</td>
<td>.75</td>
<td>.79</td>
<td>.19</td>
</tr>
</tbody>
</table>

Notes: All data are seasonally adjusted. See Table 4-1 for variable definitions.
Significance level for null hypothesis given by row heading.
### TABLE 4-78: FOUR REGIONS, LAGS, FOUR CONSTANTS

Note: All regressions are of the form:

\[
\Delta X(t) = PG(t) + NG(t) + PB(t) + NB(t) + \sum_{1=0}^{2} \beta_i P GROW(t-1) + \sum_{1=0}^{2} \gamma_i N GROW(t-1) + \sum_{1=0}^{2} \delta_i P B GROW(t-1) + \sum_{1=0}^{2} \phi_i N B GROW(t-1) + \epsilon(t)
\]

<table>
<thead>
<tr>
<th>(X)</th>
<th>HRS(^a)</th>
<th>PRODHIRS(^b)</th>
<th>MANHRS(^a)</th>
<th>CU(^c)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\sum_{1=0}^{2} \beta_i)</td>
<td>-.01</td>
<td>.33</td>
<td>.55</td>
<td>1.58</td>
</tr>
<tr>
<td>(\sum_{1=0}^{2} \gamma_i)</td>
<td>.47</td>
<td>.27</td>
<td>.97</td>
<td>2.03</td>
</tr>
<tr>
<td>(\sum_{1=0}^{2} \delta_i)</td>
<td>.22</td>
<td>.08</td>
<td>1.18</td>
<td>.97</td>
</tr>
<tr>
<td>(\sum_{1=0}^{2} \phi_i)</td>
<td>.50</td>
<td>.36</td>
<td>1.41</td>
<td>2.84</td>
</tr>
<tr>
<td>(H_0: \Sigma \beta_1 = \Sigma \gamma_1)</td>
<td>.34</td>
<td>.83</td>
<td>.31</td>
<td>.69</td>
</tr>
<tr>
<td>(H_0: \Sigma \beta_1 = \Sigma \delta_1)</td>
<td>.35</td>
<td>.11</td>
<td>.35</td>
<td>.01</td>
</tr>
<tr>
<td>(H_0: \Sigma \beta_1 = \Sigma \phi_1)</td>
<td>.47</td>
<td>.14</td>
<td>.02</td>
<td>.37</td>
</tr>
<tr>
<td>(H_0: \Sigma \gamma_1 = \Sigma \phi_1)</td>
<td>.94</td>
<td>.70</td>
<td>.18</td>
<td>.40</td>
</tr>
<tr>
<td>(R^2)</td>
<td>.06</td>
<td>.53</td>
<td>.72</td>
<td>.75</td>
</tr>
</tbody>
</table>

Notes: All data are seasonally adjusted. See Table 4-5 for variable definitions.

\(^a\)Quarterly data, 48:4-88:1. \(^b\)Quarterly data, 64:2-88:1.

\(^c\)Quarterly data, 67:2-88:1.

\(^d\)Significance level for null hypothesis given by row heading.
TABLE 4-8A: INTERACTION EFFECTS

Note: All regressions are of the form:
\[ \Delta X(t) = \alpha + \beta_0 PGROW(t) + \gamma_0 NGROW(t) + \psi_0 PGLGROW(t) + \theta_0 NGLGROW(t) + c(t) \]

<table>
<thead>
<tr>
<th></th>
<th>UR (^a)</th>
<th>Non-Ag. Emp. (^a)</th>
<th>Prod. Emp. (^b)</th>
<th>Non-Prod. Emp. (^b)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \beta_0 )</td>
<td>-.24</td>
<td>.42</td>
<td>.36</td>
<td>.002</td>
</tr>
<tr>
<td></td>
<td>(.05)</td>
<td>(.08)</td>
<td>(.10)</td>
<td>(.09)</td>
</tr>
<tr>
<td>( \gamma_0 )</td>
<td>-.30</td>
<td>.40</td>
<td>.41</td>
<td>-.03</td>
</tr>
<tr>
<td></td>
<td>(.05)</td>
<td>(.09)</td>
<td>(.11)</td>
<td>(.10)</td>
</tr>
<tr>
<td>( \psi_0 )</td>
<td>.42</td>
<td>5.13</td>
<td>6.17</td>
<td>10.80</td>
</tr>
<tr>
<td></td>
<td>(1.55)</td>
<td>(2.69)</td>
<td>(3.84)</td>
<td>(3.39)</td>
</tr>
<tr>
<td>( \theta_0 )</td>
<td>4.38</td>
<td>-10.62</td>
<td>-21.78</td>
<td>-8.86</td>
</tr>
<tr>
<td></td>
<td>(1.44)</td>
<td>(2.50)</td>
<td>(3.70)</td>
<td>(3.27)</td>
</tr>
</tbody>
</table>

\( H_0: \beta_0 = \gamma_0 \)
and \( \psi_0 = \theta_0 \)

\[ \bar{R}^2 \] | .55 | .54 | .64 | .15 |

Notes: Standard errors in parentheses. All data are seasonally adjusted. See Table 4-1 for variable definitions.

\(^a\)Quarterly data, 48:2-88:1. \(^b\)Quarterly data, 64:2-88:1. \(^c\)Significance level for null hypothesis given by row heading.
### TABLE 4-8B: INTERACTION EFFECTS

Note: All regressions are of the form:

\[ \Delta X(t) = \alpha + \beta_0 \text{PGROW}(t) + \gamma_0 \text{NGROW}(t) + \psi_0 \text{PLGROW}(t) + \theta_0 \text{NLGROW}(t) + \epsilon(t) \]

<table>
<thead>
<tr>
<th>X</th>
<th>HRS(^a)</th>
<th>PRODHRS(^b)</th>
<th>MANHRS(^a)</th>
<th>CU(^c)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\beta_0)</td>
<td>.21</td>
<td>.24</td>
<td>.63</td>
<td>.98</td>
</tr>
<tr>
<td></td>
<td>(.09)</td>
<td>(.06)</td>
<td>(.10)</td>
<td>(.21)</td>
</tr>
<tr>
<td>(\gamma_0)</td>
<td>.18</td>
<td>.20</td>
<td>.57</td>
<td>1.28</td>
</tr>
<tr>
<td></td>
<td>(.11)</td>
<td>(.06)</td>
<td>(.11)</td>
<td>(.23)</td>
</tr>
<tr>
<td>(\psi_0)</td>
<td>1.93</td>
<td>-1.45</td>
<td>3.22</td>
<td>-9.89</td>
</tr>
<tr>
<td></td>
<td>(3.12)</td>
<td>(2.17)</td>
<td>(3.32)</td>
<td>(7.75)</td>
</tr>
<tr>
<td>(\theta_0)</td>
<td>.05</td>
<td>-.41</td>
<td>-8.86</td>
<td>-23.23</td>
</tr>
<tr>
<td></td>
<td>(2.91)</td>
<td>(2.09)</td>
<td>(3.09)</td>
<td>(7.52)</td>
</tr>
</tbody>
</table>

\(H_0: \beta_0 = \gamma_0\)

and \(\psi_0 = \theta_0\)

\(R^2\) | .08       | .36            | .56          | .67     |

Notes: Standard errors in parentheses. All data are seasonally adjusted. See Table 4-5 for variable definitions.

\(^a\)Quarterly data, 48:4-88:1. \(^b\)Quarterly data, 64:2-88:1.

\(^c\)Quarterly data, 67:2-88:1.

\(^d\)Significance level for null hypothesis given by row heading.
## TABLE 4A-1: BASELINE SIMULATIONS, REPRESENTATIVE FIRM

### EXPANSIONS VS. CONTRACTIONS, NO LAGS

<table>
<thead>
<tr>
<th></th>
<th>No Productivity Shocks</th>
<th>Productivity Shocks</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\Delta E$</td>
<td>$\Delta H$</td>
</tr>
<tr>
<td>PGROW</td>
<td>1.11</td>
<td>.91</td>
</tr>
<tr>
<td>NGROW</td>
<td>1.11</td>
<td>.91</td>
</tr>
</tbody>
</table>

### FOUR REGIONS, NO LAGS, FOUR CONSTANTS

<table>
<thead>
<tr>
<th></th>
<th>PGROW</th>
<th>.00</th>
<th>2.17</th>
<th>.91</th>
<th>.62</th>
</tr>
</thead>
<tbody>
<tr>
<td>NGROW</td>
<td>.07</td>
<td>1.79</td>
<td>.00</td>
<td>1.76</td>
<td></td>
</tr>
<tr>
<td>PBGROW</td>
<td>.07</td>
<td>1.79</td>
<td>.00</td>
<td>1.39</td>
<td></td>
</tr>
<tr>
<td>NGBGROW</td>
<td>2.17</td>
<td>.00</td>
<td>1.34</td>
<td>.62</td>
<td></td>
</tr>
</tbody>
</table>

### INTERACTION EFFECTS

<table>
<thead>
<tr>
<th></th>
<th>PGROW</th>
<th>1.04</th>
<th>.95</th>
<th>1.04</th>
<th>.50</th>
<th>.96</th>
</tr>
</thead>
<tbody>
<tr>
<td>NGROW</td>
<td>.95</td>
<td>1.04</td>
<td>.72</td>
<td>1.15</td>
<td></td>
<td></td>
</tr>
<tr>
<td>PLGROW</td>
<td>9.27</td>
<td>-7.90</td>
<td>7.45</td>
<td>-6.34</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NLGROW</td>
<td>-9.27</td>
<td>7.90</td>
<td>-7.52</td>
<td>6.41</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

1 Coefficients from regressions on simulated data as in Tables 4-1 and 4-5.
2 Coefficients from regressions on simulated data as in Tables 4-7A and 4-7B.
3 Coefficients from regressions on simulated data as in Tables 4-8A and 4-8B.
4 Simulation assumes no factor productivity growth.
5 Simulation assumes positive factor productivity growth, but no trend in employment. See text for details.
### TABLE 4A-2: BASELINE SIMULATIONS, AGGREGATE

#### EXPANSIONS VS. CONTRACTIONS, NO LAGS

<table>
<thead>
<tr>
<th></th>
<th>No Productivity Shocks</th>
<th>Productivity Shocks</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>AE</td>
<td>AH</td>
</tr>
<tr>
<td>PGROW</td>
<td>1.20</td>
<td>.84</td>
</tr>
<tr>
<td>NGROW</td>
<td>1.22</td>
<td>.82</td>
</tr>
</tbody>
</table>

#### FOUR REGIONS, NO LAGS, FOUR CONSTANTS

<p>| | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>PCCGROW</td>
<td>1.56</td>
<td>.53</td>
<td>.85</td>
<td>.68</td>
</tr>
<tr>
<td>NGROW</td>
<td>1.16</td>
<td>.87</td>
<td>.78</td>
<td>1.10</td>
</tr>
<tr>
<td>PBGROW</td>
<td>1.10</td>
<td>.93</td>
<td>.69</td>
<td>.81</td>
</tr>
<tr>
<td>NBCGROW</td>
<td>1.55</td>
<td>.55</td>
<td>1.20</td>
<td>.75</td>
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</tbody>
</table>

#### INTERACTION EFFECTS

<p>| | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>PGROW</td>
<td>1.09</td>
<td>.93</td>
<td>.64</td>
<td>.85</td>
</tr>
<tr>
<td>NGROW</td>
<td>1.12</td>
<td>.90</td>
<td>.87</td>
<td>1.02</td>
</tr>
<tr>
<td>PLGROW</td>
<td>6.45</td>
<td>-5.51</td>
<td>4.85</td>
<td>-4.13</td>
</tr>
<tr>
<td>NLGROW</td>
<td>-6.05</td>
<td>5.12</td>
<td>-4.65</td>
<td>3.91</td>
</tr>
</tbody>
</table>

1. Coefficients from regressions on simulated data as in Tables 4-1 and 4-5.
2. Coefficients from regressions on simulated data as in Tables 4-7A and 4-7B.
3. Coefficients from regressions on simulated data as in Tables 4-8A and 4-8B.
4. Simulation assumes no factor productivity growth.
5. Simulation assumes positive factor productivity growth, but no trend in employment. See text for details.
<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Median</th>
<th>Skewness</th>
<th>Bootstrap Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>GNP(^{b,1})</td>
<td>.0080</td>
<td>.0089</td>
<td>-.20</td>
<td>.27</td>
</tr>
<tr>
<td>Ind. Prod.(^{b,2})</td>
<td>.0094</td>
<td>.0105</td>
<td>-.35</td>
<td>.24</td>
</tr>
<tr>
<td>Non-Ag Emp.(^{b,3})</td>
<td>.0053</td>
<td>.0087</td>
<td>-.57</td>
<td>.26</td>
</tr>
<tr>
<td>Prod. Emp.(^{c,4})</td>
<td>.0058</td>
<td>.0070</td>
<td>-1.41</td>
<td>.39</td>
</tr>
<tr>
<td>Non-Prod. Emp.(^{c,5})</td>
<td>.0070</td>
<td>.0074</td>
<td>-.18</td>
<td>.35</td>
</tr>
<tr>
<td>Hours(^{b,8})</td>
<td>-.00055</td>
<td>-.00085</td>
<td>.42</td>
<td>.27</td>
</tr>
<tr>
<td>Prod. Hrs.(^{c,7})</td>
<td>-.0012</td>
<td>-.0017</td>
<td>.09</td>
<td>.29</td>
</tr>
<tr>
<td>Manhours(^{b,8})</td>
<td>.0046</td>
<td>.0058</td>
<td>-.28</td>
<td>.21</td>
</tr>
<tr>
<td>UR(^{d,9})</td>
<td>.0119</td>
<td>-.0333</td>
<td>.97</td>
<td>.25</td>
</tr>
<tr>
<td>Cap. Util.(^{8,10})</td>
<td>-.0584</td>
<td>.1667</td>
<td>-1.21</td>
<td>.37</td>
</tr>
</tbody>
</table>

\(^{a}\)Calculated from bootstrap method described in text.

\(^{b}\)All data quarterly, 48:1-88:1.

\(^{c}\)All data quarterly, 65:1-88:1.

\(^{d}\)All data quarterly, 49:1-88:1.

\(^{1}\)All data quarterly, 68:1-88:1.

\(^{1}\)GNP: Real GNP in 1982 dollars.

\(^{2}\)Ind. Prod.: Industrial production index.

\(^{3}\)Non-Ag Emp.: Non-agricultural payroll employment.

\(^{4}\)Prod. Emp.: Non-agricultural production workers employment.

\(^{5}\)Non-Prod. Emp.: Non-agricultural non-production workers employment.

\(^{6}\)Hours: Average hours worked weekly, all workers and industries, CPS.

\(^{7}\)Prod. Hrs: Average hours worked weekly, production workers, private non-agricultural industries.

\(^{8}\)Manhours: Total employee hours worked in non-agricultural establishments, Business Conditions Digest.

\(^{8}\)UR: Civilian unemployment rate, ages 16 and over.

\(^{10}\)Cap. Util.: Capacity utilization rate, total industry.

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REFERENCES FOR CHAPTER 4


