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AN ANALYSIS OF U.S. LABOR VACANCY RATES USING A HELP-WANTED ADVERTISING PROXY

by

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All conclusions and errors in this thesis are my sole responsibility.

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(Order No.)

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Abstract

Job vacancies, a measure of labor demand, are an important but underutilized tool for solving research problems in labor economics. Using the volume of help-wanted advertising as a proxy for the number of job vacancies in the United States, this dissertation consists of three essays which examine the relation between vacancies and other macroeconomic and labor market indicators.

Beginning with an examination of the national Beveridge Curve, which relates unemployment rates to job vacancies over the business cycle, the first essay reassesses previous findings that the Beveridge curve shifted outward during the post World War II period. Outward shifts indicate an increased number of job openings per unemployed person suggesting dramatic changes in the labor market's structure.

When the help-wanted proxy is corrected for changes in advertising readership and price, the Beveridge curve is shown to be stable. Hence, outward Beveridge curve shifts are only an artifact of underlying advertising changes that were omitted in previous models.

The second essay examines whether sectoral shifts or aggregate demand shocks have been the primary cause of cyclical swings in U.S. unemployment. Results from previous empirical studies are clearly divided over the answer. Two competing lines of research are reinvestigated using the vacancy proxy. Results show that correcting the vacancy proxy for price and readership changes reconciles both lines of previous research and reveals that both now support aggregate demand shocks as the primary factor underlying cyclical unemployment.

Lastly, the third essay examines the effect of unemployment insurance on job vacancies. While substantial research has examined unemployment insurance's effect on unemployment rates, there has been scant investigation into the effects of this important program on job vacancies.

Tests on national data indicate that the level of unemployment insurance contributions is positively correlated with the job vacancy rate, holding unemployment rates constant. Additionally, the level of unemployment insurance benefits is negatively correlated with the job vacancy rate. Combining these two effects results in a small decrease in vacancies which is a previously undocumented impact of unemployment insurance on the labor market.

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Chapter I

INTRODUCTION

Most macroeconomic empirical research on the labor market has ignored job vacancy rates because direct data are unavailable. Job vacancies are important because each unfilled vacancy represents idle capital which is not producing goods and services for society.

This thesis, composed of three essays, investigates and improves the best proxy available for vacancies and uses it to refute arguments that the labor market's structure has changed, to examine the causes of cyclical unemployment, and to investigate the effects of unemployment insurance on labor markets.

Combining vacancy data with unemployment data presents a more complete picture of the national labor market than looking at either indicator alone. For example, rising unemployment with falling vacancy rates suggest the economy is not producing enough jobs. Rising unemployment with rising vacancy rates suggest a mismatch between job seekers and current openings.

The standard labor market model which combines unemployment and vacancy information is called a Beveridge curve. As this thesis will be examining vacancies as they relate to unemployment, a description of Beveridge curves is useful here. This model is named after Lord William

Beveridge because of his 1909 treatise entitled Unemployment: A Problem Of Industry.[1]

Since that first connection between unemployment and vacancies Beveridge curves have been analyzed graphically (Dow & Dicks-Mireaux 1958), theoretically (Holt & David 1966, Hansen 1970, Pissarides 1985 & 1987) and empirically (Medoff 1983, Abraham 1987, Blanchard & Diamond 1989).

All this research assumes there is a stable relation between unemployment and vacancies. This assumption is borne out by examining Beveridge curves from different countries and time periods which consistently reveal a downward sloping curve.

One explanation for this regularity is that *temporary* changes in business conditions induce firms to temporarily modify their levels of employment. During business cycle upturns it is profitable for firms to increase output by hiring more workers, hence vacancies increase and unemployment decreases. During business cycle downturns increased output is no longer profitable and jobs need to be eliminated. This reduction in employment means vacancies fall and unemployment increases. Hence, plotting these trends results in a downward sloping curve.

Many researchers also have documented inward or outward shifts over time. One explanation is that these shifts are due to *any permanent* changes in the labor market.

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[1]This book stressed that a main reason for unemployment was the way industries hired workers. Unemployment was the by-product of firms' attempts to create pools of idle laborers from which any unanticipated vacancy could be filled immediately.

Demographic changes are one of many potential reasons for shifts. Examining disaggregated unemployment data shows different unemployment rates for workers with different demographic characteristics. This occurs because some demographic groups have stronger work force attachments than others. Since different types of workers have different unemployment rates, significantly changing the labor force proportion of each group causes a shift.[2]

Another potential reason for shifts are changes in the amount of time needed to match jobs with workers. Shifts occur when workers' skills do not match firms' needs or workers change the minimum wage they are willing to accept. In both these cases the duration of each unemployment spell and the duration of each open vacancy increases, causing an outward shift.

There have been many changes such as energy price shocks, rising Japanese and German competition, and the shift toward a service economy that have affected the United States macroeconomy over the past forty years. Empirical research using Beveridge curves can potentially show if these and other changes have altered the way U.S. labor markets work.

Unfortunately, the major impediment to empirical research on U.S. Beveridge curves has been the lack of vacancy data. Since no government or private organization *directly* tracks the number of vacant jobs, indirect proxies need to be used.

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[2]For example, if there are older workers with low unemployment rates and teenagers with high rates, increasing the proportion of teenagers pushes the curve outward because overall unemployment rates increase while vacancy rates are unchanged. Conversely, increasing the proportion of older workers shifts the curve inward because overall unemployment rates fall.

The best vacancy proxy is the Conference Board's help-wanted index, based on help-wanted ads published in major U.S. newspapers.[3] To ensure researchers understand this proxy the Conference Board has published two monographs (Conf. Board 1965, Preston 1977) that explain the index's[4] construction, weighting, values and characteristics over the U.S. business cycle.

Even with this information, many authors express concern that the index is not a good vacancy proxy. The best critique (Solow 1983) compiled a long list of potential problems and highlighted the effects advertising price changes could have on the index. The first essay presented here answers many of the questions posed in the critique.

This first essay asks *can shifty Beveridge curves be trusted?* It questions outward shifts in the U.S. national Beveridge curve that were documented by previous research. These shifts are suspect since they could either reflect permanent changes in the labor market or changes in the underlying help-wanted proxy. Three approaches investigate what has caused the shifts.

First, direct vacancy surveys based on responses from industries manufacturing durable and nondurable goods are used to see if they provide a better indicator than the indirect proxy. Secondly, an

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[3]A number of papers have examined alternative proxies, such as data from private recruitment services (Conant 1966) or data from job openings registered at the Employment Service (Chavrid and Kuptzin 1966). These proxies are found to be poor vacancy measures.

[4]The index was started in the early 1920's at Brown University by Berridge (1955) in an attempt to understand the connection between business cycles and hiring. Compilation of this index was assumed by the Metropolitan Life Insurance company and finally, in 1951, passed to the Conference Board.

alternative help-wanted index based on the size of ads, instead of the number of ads, is constructed to ensure shifts are not the result of the way the proxy is measured.

Lastly, the original help-wanted proxy is corrected for changes in advertising readership and price. Significantly, this last approach leads to a stable Beveridge curve, indicating previous research has mistakenly found shifts because it omitted important variables.

The second essay builds on the results of the first by investigating the cause of cyclical unemployment. Two different theories compete to explain cyclical swings in U.S. unemployment: sectoral shifts and aggregate demand shocks.

Sectoral shifts cause unemployment by shifting demand from one sector of the economy to another while aggregate shocks cause unemployment by lowering demand in all sectors. Previous work (Abraham and Katz 1986) shows that the theories can be distinguished by examining unemployment and vacancies together.

This essay investigates the problem in two ways. First, it checks if correcting the vacancy proxy for changes in price and readership influences the previous results. This first test shows that using the corrected proxy supports aggregate demand changes as the primary cause of cyclical unemployment in the economy.

Secondly, it checks if using a stock market measure of demand shifts provides different results than using the standard labor market measure. The stock market measure is interesting because previous empirical work has used it to show that sectoral shifts are the cause of unemployment. Additionally, stock market data are potentially superior

because they should only capture permanent demand changes unlike the labor market measure which captures both permanent and temporary trends.

Tests using the uncorrected vacancy proxy with the stock market measure support sectoral shifts. However, correcting the vacancy proxy for price and readership trends reverses this result and supports aggregate demand changes as the primary cause of cyclical unemployment in the economy. This reversal shows the importance of removing nonlabor market information from the vacancy proxy.

The third essay investigates the effects of unemployment insurance on labor markets. Unemployment insurance potentially changes the behavior of unemployed workers by altering their job search intensity and unemployment duration. Unemployment insurance also potentially affects firms' employment decisions by changing the cost of employing and laying off workers.

Tests on national data indicate that the level of unemployment insurance contributions is positively correlated with the job vacancy rate, holding unemployment rates constant. Additionally, the level of unemployment insurance benefits is negatively correlated with the job vacancy rate. Combining these two effects results in a small decrease in vacancies.

To summarize, correcting the proxy for job vacancies leads to a stable Beveridge curve for the U.S. between 1951 and 1989, refuting previous claims of structural change in the labor market. This corrected vacancy proxy strongly supports aggregate demand shocks as the primary cause of cyclical unemployment. Finally, compiling corrected vacancy data for the U.S. uncovers the previously unexplored impact of

unemployment insurance: contributions increase vacancies at each rate of unemployment while benefits decrease vacancies.

Chapter II

National Beveridge Curves

Empirical research into Beveridge curves, a labor market model which connects unemployment and job vacancies, has shown outward shifts over the last forty years. Some authors attribute such outward movements to increasing skill shortages;(Medoff 1983) others to sectoral shifts in employment.(Blanchard and Diamond 1989) No matter what interpretation is claimed, the fundamental assumption underlying the entire debate is *that Beveridge curves have really shifted*. If shifts did not happen, the debate is inconsequential.

This paper asks, *can shifty Beveridge curves be trusted*? Beveridge curve shifts are suspect since they are not based on direct measures of vacancies but on a proxy, the Conference Board Help-Wanted Advertising Index (HWI). This chapter presents three different approaches to check for shifts. First, to ensure that shifts are not due to using a faulty proxy, a Beveridge curve based on vacancies directly measured in U.S. manufacturing is constructed. This neither confirms nor refutes previous claims, suggesting the need for further research.

Secondly, to ensure that shifts are not a result of measuring help-wanted ads improperly, an alternative help-wanted index based on the size of help-wanted ads is developed. This new index shows even stronger outward shifts suggesting shifts are not due to improper measurement.

Lastly, Beveridge curve shifts are suspect because the HWI proxy is not corrected for changes in readership and price, which effect advertising demand. Significantly, using data to correct the HWI results in a *stable* Beveridge curve. This last approach demonstrates that Beveridge curves have not really shifted. Shifts appeared because of a change in advertising demand, not change in the labor market.

I. Beveridge Curve: Unemployment-Vacancy Relationship

Researchers call the relation between unemployment and vacancy rates the Beveridge curve.[1] This curve is downward sloping, based on the assumption that frictions cause lags in matching workers and job openings. Holding friction constant, the curve slopes downward because when the aggregate economy is in an expansionary period there are high levels of vacancies and low unemployment. Conversely, during recessionary periods, there are low vacancies and high unemployment.

Movements along the curve are caused by changes in the business cycle, while inward or outward shifts in the curve are due to frictional and structural changes. Increases in friction, such as obsolescence of workers' skills, cause the curve to shift outwards. Conversely, decreases in friction, such as improvements in the placement efficiency of the Employment Service, shift the curve inward. Analytically the curve is described by:

1) $V_t = a_1 + a_2 U_t + a_3 F_t + e_t$

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[1]Named after Lord William Beveridge, who published the book Unemployment: A Problem Of Industry in 1909, which first discussed the relationship of vacancies and unemployment.

Where V_t is the vacancy rate in time period t, U_t is the unemployment rate, and F_t is a set of variables describing the types of labor market friction. The lower case a's stand for coefficients to be estimated, with e representing a random error term.[2]

Increased labor market friction means a changed labor market structure. Previous findings of outward shifts are interpreted differently by various authors. Some have used the findings to claim increasing skill shortages,(Medoff 1983) which can be remedied by more manpower training programs; others claim that economic problems are caused by sectoral shifts.(Blanchard and Diamond 1989) The next section reviews the literature to understand how previous authors modeled, measured and interpreted Beveridge curves.

II. Literature Review

A brief review of Beveridge curve literature shows the consensus of previous research is that structural change has occurred. This is in marked contrast to the conclusions reached by this chapter.

The curve's first theoretical exposition (Dow and Dicks-Mireaux 1958) assumed that vacancies and unemployment are associated via a rectangular hyperbola. Graphing English data from 1946-1956, they noted a major *inward* shift of the Beveridge curve.

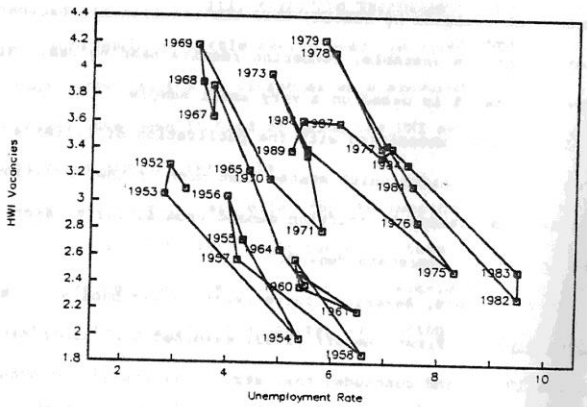
The English data are highly unusual because all American work explains *outward* shifts. U.S. shifts are plainly evident in Figure 1

[2]Without an underlying labor market model, equation (1) is an ad-hoc relation. This equation is not always ad-hoc for it can be easily derived in a dynamic labor market model. The first to investigate these dynamics was Holt and David (1966) followed by more complete models built by Hansen (1970) and Pissarides (1985 & 1987).

which plots unemployment versus vacancy rates based on the HWI, adjusted for employment growth.

Figure 1:

Beveridge Curve: HWI Vacancies Versus Unemployment
1951-1989



Except for Holzer's (1989) cross-sectional studies, U.S. research has mainly focused on deciding if movements in this graph signify structural shifts in the labor market. Over the last twenty-five years the majority of writers have decided that structural change has occurred.

The first major debate was started by Cohen and Solow in the Review of Economics and Statistics. Triggering the debate was a very sharp increase in the 1965 value of the Conference Board Help-Wanted Index (HWI). Cohen and Solow (1967 & 1970) created a simple model that

tracked the HWI, compared their predicted values with the actual values and concluded that the increase did not indicate a structural shift.

Burch and Fabricant (1968) countered with a different functional form and used HWI levels instead of changes. Based on their model they declared that a distinct shift occurred in 1957. Gujarati (1969) countered both articles by stating that the relationship between the HWI and unemployment is unstable, rendering results meaningless. His result is suspect since it is based on a very small sample.

The debate intensified with the publication of Lilien's (1982) paper on sectoral shifts which stated that much of the variation in unemployment was caused by shifting demand from sector to sector, not by changes in overall aggregate demand.[3]

In the 1980's, Beveridge curve research was published in the Brookings Papers. First, Medoff (1983) examined U.S. labor markets during the 1970's and concluded that structural change had occurred. Using the HWI as a vacancy proxy he found structural shifts and attributed them to rapid increases in employment growth rates.

Abraham (1987) then extended her earlier vacancy work (1986 & 1983) by trying to purge the HWI of any external factors that could influence results. After correcting the index for increasing monopolization in the newspaper industry, antidiscrimination laws and changing employment composition, she concluded that structural shifts had occurred.

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[3]The sectoral shift hypothesis was not tested in this chapter since only aggregate data were used to construct the curves. Sectoral shift results are presented in Chapter three.

Most recently Blanchard and Diamond (1989) used the HWI to test for labor market change. They also concluded that there were distinct Beveridge curve shifts and computed that half were due to long-run reallocation shocks and half to an unexplained trend.

III. Measuring Vacancies

There would be little debate over the interpretation of Beveridge curves shifts if vacancies were measured directly. Researchers have been limited to using the HWI as a proxy because total vacancy rates are not available.

Partial vacancy data exist for the American manufacturing sector from the 1920's until 1981. Unfortunately, this section concludes that using this vacancy measure to construct a Beveridge curve neither confirms nor refutes previous claims, suggesting that further research is still needed.

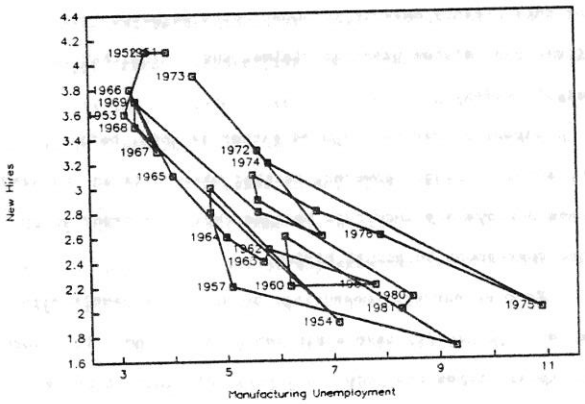
Vacancies can be computed either ex ante, before filling, or ex post, after filling. However, neither measure is an unbiased indicator. Ex ante surveys are incorrect because vacancies reported by firms often do not correspond to actual hiring.

Ex post surveys, measuring the number of people hired and recalled from layoff, have a simpler bias problem. In vigorous, expansionary times few people are available to be hired even though firms have many outstanding vacancies. Hence the depth of manpower shortages during expansionary times is not shown by these vacancy numbers. In the extreme case it is possible to show that there are more measured vacancies in recessionary than in expansionary periods.

The Bureau of Labor Statistics (BLS) has measured manufacturing vacancies using both methods. Ex post measures of total new hires were tracked from 1929 to 1981 while ex ante measures of expected vacancies were tracked from 1969 - 1973. Comparing the two indicators shows widely differing vacancy rates for the same month. Ex ante measures indicate few openings while ex post measures indicate many. Using the ex post series as the vacancy measure and manufacturing unemployment rates, a Beveridge curve for manufacturing is graphed in Figure 2 for 1951-1981.

Figure 2:

Manufacturing New Hires Versus Unemployment
1951-1981



Visually Figure 2 lacks the dramatic outward shifts found in the HWI graph and suggests a stable manufacturing Beveridge curve. The lack of agreement between the two graphs signals that HWI results may be

combining vacancy information with other factors. Further work in reconciling the differences between new hires and the HWI is not pursued for three reasons. First, the ex post manufacturing series only covers about 17% of the labor force while the HWI theoretically covers 100%. Secondly, vacancy rates at low unemployment rates are suspect. Lastly, and most importantly, the series is discontinued.[4]

Lacking direct measures, researchers needing national vacancy data use an ex ante indirect measure, the Conference Board Help-Wanted Index (HWI). Each month it tracks the total number of ads published in the classified help-wanted section in 51 major American cities. Preston (1977) explains that separate indexes are constructed by surveying the one newspaper per city that receives the majority of local help wanted advertising.

From these 51 indexes, the national HWI is created by weighting the data to reflect the number of people employed in the area. High weights are given to areas such as New York while smaller areas like Miami receive less. Weighting details are described in the appendix.

IV. Are Shifts Due To Measuring Ads Incorrectly?

Could the shifts in the HWI graph be caused by measuring help-wanted ads improperly? Researchers who use recruitment advertising as a proxy for vacancies implicitly use the following identity in their work.

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[4]Other alternative measurements of vacancies have been tried unsuccessfully. Conant (1966) examined the possibility of using data from private recruitment services and arrived at exceptionally negative conclusions. Chavrid and Kuptzin (1966) examined data from job openings registered at the Employment Service. However, since registering is voluntary, companies only post jobs there when normal hiring channels do not work. This causes the series to be a poor vacancy measure.

$$2) \quad O = \sum_{i=0}^{N} J_i$$

Where O is the number of advertised openings, J is the number of jobs per ad and N the number of ads. Measurement error is likely since the HWI only reveals N, the number of ads, even though what is really wanted is O, the number of advertised openings. This makes the HWI suspect since using it rests on the assumption that the average of J, the number of openings per ad, is constant over time.

The measurement problem is tested by creating a second index that potentially provides more accurate data. The second index, constructed in the appendix, is based on unpublished linage data from a nine newspaper sample.

The linage or size index is potentially more accurate because it gives more weight to larger ads with many openings than to tiny ads with few. This remedies a major shortcoming of the HWI which gives each ad the same weight.

Linage, or size, on which the second index is based can be interpreted as follows.

$$3) \quad S = \sum_{i=0}^{N} (J_i * I_i)$$

Where S is the total size of all ads, N is the number of ads, J is the number of jobs listed per ad and I is the amount of information

about each job.[5] The size index provides a combined signal of N, J, and I compared to the HWI signal of just N.

Table 1 lists vacancy rates based both on the HWI and the size index normalized by nonagricultural openings. Normalization compensates for labor force growth which inflates the number of jobs advertised. This deflator was chosen by Medoff (1983) and its usage is continued by later researchers.

The normalized data series are then transformed into vacancy rates by calibrating the 1965 value to the actual national vacancy rate for April 1965 as reported in U.S. Congressional hearings (1966).[6]

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[5]Information about jobs falls into two categories: firm descriptions and job descriptions. Firm descriptions range from the simple, listing a name and address, to a complete articulation of the company's goals and vision. Job descriptions range from terse phrases, like *machinist wanted*, to detailed descriptions of pay, benefits, and duties.

[6]April's value is derived from the appendix which lists results of the BLS's vacancy rate pilot survey. The vacancy rate of 3.24% is computed by weighting each surveyed area by its employment share.

Table 1:

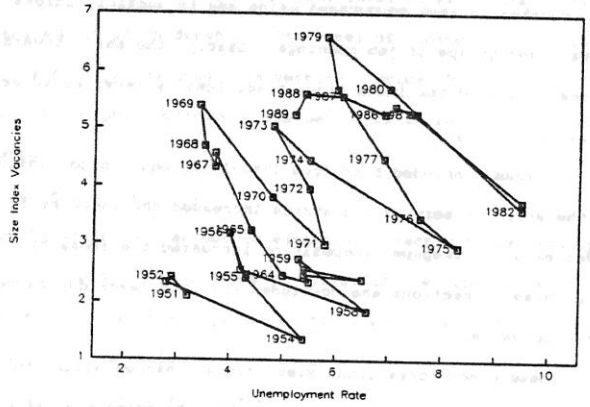
1951-1989 U.S. Vacancy Rates Derived From HWI and Size Index

Year	HWI	Size	Year	HWI	Size
1951	3.09	2.10	1971	2.79	3.00
1952	3.27	2.42	1972	3.35	3.96
1953	3.05	2.33	1973	3.96	5.03
1954	1.98	1.36	1974	3.40	4.46
1955	2.72	2.42	1975	2.50	2.95
1956	3.04	3.18	1976	2.86	3.47
1957	2.57	2.55	1977	3.41	4.48
1958	1.86	1.85	1978	4.12	5.68
1959	2.57	2.74	1979	4.22	6.59
1960	2.37	2.47	1980	3.43	5.71
1961	2.18	2.40	1981	3.13	5.26
1962	2.46	2.57	1982	2.30	3.62
1963	2.38	2.35	1983	2.50	3.75
1964	2.65	2.46	1984	3.29	5.28
1965	3.24	3.24	1985	3.41	5.39
1966	3.87	4.57	1986	3.34	5.26
1967	3.64	4.34	1987	3.60	5.57
1968	3.90	4.69	1988	3.61	5.61
1969	4.18	5.40	1989	3.38	5.25
1970	3.17	3.82			

Figure 3 plots a different Beveridge curve, now using the size index as a vacancy proxy. It shows even greater structural shifts than the HWI curve. This confirmation of previous findings strongly indicates that Beveridge curve shifts are not caused by incorrectly measuring help-wanted ads.

Figure 3:

Beveridge Curve Size Index Vacancies Versus Unemployment 1951-1989



V. Are Help-Wanted Ads A Good Vacancy Proxy?

Tests to check the HWI's ability to track vacancies were done by Abraham (1987) who compared the Minnesota index with vacancy survey data. This showed the index was a good short-run vacancy proxy. Unfortunately, additional short-run tests are not possible since there are no new general vacancy surveys.

Ensuring that the HWI is a good long-run vacancy proxy is done by adjusting it for underlying structural changes. The only previous adjustments were done by Abraham (1987) who checked for three changes: the newspaper industry's 1960's and 1970's shakeout, changes in antidiscrimination laws and shifting industrial composition. Each theoretically increased the index. The failure of many newspapers potentially moved advertising into papers which comprised the HWI. Equal opportunity laws encouraged using ads to publicly inform disadvantaged groups of job openings. Lastly, the shift towards services bolstered the index since traditionally services advertise more than manufacturing.

Abraham concluded that from 1960-1985, equal opportunity laws plus the shift to service industries increased the index by 12.5%, while the decrease in newspaper competition increased the index by 18%. After making these corrections she concluded that the Beveridge curve still shifted outwards.

These minor corrections miss crucial changes occurring in help-wanted advertising pricing and readership. To correctly estimate a vacancy proxy, price and readership changes must be removed. This chapter removes these factors in four steps. First, a corrected vacancy index is designed based on a demand curve for ads. Then, data are compiled for readership and price. Next, the demand curve is estimated. Lastly, the corrected index is computed by subtracting price and readership effects.

VI. Corrected Vacancy Index Model

Modeling the demand for help-wanted advertisements is the first step in creating a corrected vacancy index. Two equations form the basis for the demand curve. In these equations the subscript t stands for time, the symbol G(·) stands for a general function and e for a normally distributed error term.

The first equation hypothesizes that the demand for help-wanted advertising depends on three factors: level of vacancies, real price of ads and amount of readership. The level of vacancies, V, determines how many positions firms need to advertise. Price, P, and readership, R, determine how price-effective the medium is in reaching the targeted audience.

4) $Q_t = G(V_t, P_t, R_t)$

Equation (4) can not be estimated directly since vacancy data are unavailable. This problem is solved in the literature by using equation (1), the Beveridge curve, to relate vacancies to unemployment. Repeating this equation for convenience:

1) $V_t = a_1 + a_2 U_t + a_3 F_t + e_t$

Equation (5) is created by inserting (1) into (4). This new equation assumes there are no interaction terms[7] and F_t, the variables describing labor market frictions, are constant. If frictions do vary,

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[7] Interaction between unemployment and readership is possible since readership may depend on the economy's state. However, this term is not added to the model because readership data in this chapter are based only on responses by the unemployed. To check this, econometric tests were also run with interaction terms yielding nonsignificant coefficients and no change in R^2.

the econometric fit of the model will be poor and shifts will still appear.

5) $Q_t = a + bU_t + cP_t + dR_t + e_t$

Increasing unemployment decreases ad demand since finding qualified applicants is easier or because it corresponds to fewer vacancies. Increasing advertising's real price decreases ad demand since demand curves slope downward. Lastly, increasing readership increases ad demand since ads are more effective tools for finding applicants.

If unemployment, price and readership are exogenous this equation is identified and can be estimated by ordinary least squares (OLS). The system can not be estimated by OLS if the quantity of help-wanted ads affects any of the variables on the right hand side of the equation. This chapter focuses on the OLS results. Instrumental variables estimates are presented in the section entitled Alternative Tests.

Finally, a corrected vacancy index is produced by removing readership and price changes. Analytically, this is shown by equation (6).

6) $\hat{V}_t = Q_t - cP_t - dR_t$

The ^ sign signifies the corrected vacancy index at time t, while c and d are the coefficients from equation (5). The corrected index is a better signal of labor market trends because it no longer includes spurious advertising information.

The following sections create data series to estimate equations (5) and (6) and argue that the explanatory variables are exogenous.

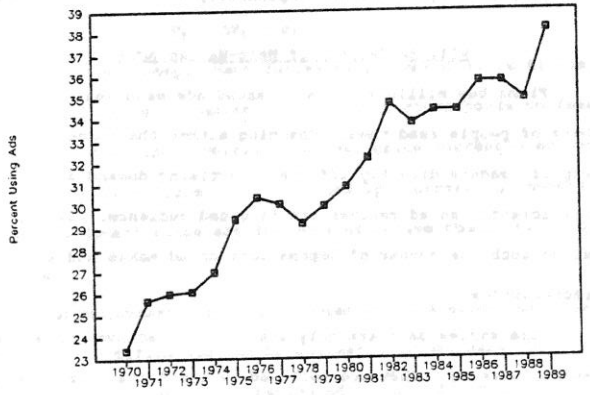
VII. Readership of Help-Wanted Advertising

Firms buy millions of help-wanted ads each year because large numbers of people read them. Changing either the number or demographic makeup of readers directly affects advertising demand since this alters how efficiently an ad reaches its targeted audience. Efficiency is based on both the number of impressions an ad makes and audience characteristics.

Time series data are only available on active job seekers not presently working. They are followed by the BLS's Current Population Survey, which asks all unemployed people not on temporary layoff, question 22A, "What has _____ been doing in the last 4 weeks to find work?" (BLS 1988) The percentage responding "placed or answered an ad" has risen almost sixty percent over the last twenty years. Figure 4 shows this sharp rise in readership.

Figure 4:

Percentage Of Unemployed Using Ads



Labeling the percentage of readers R and a simple time trend T, the OLS estimate is $R = 24.7 + .66\ T$. Both coefficients are significant at the 1% level, and correcting for serial correlation does not significantly affect the results. Using this equation, the presurvey years of 1951 to 1969 are estimated by backcasting. Table 2 shows the actual values from 1970 to 1989 and estimated values from 1951 to 1969.

Table 2:

Unemployed Readership Of Help-Wanted Ads 1951-1989

Year	% Readers	Year	% Readers
1951	12.05	1971	25.70
1952	12.72	1972	26.00
1953	13.39	1973	26.10
1954	14.06	1974	27.00
1955	14.73	1975	29.40
1956	15.40	1976	30.40
1957	16.06	1977	30.10
1958	16.73	1978	29.20
1959	17.40	1979	30.00
1960	18.07	1980	30.90
1961	18.74	1981	32.20
1962	19.41	1982	34.70
1963	20.07	1983	33.80
1964	20.74	1984	34.40
1965	21.41	1985	34.40
1966	22.08	1986	35.70
1967	22.75	1987	35.70
1968	23.42	1988	34.90
1969	24.09	1989	38.10
1970	23.40		

Two reasons suggest that the backcasted data are accurate. First, data from the Ad Research Foundation, which tracked readership of selected newspaper pages and ads, indicates rising readership over time. In the 1940's many help-wanted ads had a 1% readership while by the mid 1950's many had readership in the low teens. Secondly, later conclusions are not modified by changing readership's functional form to a nonlinear structure, which increases readership gradually over time.[8]

[8]Labeling the percentage of readers R and trend T, a modified logistic equation is $R = 1/(1 + \exp(-0.027 * T) - 0.25$. Both coefficients are significant at the 1% level and for the period 1951-1969 result in backcasted values that are very close to the linear ones.

Why has readership increased over time? First, disaggregating the BLS data by sex shows that unemployed females use ads more than males. Hence, the dramatic increase in participation by females in the labor force has increased total readership. Second, a 1986 cross-sectional study from the Newspaper Advertising Bureau suggests that educational attainment is an important determinant of newspaper readership. Hence, overall increases in U.S. educational levels also explains why readership has soared over time.

Holding other factors constant, advertising demand should have increased over time to reflect the increased readership levels. Rising readership boosts demand because it transforms help-wanted ads into a more efficient method of reaching job seekers.

VIII. Price Of Help-Wanted Advertising

Firms base their demand for help-wanted ads on more than how efficiently job seekers can be reached. Unless firms have perfectly inelastic demand curves, price considerations play an important role in deciding the size and number of help-wanted ads bought.

Solow (1983) noted that finding a falling real ad price would explain outward Beveridge curve shifts. Falling prices cause businesses to increase their ad buying at every unemployment level, resulting in the appearance of an outward shift.

Did real ad prices fall? To provide data to answer this question and to estimate the demand curve, two classified price indexes are constructed and listed in Table 3. Details of their construction appear in the appendix. These indexes show that over the last four

decades nominal help-wanted rates rose by 1,156%, and general classified rates rose by 991%. During the same time, consumer prices rose by only 388%.

Table 3:

Classified Price Indexes Base 1982 = 100

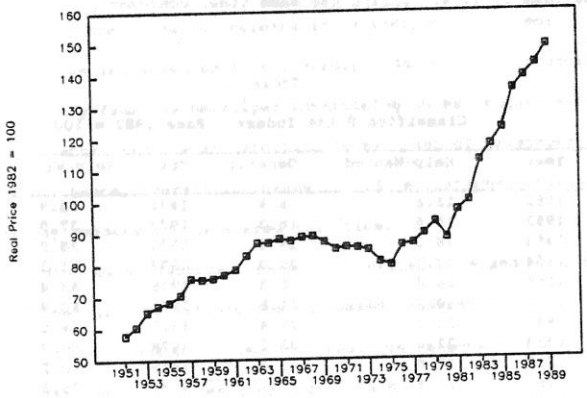
Year	Help-Wanted	General	Year	Help-Wanted	General
1951	15.6	18.9	1971	35.9	36.6
1952	16.6	18.3	1972	37.0	37.7
1953	18.0	19.4	1973	38.9	39.9
1954	18.7	20.0	1974	41.3	43.7
1955	18.9	20.5	1975	44.4	47.4
1956	19.9	21.8	1976	50.8	54.2
1957	22.0	22.4	1977	54.5	59.1
1958	22.6	23.0	1978	60.7	66.3
1959	22.8	23.2	1979	70.2	73.6
1960	23.6	23.9	1980	75.3	78.1
1961	24.4	24.5	1981	91.5	94.0
1962	26.0	25.6	1982	100.0	100.0
1963	27.6	27.0	1983	116.2	120.4
1964	28.0	27.4	1984	126.6	134.1
1965	28.8	28.2	1985	136.7	144.9
1966	29.4	29.3	1986	153.6	159.2
1967	30.7	30.9	1987	163.6	169.1
1968	32.1	32.3	1988	175.5	186.7
1969	33.2	33.3	1989	195.8	206.1
1970	34.2	34.3			

To create the real price of help-wanted ads, the data in Table 3 must be deflated by a price index. The obvious choice is the Consumer Price Index (CPI) because demand is based on the price paid by consumers in relation to all other consumer prices. Costs of newspaper production should not be used since costs affect the supply curve, not the demand.

Help-wanted prices deflated by the CPI are shown in Figure 5. This graph clearly shows that prices rose in the 1950's, were stagnant in the 1960's and 1970's, and rose again in the 1980's.

Figure 5:

Real Price Help-Wanted Advertising 1951-1989



With this graph, the upward trend of real ad prices is clear. We can conclude that Beveridge curve shifts were not caused by a falling real price of ads.

IX. Are Price Increases Exogenous To Demand?

If ad demand does not affect price then OLS can be used to estimate the demand curve. However, if pricing is endogenously determined OLS can not be used. This section builds a strong case for considering pricing to be exogenous while the later section entitled Alternative Tests considers the effect of endogenous prices.

Help-wanted pricing can not be considered in isolation from other profit maximizing newspaper pricing decisions because readers buy a bundled product of news and *n* ad types for a single price. This

suggests that help-wanted price increases are primarily caused by one of three factors:

A) Falling elasticity of help-wanted demand.

B) Rising elasticity of other ad types. (national, retail, etc.)[9]

C) Cost increases.

Only case (A) indicates that pricing is endogenous, since demand changes are driving price adjustments. Price changes caused by either (B) or (C) indicate that pricing is exogenous since help-wanted prices are changing due to factors other than help-wanted demand.

Case (A), falling help-wanted elasticity, occurs if help-wanted buyers become less price responsive. Conversely, case (B), rising elasticity of other ad types, means that other categories are becoming more price responsive. Help-wanted prices must then rise to cover production cost increases since other rates can not.

If either case (A) or (B) is behind pricing decisions, advertising rates over time should be diverging. Figure 6 shows that pricing for national ads, general classified and help-wanted have all risen at roughly coinciding rates.

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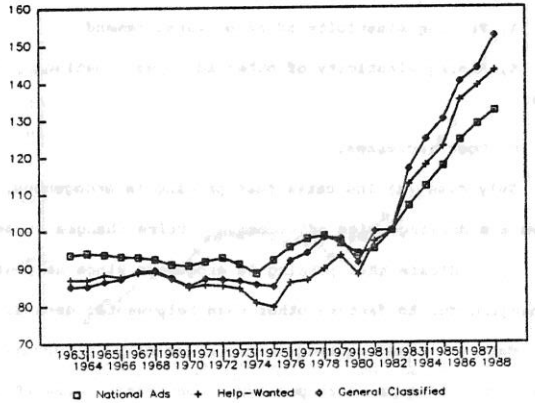
[9]National ads primarily showcase a single product (Ford car ads). Retail ads contain local prices for a variety of products (supermarket ads). While national and retail ads are printed throughout newspapers, classified ads are collected together in a special section.

Figure 6:

Real Ad Price National, Help-Wanted, and General 1963-1988



If prices only rose at the rate of inflation, Figure 6 would be a straight line. However, from 1963 to 1988 rates for national ads rose 41% more than inflation, help-wanted classified rose 64% and general classified rose 78%. This similar increase over inflation by the three different advertising categories suggests that cases (A) and (B), individual elasticity changes, are not causing pricing changes. The coincident movement suggests that either all elasticities are moving jointly or that case (C), cost changes, is determining pricing. The last case seems more plausible, in which case OLS is consistent and efficient.

Testing if cost changes determine ad pricing is simpler than testing joint elasticity changes. Data on the total amount spent by all newspapers for payroll, raw materials, new capital equipment, and

inventories are available in the Census of Manufactures and are summarized in Table 4.[10]

Table 4's first section is changes in CPI, help-wanted prices and total newspaper costs. The second section shows total production costs adjusted to account for five different measures of industry size. These five indicators show that the various cost measures bracket the rise in help-wanted prices. This strongly suggests that prices were pushed upwards by production costs.

Table 4:

Advertising Cost Rise 1958 - 1987

Consumer Price Index	292%
Help-Wanted Price Index	625%
Total Production Costs	537%
Total Production Costs Deflated By	
Number Daily papers	578%
Total Number Newspapers	701%
Number Newspaper Establishments	488%
Number Newspaper Companies	578%
Circulation of Daily and Sunday	471%

X. Is Readership Exogenous?

Evidence suggests that price is exogenous to demand. However, results in this chapter depend on both price and readership variables. This section builds a strong case for considering readership to be exogenous.

Three potential reasons why readership may be endogenous are first the number of help-wanted ads may influence readership. Secondly,

[10]Data on all four costs are available from 1958 to 1987. Information is based on a full census, taken approximately every five years, and a sample census, taken during intervening years.

readership may by proxying for F, labor market frictions. Lastly, the readership series used may be a biased indicator of true readership.

The first potential problem occurs if readers are attracted to larger help-wanted sections because of more information and are repelled by smaller sections with little information. This means a direct relation between the number of ads and readers. However, visual and econometric tests comparing actual readership data from 1970-1989 versus the HWI shows that help-wanted readership is inversely related to the number of ads placed. Since lower readership occurs when there are larger help-wanted sections this reason is not a problem.

Secondly, readership may be proxying for labor market frictions which means the corrected help-wanted index has been purged of the very items of interest. Sectoral shifts (Lilien 1982) are the primary frictional change that may be hidden inside readership. If workers have no informal methods of finding a job outside their sector then increases in the number of people shifting to a new sector increases ad readership.

This means a positive relation between Lilien's measure of sectoral shifts (sigma) and readership. Regressing readership on sigma results in a nonsignificant negative coefficient[11] suggesting this also is not a problem.

Lastly, unemployed readership may be a biased indicator of true readership since it does not include job-to-job movers. Figure 4, shows that unemployed readership has a strong upward trend that varies counter

[11]More complex models sometimes changed sigma's sign to an nonsignificant positive number.

to the business cycle. Since job-to-job movers follow the business cycle combining the groups potentially cause the cycles to offset each other, suggesting true readership is approximated by a trend. Replacing readership with a trend does not substantially modify later conclusions. Hence, evidence in this section suggests that readership, like price, is exogenous to demand.

XI. Demand Curve Estimation

The next step in creating a corrected vacancy index is to estimate the demand curve with the new data. The demand curve specified in equation (5), and repeated below, states that demand is a function of unemployment,[12] price and readership.

5) $Q_t = a + bU_t + cP_t + dR_t + e_t$

OLS estimates for both advertising measures, reported in Table 5, show demand is significantly affected by all three factors. Hence, vacancy indexes based on help-wanted ads need to be corrected for price and readership influences to reveal underlying labor market trends.

[12]Four different types of unemployment series are available from 1951 to 1989: civilian, individuals searching more than 15 weeks, people over 25 years old, and civilian plus resident armed forces. Given that the four series track each other very closely, only the civilian plus armed forces rate is used in the econometric tests.

Table 5:

Help-Wanted Demand Curve Regressions 1951-1989

HWI VACANCY = C		UNEMP	PRICE	READERSHIP	
Coeff.	3.89	-0.46	-0.02	0.14	
T-stat	18.9	13	5.5	11.1	
R^2 = .85 Adj. R^2 = .84 D.W. = 1.32 Sum Sq. Res 2.11					
HWI VACANCY = C		UNEMP	PRICE	READERSHIP	AR1
Coeff.	3.92	-0.45	-0.02	0.14	.32
T-stat	13.4	10.5	3.96	7.9	1.6
R^2 = .86 Adj. R^2 = .84 D.W. = 1.63 Sum Sq. Res 1.94					
SIZE VACANCY = C		UNEMP	PRICE	READERSHIP	
Coeff.	2.2	-0.56	-0.02	0.28	
T-stat	4.5	6.79	2.72	8.96	
R^2 = .83 Adj. R^2 = .82 D.W. = .96 Sum Sq. Res 11.85					
SIZE VACANCY = C		UNEMP	PRICE	READERSHIP	AR1
Coeff.	18.0	-0.64	-0.02	-0.08	.96
T-stat	2.03	8.57	1.11	.88	32
R^2 = .90 Adj. R^2 = .89 D.W. = 2.23 Sum Sq. Res 6.32					

Table 5 contains four equations. The first equation's dependent variable is the HWI, adjusted for employment growth. Since the Durbin-Watson (D.W.) statistic is .01 below the five percent cutoff value of 1.33, a second regression using an AR(1) correction is shown. Examination of the AR(1) equation's coefficients and t-statistics show that first regression results are accurate.

The third equation replaces the HWI with the adjusted size index. Since the Durbin-Watson statistic clearly indicates serial correlation a fourth equation was run with an AR(1) correction.

All anticipated signs appear as expected and coefficients in the HWI equations are highly significant. The only coefficient incorrectly signed is readership in the fourth equation but this number is not

significantly different from zero so the sign is statistically indeterminate.[13]

XII. Corrected Vacancy Indexes

Corrected vacancy indexes are produced by removing price and readership effects using the demand curve's coefficients. The theoretical basis for the corrections was specified in equation (6) and is repeated below.

6) $\hat{V}_t = Q_t - cP_t - dR_t$

Table 6 is derived by solving this equation, using the values of coefficients c and d taken from Table 5, for each time period t and then transforming the series to match the 1965 vacancy rate computed from the BLS's pilot survey (U.S. Congress 1966).

[13]Unit roots are rejected at the 1% level for the HWI and at the 5% level for the size index. Preston's (1977) comment that the HWI has drifted over time indicated that Dickey and Fuller's (1979) second equation which includes a drift term is the proper model for unit root tests. Critical values are taken from Schmidt's (1990) tables.

Table 6:

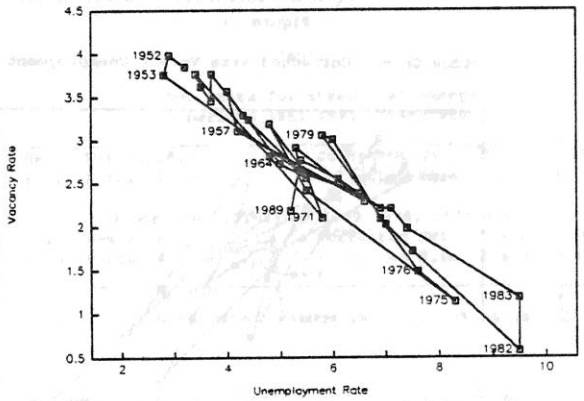
1951-1989 Corrected U.S. Vacancy Rates From HWI and Size Index

Year	HWI	Size	Year	HWI	Size
1951	3.84	4.01	1971	2.10	1.72
1952	3.98	4.20	1972	2.61	2.59
1953	3.76	4.03	1973	3.19	3.62
1954	2.63	2.93	1974	2.41	2.69
1955	3.29	3.82	1975	1.13	0.48
1956	3.56	4.45	1976	1.48	0.87
1957	3.10	3.76	1977	2.09	1.99
1958	2.28	2.86	1978	3.00	3.52
1959	2.90	3.57	1979	3.05	4.29
1960	2.62	3.14	1980	2.02	3.02
1961	2.38	2.92	1981	1.71	2.43
1962	2.65	3.01	1982	0.57	0.14
1963	2.56	2.69	1983	1.18	0.84
1964	2.72	2.62	1984	1.98	2.32
1965	3.24	3.24	1985	2.20	2.55
1966	3.76	4.37	1986	2.21	2.37
1967	3.45	3.97	1987	2.54	2.77
1968	3.62	4.14	1988	2.76	3.13
1969	3.76	4.62	1989	2.18	2.00
1970	2.81	3.17			

Did previous researchers truly find shifting Beveridge curves? Figure 7 replots the Beveridge curve using the corrected HWI index and shows no shifts! Shifts seen in previous research are removed by adjusting for readership and price changes.

Figure 7:

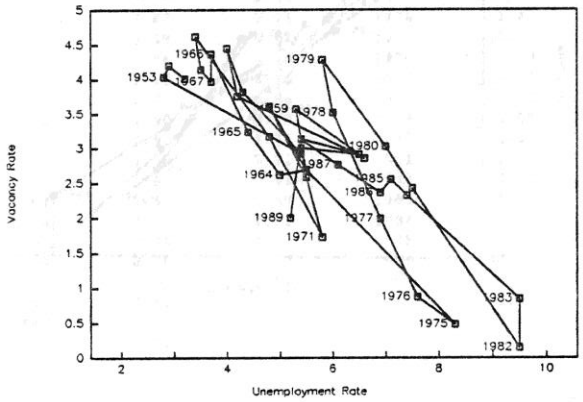
Beveridge Curve: Corrected HWI Versus Unemployment



Replotting the Beveridge curve, in Figure 8, using the corrected size index shows that most, but not all shifts have been removed.

Figure 8:

Beveridge Curve: Corrected Size Versus Unemployment



Chow tests econometrically confirm the visual findings in two separate tests. One test follows Abraham (1987) and divides the sample at 1974. The other test uses apparent shift points in Figure 1 to divide the sample into three pieces: 1951-1968, 1969-1974, and 1975-1989. This second test is very stringent since choosing shift points after examining the data biases the test in favor of finding structural change.

Chow test results are listed in Table 7. Both the original HWI and size indexes clearly indicate structural changes. After correcting for price and readership changes, the HWI shows no structural change in both tests. Correcting the size index produces mixed results:

structural change is rejected in the two period case but can not be ruled out in the more stringent three period case.

Table 7:

Chow tests for structural change

2 periods 1951-1973, 1974-1989			
HWI	F-stat 18.6	Corrected HWI	F-stat 0.39
Size	F-stat 20.0	Corrected Size	F-stat 0.57
3 periods 1951-1968, 1969-1974, 1975-1989			
HWI	F-stat 42	Corrected HWI	F-stat 2.46
Size	F-stat 42	Corrected Size	F-stat 3.82

Note: 1% value to reject change is 5.28. 5% value 3.29

Why does removing readership and price eliminate structural change? The explanation is seen pictorially by combining Figures 4 and 5.

Figure 4 showed the strong growth in help-wanted readership. This growth caused an increase in demand since ads became a more effective recruiting mechanism. Figure 5 showed trends in the real price of ads. Increased rates completely counteracted increased demand during the 1950's and 1980's. However, during the 1960's and 1970's, the real price of ads stayed constant and did not counteract the rising demand. When readership was not counteracted researchers saw a structural shift; however, it was only the abatement of the real price increase's counterbalancing force.

XIII. Alternative Tests

The corrected vacancy index was econometrically estimated using OLS based on the assumption that price is exogenously determined. Do the results change if this assumption is dropped? Allowing price to be endogenously determined means the demand curve must be estimated as part of a system of simultaneous supply and demand equations. This chapter uses two stage least squares (TSLS) to estimate the single demand curve.

TSLS uses instruments from the supply curve that are uncorrelated with the demand curve's error term. Table 8's first section shows the results of TSLS regression using real costs[14] as an instrument. The second regression is TSLS results corrected for serial correlation[15] where the symbol (-1) stands for values lagged one period.

[14]Total costs, recorded in the Census of Manufactures from 1958-1987, are corrected for industry growth by dividing by the number of newspapers sold. This correction is computed by weighting Sunday circulation by 1/7 and daily by 6/7. The CPI is then used to transform costs into real terms.

[15]The additional instruments are based on Fair (1970) which shows that adding all endogenous and exogenous variables lagged one period results in consistent estimators.

Table 8:

1958-1987 TSLS Estimate Of Help-Wanted Demand

Instruments C, UNEMP, RCOSTS, READERSHIP

HWI VACANCY = C		UNEMP	PRICE	READERSHIP	
Coeff.	4.52	-.54	-.04	.21	
T-stat	7.74	9.15	3.17	6.16	

R^2 = .74 Adj. R^2 = .71 D.W. = .81 Sum Sq. Res 3.1

Inst: C, RCOSTS, HWI(-1), UNEMP(-1), PRICE(-1), READERSHIP(-1)

HWI VACANCY = C		UNEMP	PRICE	READERSHIP	AR1
Coeff.	3.60	-.48	-.02	.16	.27
T-stat	9.35	7.2	3.1	7.3	1.33

R^2 = .89 Adj. R^2 = .87 D.W. = 1.74 Sum Sq. Res 1.28

OLS Comparison Equation

HWI VACANCY = C		UNEMP	PRICE	READERSHIP
Coeff.	3.56	-.48	-.015	.15
T-stat	13.7	13.7	3.71	10.8

R^2 = .89 Adj. R^2 = .87 D.W. = 1.34 Sum Sq. Res 1.34

Comparing the TSLS coefficients with their OLS counterparts shows a very high degree of similarity. Since the second equation is overidentified a generalized method of moments or Sargan test (Hansen 1982) can be run to ensure all the excess instruments are legitimate first stage regressors.[16] Since the Sargan test's 5% value of 4.26 is less than the critical value of 5.99 the additional regressors are appropriate.

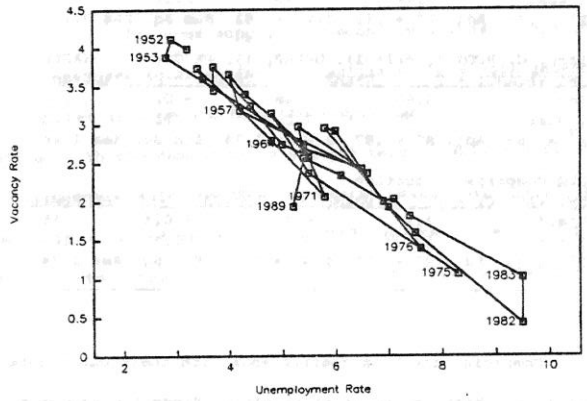
Creating a new, corrected index using these TSLS coefficients and viewing the resulting Beveridge curve in Figure 9 demonstrates that

[16]This asymptotic test regresses the residuals from TSLS on the first stage instruments using OLS. OLS's R^2 times the number of observations is distributed chi-squared with the degrees of freedom equal to the number of excess instruments.

it does not matter whether price is endogenous or exogenous. Shifts are removed when advertising changes are included in the model.

Figure 9:

Beveridge Curve: TSLS Corrected HWI Versus Unemployment



The second approach to ensuring that results are robust is to alter the variables used to estimate the model. This is done by rerunning the regressions eliminating variables. Elimination of even one series causes the equations to have very low Durbin-Watson statistics, suggesting both correction for serial correlation and potential model misspecification.

Results in Table 9 show that unemployment combined with an AR(1) process provides roughly the same fit as the original complete equation. This shows that readership and price are important explanatory variables. Additionally, Table 9 shows that readership and price alone do not provide a good explanation of demand since demand is primarily

based on the economy's state and secondarily based on price and readership.

Table 9:

Alternative Demand Curve Specifications 1952-1989

	OLS regressions. Dependant variable HWI VACANCY					
CONST	7.6	6.93	2.19	5.98	2.16	2.46
t stat	3.6	3.2	2.5	8.7	2.7	3.8
UNEMP	-.45	-.43		-.44		
t stat	11.8	10.9		11.8		
RLPRICE	-.01		.013		.01	
t stat	.97		.87		1.2	
READER		-.02	-.013			.02
t stat		.50	.26			1.02
AR(1)	.94	.94	.62	.93	.60	.56
t stat	20.4	20.9	4.18	19.0	4.4	4.1
R^2	.86	.86	.43	.86	.43	.41
Adj. R^2	.85	.85	.38	.85	.39	.38
D.W.	2.16	2.07	1.59	2.02	1.58	1.57
SSR	1.90	1.95	8.22	1.96	8.23	8.40

XIV. Conclusions

Beveridge curves are analytical and graphical tools which connect unemployment and vacancies. Previous research on U.S. data documented a strong outward shift in the Beveridge curve over time. Since total vacancy rates are not measured, these curves were based on a vacancy proxy, the help-wanted advertising index (HWI).

Correcting the HWI for sweeping changes that occurred in help-wanted pricing and readership results in a *stable* Beveridge curve. The transformation is illustrated by comparing the original Beveridge curve

in Figure 1 with the curve corrected for advertising changes, shown in Figure 7.

Figure 1: HWI Vs Unemployment

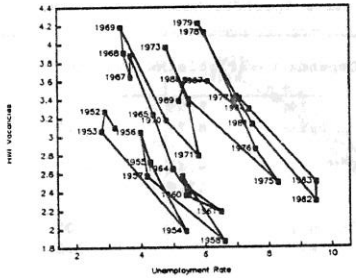
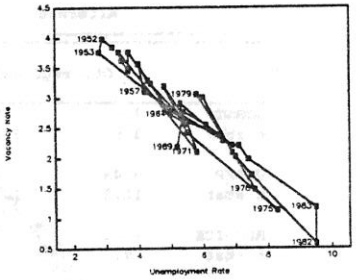


Figure 7: Corrected HWI Vs Unemployment



This chapter investigated the question, *"Have Beveridge curves really shifted?"* The answer is clear: outward Beveridge curve shifts are only an artifact of underlying advertising changes that were omitted in previous models. U.S. Beveridge curves show shifts in advertising, not in the labor market.

Appendix

This appendix contains detailed information on the creation of the price and size indexes. It is divided into four sections: sample selection, index weighting, price index creation and size index creation.

A. Sample Selection

Both indexes are based on a sample of major newspapers, not the entire industry. A complete survey is impractical since the American newspaper industry currently contains 1,642 daily and 840 Sunday newspapers. This chapter's price and size indexes are based on data from nine major American newspapers that provide confidential information to the Conference Board.[17] The location of each paper is listed in Table A1.

Table A1:

Cities Comprising Sample

Boston	Chicago
Detroit	Houston
Washington	Philadelphia
New York	Miami
Los Angeles	

These nine newspapers were selected because they:

-Are in the list of top 20 circulations in 1988.

-Provide data for the Conference Board Index (HWI).

-Provided linage data for this study.

[17] The nine are easy to ascertain since only the *major* paper is sampled in each city.

Of the three remaining papers meeting the first two criteria, San Francisco could only provide data for one year while Cleveland and Minneapolis did not respond. Even without these last three, a rough estimate suggests that the nine papers earned approximately 33% of 1988 American help-wanted dollars.

Pertinent results are derived from this sample since they print a significant percentage of all help-wanted ads, cover geographically diverse areas and, as the next section shows, contribute half the weight to the HWI.

B. Index Weighting

The HWI weights data in proportion to the area's employment level. This ensures that changes in large labor markets affect the index more than equivalent changes in smaller markets. Table A2 shows that the sample comprises roughly fifty percent of the HWI weight.

Table A2:

Sample City Weights From Conference Board Index

	Post 1974	Pre 1974
Boston	3.4%	3.2%
Chicago	7.9%	8.6%
Detroit	4.4%	4.4%
Houston	2.5%	1.5%
Los Angeles	8.1%	8.4%
Miami	1.6%	1.2%
New York	12.2%	19.1%
Philadelphia	4.9%	5.3%
Washington	3.5%	2.5%
Total	48.5%	54.2%

Two sets of weights are used in calculating the HWI.(Conference Board 1964, Preston 1977)[18] The 1974 weights are used from 1974 to present, while the 1960 weights are applied to data before 1974. The sets mainly differ in their treatment of New York City. After 1974, NYC's weight was reduced by 7% and spread among the other cities.

These numbers are used differently in the linage and price indexes. Since pricing data are available for all nine papers from 1951 to 1989 the price weights are the values in Table A2 times a conversion factor that ensures each column totals 100 percent. Price weights are roughly double the values listed in Table A2.

Creation of linage weights are more complicated because linage data are incomplete from 1951 to 1989. A simple algorithm allows for missing observations. Each year the weights of all newspapers that provided data are totaled. The correct weight for each data provider are the numbers in Table A2 divided by this total. Table A3 contains these weights and also shows on what data the size index are based.

[18]Conversation with Kenneth Goldstein, Conference Board.

Table A3:

Weights Used to Construct Size Index From Sample

Year	Boston	Chicago	Detroit	Houston	Los Angeles	Miami	New York	Philadelphia	Washington
1951	0.27	0.73							
1952	0.27	0.73							
1953	0.27	0.73							
1954	0.27	0.73							
1955	0.16	0.43			0.42				
1956	0.16	0.43			0.42				
1957	0.16	0.43			0.42				
1958	0.16	0.43			0.42				
1959	0.16	0.43			0.42				
1960	0.16	0.43			0.42				
1961	0.16	0.43			0.42				
1962	0.13	0.34			0.33			0.21	
1963	0.13	0.34			0.33			0.21	
1964	0.11	0.31			0.30			0.19	0.09
1965	0.06	0.17	0.09		0.16		0.37	0.10	0.05
1966	0.06	0.17	0.09		0.16		0.37	0.10	0.05
1967	0.06	0.17	0.09		0.16		0.37	0.10	0.05
1968	0.06	0.17	0.09		0.16		0.37	0.10	0.05
1969	0.06	0.17	0.09		0.16		0.37	0.10	0.05
1970	0.07	0.19	0.10		0.18		0.41		0.05
1971	0.06	0.17	0.09		0.16		0.37	0.10	0.05
1972	0.07	0.19	0.10		0.18		0.41		0.05
1973	0.07	0.19	0.10		0.18		0.41		0.05
1974	0.09	0.20	0.11		0.21		0.31		0.09
1975	0.09	0.20	0.11		0.21		0.31		0.09
1976	0.08	0.19	0.11		0.20	0.04	0.30		0.09
1977	0.08	0.18	0.10	0.06	0.19	0.04	0.28		0.08
1978	0.08	0.18	0.10	0.06	0.19	0.04	0.28		0.08
1979	0.08	0.18	0.10	0.06	0.19	0.04	0.28		0.08
1980	0.08	0.18	0.10	0.06	0.19	0.04	0.28		0.08
1981	0.08	0.18	0.10	0.06	0.19	0.04	0.28		0.08
1982	0.07	0.16	0.09	0.05	0.17	0.03	0.25	0.10	0.07
1983	0.07	0.16	0.09	0.05	0.17	0.03	0.25	0.10	0.07
1984	0.07	0.16	0.09	0.05	0.17	0.03	0.25	0.10	0.07
1985	0.07	0.16	0.09	0.05	0.17	0.03	0.25	0.10	0.07
1986	0.07	0.16	0.09	0.05	0.17	0.03	0.25	0.10	0.07
1987	0.07	0.16	0.09	0.05	0.17	0.03	0.25	0.10	0.07
1988	0.07	0.16	0.09	0.05	0.17	0.03	0.25	0.10	0.07
1989	0.19		0.06	0.20	0.04	0.30	0.12	0.09	

C. Price Index Creation

Briefly, the help-wanted price index is constructed by recording the daily and Sunday recruitment rate per newspaper. After collecting the data, the index is constructed in two stages. First two separate indexes, daily and Sunday, are created by multiplying the rates times table A3's weights. Then a combined index is created by weighting daily rates by two thirds and Sunday rates by one third. The following paragraphs detail the index's construction.

Advertising rates from the nine sample newspapers during the years 1951-1989 form the index. All rates were collected from the periodical Standard Rate and Data Services which is the general source of information out-of-state advertisers use when placing ads. Rates from the January edition were used if possible.[19]

Two different classified rates were collected per paper: general and help-wanted. Since, not all papers listed both rates the general rate was used if the help-wanted rate did not exist. Since most newspapers listed a different rate for daily printings versus Sunday, a maximum of four prices were collected for each paper.

The diversity in classified rate structures is enormous, ranging from one rate for the Detroit News to 391 rates for the New York Times. When multiple help-wanted rates were listed, the rate selected was for a

[19] Four January editions were not available. Substitute dates were March 1965 and July 1974, 1978, 1979, the closest available.

full run single insertion of one classified line by a national advertiser.[20]

Daily and Sunday indexes are constructed by multiplying the recorded prices times the values in Table A3 and dividing by the total 1982 price. 1982 was chosen as a base to match most U.S. statistical series.

These steps produce daily and Sunday indexes which are very similar. Regressing them together produces a beta coefficient of .99, significant at 1%, and an R^2 of .99. Consolidating the indexes is done by weighting the daily index by two thirds and the Sunday by one third. Optimally, weights should reflect the relative quantity of ads appearing in daily and Sunday papers. In the absence of these figures, historical census series R222 and R223 (1970) provides weights based on the relative number of pages published.

Repeating the same procedure using the general classified rates collected yields the general classified price index.

D. Size Index Creation

Briefly, the size index is constructed by first creating two indexes based on the nine paper sample. One help-wanted index is total lines published and the other is the number of ads printed. Dividing the two results in the average size per ad over time, which when multiplied by the HWI results in a national size index.

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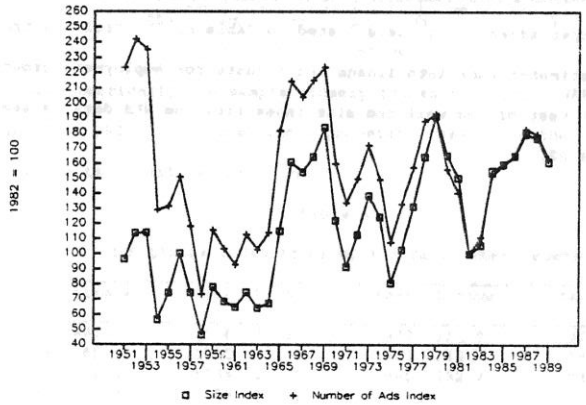
[20] From 1975-1988 two papers listed special volume discounts for recruitment agencies. The Boston Globe gave a 4% daily discount and a 8% Sunday discount while the New York Daily News gave a 50% daily discount and 45% Sunday discount. Volume discounts do not alter the index if the ratio of discounted ads to nondiscounted ads stays constant.

Total linage published by each major newspaper is private information and were obtained directly from the nine sample papers. Total number of ads published is compiled from the separate city indexes published by the Conference Board.

Using Table A3's weights a linage index and number of ad index were created and drawn in Figure A1. Two features are readily visible: the turning points for both series are identical and ad size has grown rapidly.

Figure A1:

Sample Size Index vs. Number Of Ads Index



Turning points are evaluated by comparing the first derivative signs. All signs are identical except for 1953, when the linage index was unchanged while the number index fell slightly.

Ad size growth means that average ad size has increased over time. Since the turning points are identical the only difference

between the two sample indexes is the average size. Because of this fact, the national size index is computed by multiplying average size by the HWI.

Tests based on the size index must assume that the nine paper sample is a good national proxy. This assumption is tested from 1975 to 1988 using data from the Newspaper Advertising Bureau, (NAB).

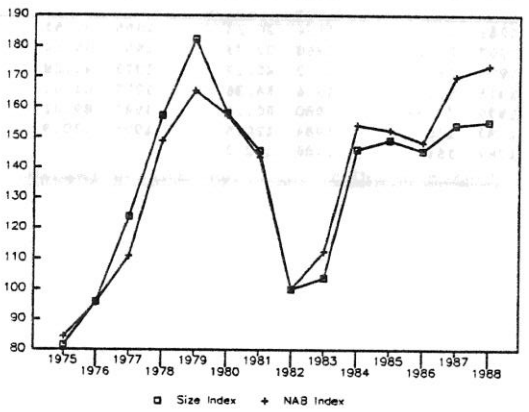
The NAB estimates nationally the money spent on classified advertising via a confidential survey of newspapers.[21] The NAB does not directly release total linage but instead releases a national estimate of dollars spent on help-wanted ads. This estimate is derived by multiplying results from its linage survey by their internal index of newspaper advertising costs listed in Table A5.[22] Table A4 transforms the estimates back into linage and adjusts for employment growth. A visual test of how well the size index fits the NAB data is seen in Figure A2.

[21]The overlap between the NAB and Conference Board surveys is probably quite large because they survey approximately the same number and types of papers. Since both groups will not reveal the names of survey participants the overlap is not checkable.

[22]Yannis Takos, of the NAB was very helpful in explaining how the expenditure data was compiled and providing their cost index.

Figure A2:

NAB and Size Index 1975-1988



Econometrically the sample closely tracks the larger NAB index with an R^2 of .93. The visual and econometric tests show that the nine paper sample is a good national proxy.

Table A4:

NAB Linage Index Adjusted For Employment Growth

Year	Linage	Year	Linage	Year	Linage	Year	Linage
1975	84.3	1976	95.6	1977	110.9	1978	148.7
1979	165.3	1980	157.3	1981	143.4	1982	100.0
1983	112.4	1984	153.9	1985	152.2	1986	148.3
1987	170.0	1988	173.6				

Table A5:

NAB National Newspaper Ad Price Index 1982=100

Year	Price	Year	Price	Year	Price	Year	Price
1963	29.70	1964	30.23	1965	30.61	1966	31.29
1967	32.17	1968	33.33	1969	34.64	1970	36.46
1971	38.51	1972	40.17	1973	41.88	1974	45.26
1975	51.34	1976	56.36	1977	61.46	1978	66.61
1979	72.66	1980	80.14	1981	89.61	1982	100.0
1983	110.1	1984	120.5	1985	130.9	1986	141.3
1987	151.3	1988	162.2				

Chapter III

Vacancies And The Cause Of Unemployment

What is the primary cause of cyclical variations in unemployment? Two different theories compete to explain swings in U.S. unemployment: sectoral shifts and aggregate demand shocks. Sectoral shifts (Lilien 1982) cause unemployment by shifting demand between industrial sectors. Aggregate shocks cause unemployment by lowering demand in all sectors.

Previous research by Abraham and Katz (1986) showed that the theories can be distinguished by examining how unemployment and vacancies react to economic shocks. However, their empirical results are suspect for two reasons. First, the vacancy measure used was a proxy that Chapter Two showed needed to be corrected for changes in price and readership. Secondly, Loungani, Rush and Tave (1990) suggest that the dispersion index which measures economic shocks is not an accurate proxy.

This chapter solves these problems by first correcting the vacancy proxy for price and readership changes and then replacing the dispersion index based on employment growth rates with one based on stock market price growth rates. Using a model constructed in the next section, this chapter finds that cyclical unemployment is mainly caused by shifts in aggregate labor demand.

I. Model

Sectoral shifts (Lilien 1982), in which demand moves from falling industrial sectors to rising industrial sectors, are a provocative explanation for variation in unemployment. Before the sectoral shift hypothesis; most economic models assumed that holding GNP constant resulted in stable labor market conditions. With sectoral shifts, unemployment rates change even though total demand in the economy stays constant.

The sectoral shift hypothesis is provocative, but does not stand up to Abraham and Katz's (1986) critique. The critique noted that analyzing only unemployment's response to sectoral change mistakenly overstates its importance. Extending the analysis to include vacancy information reverses the findings. Hence, only through simultaneous examination of unemployment and vacancies can the two hypotheses, aggregate demand and sectoral shocks, be distinguished.[1]

This debate over the cause of unemployment can be clarified using a simple model, presented by equations (1)-(6). While this model is not directly described in either Lilien (1982) or Abraham and Katz (1986), it succinctly captures the main ideas of these two articles.

Workers and firms are divided into N different industrial sectors where the letter i denotes the i^{th} sector. The number of

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[1] An alternative approach uses cross section data (Murphy and Topel 1987, Loungani and Rogerson 1989) to see if unemployed workers switch sectors permanently or temporarily. Permanent switching indicates sectoral shifts are causing unemployment while temporary switching indicates aggregate demand. However, this approach has led to conflicting conclusions.

workers employed in the sector is denoted E while those unemployed and searching for work are denoted U.

The model's primary assumption is that firms asymmetrically adjust their work force because companies find reducing the number of employees easier than increasing the number of employees. Firing or layoff decisions are completely implemented in one time period while hiring decisions are only partially implemented each period. In each period only alpha (α) percent of all hiring decisions are implemented.

Asymmetrical adjustment is explained by businesses having higher costs and longer lead times adding employees than in removing an equal number. Hiring costs are larger because firms must advertise, screen, select and train new workers which is usually far more costly than severance packages for fired workers. Hiring times are longer because both employer and employee must make a decision, unlike firing times where only the employer decides.

To simplify the model each sector's output Y, during time period t, depends only on a function of the number of workers employed. This is written:

1) $Y_{it} = F(E_{it})$

Denoting F^{-1} as the inverse of the function allows employment or E to be derived from equation (1). If sectors know or estimate their expected output level in the period then the optimal number of workers in each sector can be derived. This is shown as equation (2) where the optimal number is represented by a *.

2) $E^*_{it} = F^{-1}(Y^*_{it})$

Changes in output over time ($Y_{it} - Y_{it-1}$) must change the optimal number of workers. Expanding sectors needing more output have vacancies and no layoffs while downsizing sectors will have the converse: layoffs and no vacancies. Each sector will report V vacancies based on equation (3) and L layoffs based on equation (4).

3) $V_{it} = \text{Max}(0, E^*_{it} - E_{it-1})$

4) $L_{it} = \text{Min}(0, E^*_{it} - E_{it-1})$

Equation (3) states that vacancies are equal to the maximum of zero or the desired change in the sector's employment. Similarly, equation (4) states that layoffs are equal to the minimum of zero or the employment change.

In this model *sectoral shocks increase both vacancies and unemployment*. Vacancies rise because workers removed from the shrinking sectors are not completely absorbed by the growing sectors. Since hiring decisions are only partially implemented each period, total employment decreases. Hence, total employment falls and unemployment rates rise.

A two sector example shows why sectoral shifts increase both vacancies and unemployment. Assume each sector has 10 workers and half of all hiring decisions are implemented each period. (α is 0.5) If the economy is shocked so that four workers need to shift sectors the shrinking sector will lay off four workers. However, even though the growing sector wants to hire four workers, it can only hire two, leaving two workers unemployed. In this example, the sectoral shock increases unemployment and vacancies by two.

In this model *aggregate demand shocks move vacancies and unemployment in opposite directions*. A positive shock causes the

average sector to need more workers, increasing vacancies and lowering unemployment both with and without asymmetric adjustment. Conversely, a negative shock results in decreased vacancies and increased unemployment.

Another two sector example shows why aggregate demand shocks move vacancies and unemployment in opposite directions. Assume each sector has 9 workers and 1 vacancy. If an aggregate shock occurs that forces both sectors to shed two positions then both vacancies are canceled and two workers are fired. In this example since vacancies fall by two and unemployment grows by two unemployment and vacancies move in opposite directions.

Since each theory postulates a different reaction to shocks the theories are differentiated by empirically estimating equations (5) and (6). In these equations sigma, σ, is a measure of sectoral dispersion, U is the unemployment rate, V is the vacancy rate and e_t is a random error term.

5) $U_t = a_1 + a_2\sigma_t + e_t$

6) $V_t = b_1 + b_2\sigma_t + e_t$

The above logic shows that if coefficients a_2 and b_2 have the same sign, sectoral shifts are causing cyclical unemployment. However if coefficients a_2 and b_2 have opposite signs, aggregate demand shocks are causing cyclical unemployment.

II. Vacancy Data

Previous empirical tests (Abraham and Katz 1986) used unemployment and vacancy data to show that aggregate demand shocks are

primarily causing unemployment changes. These results are suspect since vacancies are not directly collected but instead are proxied by the Conference Board Help-Wanted Index (HWI).[2]

Previously, researchers using this index adjusted it for labor market growth by dividing by nonfarm employment. However, as Chapter Two showed, this index needs to be adjusted for advertising price and readership changes in addition to labor market growth.

Readership is very important because firms buy millions of help-wanted ads each year to reach the large numbers of people who read them. Changing the number of readers directly affects advertising demand since this alters how efficiently an ad reaches its targeted audience. Significantly, over the last twenty years readership of ads by the unemployed has soared almost sixty percent.

Price considerations also play a very important role in deciding the size and number of help-wanted ads bought, unless firms have perfectly inelastic demand curves. Over the last forty years newspapers have increased the real price of help-wanted ads by over 157%. Price and readership factors must be taken into account to remove these non-labor market trends from the vacancy proxy.

The HWI proxy listed in Table 1 is corrected only for labor force growth and rebased to correspond to the national vacancy rate which is known for April 1965 (U.S. Congress 1966). This table shows the national percentage of open jobs which is interpreted in a similar fashion to unemployment rates.

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[2]This index measures the number of employment classified ads placed in 51 major U.S. newspapers since 1951 (Preston 1977).

Table 1:

U.S. National Help-Wanted Index 1951-1989
Transformed Into Percentage of Vacant Jobs.[a]

Year	HWI	Year	HWI
1951	3.09	1971	2.79
1952	3.27	1972	3.35
1953	3.05	1973	3.96
1954	1.98	1974	3.40
1955	2.72	1975	2.50
1956	3.04	1976	2.86
1957	2.57	1977	3.41
1958	1.86	1978	4.12
1959	2.57	1979	4.22
1960	2.37	1980	3.43
1961	2.18	1981	3.13
1962	2.46	1982	2.30
1963	2.38	1983	2.50
1964	2.65	1984	3.29
1965	3.24	1985	3.41
1966	3.87	1986	3.34
1967	3.64	1987	3.60
1968	3.90	1988	3.61
1969	4.18	1989	3.38
1970	3.17		

[a]Note: 1965 value is equal to national vacancy rate computed from BLS survey.

Readership time series data listed in Table 2 are based on active job seekers not presently working. They are followed by the BLS's Current Population Survey, which asks all unemployed people not on temporary layoff, question 22A, "What has _____ been doing in the last 4 weeks to find work?" Comparing the values from 1970 to 1989 shows the rise of almost sixty percent.

Table 2:

Percent of Unemployed Using Help-Wanted Ads To Find Work
1951-1989

Year	% Readers	Year	% Readers
1951	12.05	1971	25.70
1952	12.72	1972	26.00
1953	13.39	1973	26.10
1954	14.06	1974	27.00
1955	14.73	1975	29.40
1956	15.40	1976	30.40
1957	16.06	1977	30.10
1958	16.73	1978	29.20
1959	17.40	1979	30.00
1960	18.07	1980	30.90
1961	18.74	1981	32.20
1962	19.41	1982	34.70
1963	20.07	1983	33.80
1964	20.74	1984	34.40
1965	21.41	1985	34.40
1966	22.08	1986	35.70
1967	22.75	1987	35.70
1968	23.42	1988	34.90
1969	24.09	1989	38.10
1970	23.40		

Why has readership increased over time? First, disaggregating the BLS data by sex shows that unemployed females use ads more than males. Hence, the dramatic increase in participation by females in the labor force has increased total readership. Second, a 1986 cross-sectional study from the Newspaper Advertising Bureau suggests that educational attainment is an important determinant of newspaper readership. Hence, overall increases in U.S. educational levels can also explain why readership has soared over time.

Holding other factors constant, advertising demand should have increased over time to reflect the increased readership levels. Rising

readership boosts demand because it transforms help-wanted ads into a more efficient method of reaching job seekers.

The price index, Table 3, is constructed by looking up advertising rates from the periodical Standard Rate and Data Services, which contains price information for out-of-state advertisers.[3] These nominal prices are then deflated by the Consumer Price Index because demand is based on the price paid by consumers in relation to all other consumer prices. Chapter Two suggests that the rise in real prices was fueled by large increases in newspaper production costs.

Researchers who use the vacancy proxy listed in Table 1, need to apply the data listed in Tables 2 and 3 to account for price and readership effects. Adding these variables results in a better signal of labor market demand because it corrects for advertising information biasing the index.

[3]If a newspaper did not list a help-wanted rate, the general classified rate was used instead. Both the daily and Sunday rates were collected for each newspaper. Daily prices were weighted by two-thirds and the Sunday by one-third to roughly reflect the relative quantity of ads appearing in daily and Sunday papers. When a paper listed multiple help-wanted rates, the rate selected was a full-run single insertion of one classified line by an out-of-state advertiser.

Table 3:

Nominal Help-Wanted Price Index
Base Year 1982 = 100[a]

Year	Help-Wanted	Year	Help-Wanted
1951	15.6	1971	35.9
1952	16.6	1972	37.0
1953	18.0	1973	38.9
1954	18.7	1974	41.3
1955	18.9	1975	44.4
1956	19.9	1976	50.8
1957	22.0	1977	54.5
1958	22.6	1978	60.7
1959	22.8	1979	70.2
1960	23.6	1980	75.3
1961	24.4	1981	91.5
1962	26.0	1982	100.0
1963	27.6	1983	116.2
1964	28.0	1984	126.6
1965	28.8	1985	136.7
1966	29.4	1986	153.6
1967	30.7	1987	163.6
1968	32.1	1988	175.5
1969	33.2	1989	195.8
1970	34.2		

[a]Note: Based on the cost per line of a help-wanted ad in 9 major U.S. newspapers.

III. Empirical Tests

The model constructed in section II resulted in a simple two-equation regression test shown by equations (5) and (6), repeated below.

5) $U_t = a_1 + a_2\sigma_t + e_t$

6) $V_t = b_1 + b_2\sigma_t + e_t$

Regressing unemployment against σ (the measure of sectoral dispersion) and then regressing vacancies against σ provides coefficients a_2 and b_2. If coefficients a_2 and b_2 have the same sign sectoral shifts are causing cyclical unemployment; if coefficients a_2

and b_2 have opposite signs, aggregate demand shocks are causing cyclical unemployment changes.

The computation of sigma, the sectoral dispersion variable, is described in Lilien (1982). This variable captures the dispersion in observed employment growth rates across the 11 major industrial classifications in the U.S. Lilien tabulates the values of this variable until 1980. Table 4 lists values calculated using his procedure for nine more recent years.

Table 4:

Calculated Values of σ (Sigma) 1981-1989[a]
Employment Measure of Sectoral Dispersion

Year	Sigma	Year	Sigma
1981	.0240	1986	.0293
1982	.0303	1987	.0189
1983	.0330	1988	.0154
1984	.0235	1989	.0182
1985	.0248		

[a]Note: Values calculated using procedure outlined in Lilien (1982).

Using these values, coefficients for equations (5) and (6) can be computed for the period 1952 to 1989. Values in Table 5's first column estimate equation (5) using the total unemployment rate as the dependent variable. The second and third columns estimate equation (6) using the help-wanted index as the vacancy proxy.

Table 5:

OLS Test Using Lilien's Measure of Dispersion, Sigma
1951-1989. t-statistics in ( )[a]

Dependent Var.	Unemploy	Vacancy	Vacancy
Constant	4.19	3.70	3.11
	(10.0)	(22.7)	(8.86)
$Sigma_t$	65.41	-25.8	-25.1
	(4.09)	(4.16)	(4.06)
Price			-0.003
			(0.54)
Readership			0.035
			(2.08)
MA(1)	0.83	0.65	0.65
	(10.7)	(5.44)	(5.43)
R^2	.61	.55	.59
Adj. R^2	.59	.53	.55
D.W.	1.44	1.54	1.70
SSR	41.5	6.50	5.81

[a]Note: Column 1 estimates equation (5). Column 2 estimates equation (6). Column 3 adds variables to correct the HWI for advertising changes.

After correcting all three equations for serial correlation with a moving average MA(1) correction to save degrees of freedom, the results in Table 5 show two features. First, because the signs on the sigma coefficients are opposites, aggregate demand shocks are a better explanation of cyclical unemployment than sectoral shifts.

Secondly, correcting the HWI for price and readership changes confirms Abraham and Katz's results. The unchanged coefficient shows that the results are neither stronger nor weaker than before. However, adding price and readership variables provides a better fit as seen by a higher R^2 and adjusted R^2 in the equation containing these additional variables.

The second empirical test in this chapter is the more extensive specification proposed by Lilien, and shown below as equations (7) and (8). Lilien believed that civilian unemployment is dependent on sectoral dispersion but added terms to track unanticipated money shocks, lagged unemployment and a time trend.

$$7)\ U_t = a_1 + a_2\sigma_t + a_3\sigma_{t-1} + a_4DMR_t + a_5DMR_{t-1} + a_6DMR_{t-2} + a_7U_{t-1} + a_8t + e_t$$

$$8)\ V_t = b_1 + b_2\sigma_t + b_3\sigma_{t-1} + b_4DMR_t + b_5DMR_{t-1} + b_6DMR_{t-2} + b_7V_{t-1} + b_8t + e_t$$

Both the unemployment and vacancy equations contain lagged dependent value terms to remove the need for serial correction. Additionally, Lilien inserted the DMR terms to measure the effect of unanticipated changes in the money supply. These are theoretically important since unanticipated money increases could temporarily fool people into working harder.

The unanticipated money series, named DMR, is designed in Barro (1977) using the M1 monetary aggregate and is calculated by Barro and Hercowitz until 1977 (1980). More recent DMR values, calculated using the coefficients given in Barro (1978), are listed in Table 6.

Table 6:

Calculated Values of DMR 1978-1989
Barro's Series of Unanticipated Money

Year	DMR	Year	DMR
1978	.0187	1979	.0130
1980	.0041	1981	-.0012
1982	.0160	1983	.0141
1984	-.0316	1985	.0449
1986	.0714	1987	-.0779
1988	-.0144	1989	-.0288

Results from estimating equation (7) and (8) are shown in Table 7. Using this more extensive specification shows two different features. First the opposite coefficient signs on the sum of all sigma variables again show that aggregate demand shocks are a better explanation of labor market change than sectoral shifts. Secondly, correcting for advertising change reduces the affect sigma has on vacancies. This is seen by the smaller sigma coefficients in column three.

Additionally, the more extensive specification shows that DMR, or unanticipated money, is not a significant factor in changing vacancies or unemployment. This result contradicts the findings reported by both Lilien and Barro and suggests that either unanticipated money based on the M1 is too narrowly defined for a long-run proxy or that unanticipated money is no longer a significant force in labor markets.

Table 7:

OLS Test Using More Extensive Specification
1952-1989. t-statistics in ( )[a]

Dependent Var.	Unemploy	Vacancy	Vacancy
Constant	-.73	2.07	3.64
	(1.53)	(4.78)	(2.48)
$Sigma_t$	81.2	-32.7	-30.5
	(8.32)	(6.47)	(5.55)
$Sigma_{t-1}$	-.27	-2.79	-1.32
	(0.02)	(0.51)	(0.22)
DMR_t	1.37	3.86	3.3
	(0.30)	(1.63)	(1.33)
DMR_{t-1}	-4.3	4.44	4.48
	(0.96)	(1.85)	(1.84)
DMR_{t-2}	-1.3	2.56	0.70
	(0.28)	(1.00)	(0.23)
$Unemp_{t-1}$	0.75		
	(8.02)		
Adj HWI_{t-1}		.55	.50
		(4.66)	(4.07)
Price			-0.03
			(0.60)
Reader			-0.13
			(1.21)
Trend	.016	.008	0.10
	(1.17)	(1.58)	(1.33)
R^2	.88	.78	.80
Adj. R^2	.86	.73	.73
D.W.	1.65	1.71	1.66
SSR	11.2	3.07	2.92

[a]Note: Column 1 estimates equation (7). Column 2 estimates equation (8). Column 3 adds variables to correct the HWI for advertising changes.

IV. Alternative Measure of Sectoral Dispersion

The sigma measure of dispersion, (Lilien 1982) used in the above tests is suspect as a measure of sectoral shifts. The primary problem is that the series is changed by both permanent and temporary labor market shocks. This problem arises because the variable is calculated using only the current and most recent previous level of employment in

each sector. Since only two periods of data are used, any temporary shock will cause sigma to change sharply even if all economic agents know it is temporary or are completely expecting the change.

Another problem with sigma is that it is often unclear to BLS survey takers in what industry workers should be classified.[4] If some workers are arbitrarily reclassified each year then sigma can change even when no worker has switched jobs.

Loungani, Rush and Tave (1990) create a dispersion measure, called Stock and listed in Table 8, based on stock market prices in 45 industries. They state that this measure is potentially more accurate than sigma because *"sectoral stock prices largely react to disturbances that are perceived to be permanent."*[5] Additionally, since the measure is not based on labor market data it does not suffer the same measurement problems as sigma.

[4]For example, if a manufacturing firm has some employees engaged in managing a pension fund, should these workers be counted in the service category or manufacturing?

[5]This measure assumes that all stock market traders are fully informed and rational. These assumptions are seriously questioned in financial models with uninformed "noise" traders. (Shleifer and Summers 1990)

Table 8:

Stock Market Dispersion 1951-1987

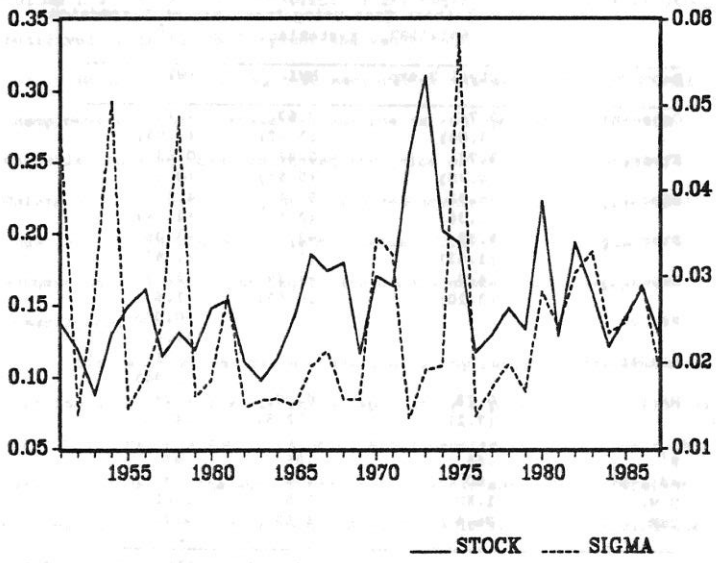
Year	Stock	Year	Stock
1951	0.13700	1970	0.17010
1952	0.11900	1971	0.16310
1953	0.08770	1972	0.25490
1954	0.13080	1973	0.31080
1955	0.14960	1974	0.20210
1956	0.16150	1975	0.19390
1957	0.11470	1976	0.11740
1958	0.13150	1977	0.12980
1959	0.11910	1978	0.14800
1960	0.14810	1979	0.13330
1961	0.15380	1980	0.22280
1962	0.11080	1981	0.12910
1963	0.09720	1982	0.19370
1964	0.11340	1983	0.15830
1965	0.14240	1984	0.12110
1966	0.18550	1985	0.14180
1967	0.17400	1986	0.16250
1968	0.17970	1987	0.12890
1969	0.11700		

The smaller reaction to temporary shocks is seen by the smaller variance of the stock market measure. Stock has a mean of 0.15 with a 0.04 standard deviation compared to sigma's mean of 0.02 with a 0.01 standard deviation. Additionally, graphing the two series in Figure 1 shows that while currently the two series follow a similar trend, during the 1950's and 1960's sigma often changed radically compared to the stock market measure's smoother behavior.

Figure 1:

Sectoral Dispersion Variables Sigma and Stock:

Stock y-axis on left. Sigma y-axis on right.
Sigma is based on employment and Stock on the stock market.



Using this new sectoral dispersion series, the empirical tests are rerun for the period 1951 to 1987. Three lagged values are added to the econometric tests, following Loungani et al, because stock prices are a leading indicator of future economic trends. Values in Table 9's first column estimate equation (5) while the second and third columns estimate equation (6).

After corrections for serial correlation, the higher R^2 and adjusted R^2 in Table 9 show that adding price and readership variables provides a better fitting model.

Table 9:

OLS Sectoral Shift Test Using Stock Market Dispersion
1951-1987. t-statistics in ( )[a]

Dependent Var.	Civil Unemp	HWI	HWI
Constant	2.74	2.63	2.45
	(3.04)	(7.40)	(3.95)
$Stock_t$	3.74	0.99	0.63
	(0.78)	(0.52)	(0.33)
$Stock_{t-1}$	-6.92	5.24	4.2
	(1.35)	(2.55)	(2.14)
$Stock_{t-2}$	8.39	-2.11	-3.35
	(1.63)	(1.03)	(1.63)
$Stock_{t-3}$	14.9	-1.29	-3.65
	(3.20)	(0.69)	(1.83)
Price			-0.003
			(0.40)
Reader			0.05
			(1.96)
MA(1)	0.73	0.98	0.98
	(7.27)	(22.5)	(47.1)
R^2	.66	.59	.66
Adj. R^2	.60	.53	.58
D.W.	1.50	1.81	1.80
SSR	36.6	5.69	4.71

[a]Note: Column 1 estimates equation (5) replacing Sigma with Stock. Column 2 estimates equation (6) also using stock. Column 3 adds variables to correct the HWI for advertising changes.

Which theory do the results in Table 9 support? If the signs are the same on the sums of all Stock coefficients in columns 1 and 2 then sectoral shifts are supported. Otherwise, aggregate demand shocks are supported. Summing column 1 (value: 20.11 std-error: 5.83) and column 2's (value: 2.83 std-error: 2.29) coefficients shows that Stock positively affects unemployment and vacancies.

However, concluding that sectoral shifts are causing cyclical unemployment based on these regressions is not appropriate because vacancies have not been corrected for price or readership changes. Column 3 shows that adding price and readership factors results in a negative total Stock coefficient, (value: -2.17 std-error: 3.26) suggesting once again that aggregate demand shocks cause cyclical unemployment.

The results from Table 9 are checked by rerunning the equations with the separate Stock variables replaced by a polynomial distributed lag (PDL). Using a PDL function of Stock permits the weight of each variable to vary. The sum of the Stock coefficients using different degrees and constraints is reported in Table 10 to see if varying the functional form affects the results.[6]

Table 10 indicates that changing the PDL function does not significantly affect the results. Correcting the vacancy proxy for price and readership again shows aggregate demand shocks are the primary cause behind cyclical unemployment.

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[6]The tests vary the polynomial's degree which affects the influence each year is given, and also tries a near point constraint which forces the stock market indicator's influence to start out close to zero.

Table 10:

Sum Of Lagged Stock Coefficients Using Various PDL Forms
Time Period 1951-1987. T-statistics in ( ) 3 Lags Used

Civilian Unemployment		Constrained Near Point	No Constraint
PDL Order	1	24.20 (4.28)	16.3 (2.61)
	2	22.29 (3.77)	20.3 (3.13)
	3	21.71 (3.35)	22.9 (3.90)
HWI		**Constrained Near Point**	**No Constraint**
PDL Order	1	1.43 (0.61)	2.64 (1.04)
	2	2.37 (0.98)	0.91 (0.34)
	3	2.80 (1.08)	3.17 (1.37)
HWI With Price & Readership		Constrained Near Point	No Constraint
PDL Order	1	-3.1 (0.94)	-1.55 (0.42)
	2	-3.3 (0.92)	-1.32 (0.32)
	3	-3.1 (0.79)	-2.58 (0.78)

V. Conclusions

This chapter sought to determine the primary cause of cyclical variations in unemployment. Lilien's (1982) theoretical and empirical work showed that sectoral shifts, where demand moves between industrial sectors, cause cyclical unemployment.

Lilien's work was refuted by Abraham and Katz (1986) who showed that examining unemployment and vacancies together establishes aggregate demand shocks (the simultaneous lowering of demand in all sectors) as the primary cause of cyclical unemployment.

Abraham and Katz's result was then overturned by Loungani, Rush, and Tave (1990) who used a better measure of sectoral dispersion, based

on stock market prices, and found shifts were the primary cause of cyclical unemployment.

This chapter reverses Loungani et al's results by adding corrections for price and readership changes to the vacancy proxy. Using this corrected vacancy proxy and the stock market measure for sectoral dispersion once again shows that aggregate demand shocks are the primary cause of cyclical unemployment.

Chapter IV

Vacancies And Unemployment Insurance

What are the effects of unemployment insurance (UI) on the labor market? While substantial research has examined UI's effect on unemployment rates,[1] there has been scant investigation into the effects of this important program on job vacancies.

Unemployment insurance is an important program because it spends and receives large amounts of money to protect experienced workers from temporary changes in labor market conditions. For instance, in 1987 the program collected over $17.5 billion dollars in taxes from employers and paid over $13.6 billion dollars in benefits.

The program is also important because it encompasses most of the work force. In 1987, 85% of all workers were in jobs covered by the program[2] and 6% of the labor force received at least one UI payment.

This chapter empirically examines the previously unexplored effects of UI on vacancies. It finds that the level of unemployment insurance contributions is positively correlated with the job vacancy rate, holding unemployment rates constant. Additionally, the level of unemployment insurance benefits is negatively correlated with the job vacancy rate. Combining these two effects results in a small decrease

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[1] Literature surveys of the effects of UI can be found in Burtless (1990), Topel and Welch (1980) and Hamermesh (1977).

[2] The figure jumps to 95% if all self-employed workers who are not required by law to participate are excluded.

in vacancies which is a previously undocumented impact of unemployment insurance on the labor market.

I. UI Effects on Vacancies

Vacancy rates, the number of unfilled jobs divided by the number of filled and unfilled jobs, can also be calculated by multiplying the number of job openings times the average duration each vacancy is open. This is formally stated in equation (1) where V_t stands for the percentage of vacant jobs at time t, O stands for the number of unfilled positions open and D for average duration of time it takes each opening to be filled.

1) $V_t = O_t * D_t$

Equation (1) shows that UI can affect vacancies by influencing the number of openings, average duration or both. Previous research (Burtless 1990; Hamermesh 1977) suggests that UI benefits change the length of time it takes unemployed workers to find a new job. This increase presumably causes a change in the duration of vacancies. Additional research (Becker 1970; Feldstein 1975, 1976, 1978; Topel 1990) shows that UI contributions change the cost of employing or laying off workers, causing a change in the number of openings. Hence, empirical tests should include both of these UI indicators.

Using these indicators the effect of UI on vacancies is examined by extending the Beveridge curve,[3] a statistical relation between unemployment and vacancy rates. This relation is shown by equation (2).

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[3]Beveridge curves are the product of dynamic labor market models in Hansen (1970) and Pissarides (1985 & 1987).

2) $V_t = a_1 + a_2U_t + a_3F_t + e_t$

where V_t is the vacancy rate in time period t, U_t is the unemployment rate, and F_t is a set of variables describing the different forces that could alter the labor market. The lower case a's stand for coefficients to be estimated, with e representing a random error term.

Beveridge curves are assumed to be downward sloping because when the aggregate economy is in an expansionary period there are high levels of vacancies and low unemployment. Conversely, during recessionary periods, there are low vacancies and high unemployment.

This chapter investigates the effect of UI on vacancies by placing different measures of contributions and benefits in the F vector. Additionally, to test how sensitive the results are to changes demographic variables and lagged explanatory variables are added to the F vector.

Equation (2) also needs additional terms since U.S. vacancy data are not directly collected but are proxied by the Conference Board help-wanted index (HWI). Creating Beveridge curves using this vacancy proxy shows dramatic outward shifts. However, these shifts are suspect since the HWI proxy is only measuring the *total number of help-wanted ads* published, not actual vacancies. Chapter Two shows that the vacancy proxy must be adjusted for underlying price and readership changes in the newspaper market. Thus two additional advertising variables, P price and R readership, need to be added to the function.

3) $V_t = a_1 + a_2U_t + a_3P_t + a_4R_t + a_5F_t + e_t$

Equation (3) hypothesizes that in each time period t the vacancy proxy is a function of: the state of the economy, labor market variables

and advertising changes. Coefficient a_2 should be negative since unemployment and vacancies are observed to be inversely related. Similarly, a_3 is negative since increases in advertising's real price make finding applicants more costly, lowering the number of advertised vacancies. Coefficient a_4 should be positive since increasing readership makes ads a more effective tool for finding applicants. The signs on the F coefficients can not be specified in advance.

The rest of this chapter discusses data needed to run the empirical tests and then focuses on what the empirical results mean.

II. Beveridge Curve Data

To empirically estimate U.S. Beveridge curves researchers need: the vacancy proxy, unemployment, price and readership data. The vacancy proxy and unemployment data are needed because Beveridge curves directly relate these two indicators. Price and readership data are needed in the U.S. to correct the vacancy proxy. This section briefly discusses data used for these series.

The Conference Board Help-Wanted Index (HWI) is the most frequently used U.S. vacancy proxy in empirical research (Abraham 1987; Blanchard and Diamond 1989; Cohen and Solow 1967, 1970; Medoff 1983). The national index tracks the number of help-wanted advertisements published in 51 major U.S. newspapers. Fifty one additional indexes are also released so that researchers can track vacancies in local areas.

The HWI is modified before being used in the empirical tests. First, the index[4] is divided by the series tallying the number of individuals in the labor force. This compensates for the upward growth in employment which inflates the number of jobs advertised.

Secondly, the adjusted series is then transformed into a vacancy proxy by calibrating the 1965 value to the BLS's estimated vacancy rate for April of that year (3.24%). Using these two steps allows regression coefficients to be interpreted as the increase or decrease in the vacancy rate given a one unit change in the regressor.

The accuracy of the survey is not important to this paper's results since a different number would only cause the proxy to shift by a constant. However, rebasing the series allows a more intuitive examination of the data.

Chapter Two clearly showed that the adjusted HWI vacancy proxy was affected by changes in advertising price and readership. Readership time series data listed in Table 1 are based on active job seekers not presently working. They are followed by the BLS's Current Population Survey, which asks all unemployed people not on temporary layoff, question 22A, "What has _____ been doing in the last 4 weeks to find work?" Comparing the values from 1970 to 1989 shows a rise of almost sixty percent.

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[4]National and local indexes are found in the back of Preston (1977) and in the Conference Board Record. I thank the Conference Board's Kenneth Goldstein for providing the data on floppies.

Table 1:

Percent of Unemployed Using Help-Wanted Ads To Find Work
1951-1989

Year	% Readers	Year	% Readers
1951	12.05	1971	25.70
1952	12.72	1972	26.00
1953	13.39	1973	26.10
1954	14.06	1974	27.00
1955	14.73	1975	29.40
1956	15.40	1976	30.40
1957	16.06	1977	30.10
1958	16.73	1978	29.20
1959	17.40	1979	30.00
1960	18.07	1980	30.90
1961	18.74	1981	32.20
1962	19.41	1982	34.70
1963	20.07	1983	33.80
1964	20.74	1984	34.40
1965	21.41	1985	34.40
1966	22.08	1986	35.70
1967	22.75	1987	35.70
1968	23.42	1988	34.90
1969	24.09	1989	38.10
1970	23.40		

Why has readership increased over time? First, disaggregating the BLS data by sex shows that unemployed females use ads more than males. Hence, the dramatic increase in participation by females in the labor force has increased total readership. Second, a 1986 cross-sectional study from the Newspaper Advertising Bureau suggests that educational attainment is an important determinant of newspaper readership. Hence, overall increases in U.S. educational levels can also explain why readership has soared over time.

Holding other factors constant, advertising demand should have increased over time to reflect the increased readership levels. Rising

readership boosts demand because it transforms help-wanted ads into a more efficient method of reaching job seekers.

Price considerations also play an important role in deciding the size and number of help-wanted ads bought. The price index, Table 2, is constructed by looking up advertising rates from the periodical Standard Rate and Data Services, which contains price information for out-of-state advertisers. The index is based upon prices listed for the primary newspaper in nine major cities.[5] While rates from the January edition were used when possible, four editions were not available and March 1965, July 1974, 1978, 1979 were substituted.

Since not all papers maintain a help-wanted rate the general classified rate was used in its absence. In cases when a paper listed multiple help-wanted rates, the rate selected was for a full-run single insertion of one classified line by an out-of-state advertiser.[6]

This nominal index was then deflated by the national Consumer Price Index (CPI) because demand is based on the price paid by consumers in relation to all other consumer prices. Chapter Two suggests that the help-wanted price rise was fueled by large increases in newspaper production costs.

Researchers who use the HWI vacancy proxy need to apply the data listed in Tables 1 and 2 to account for price and readership effects.

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[5]Boston, Chicago, Detroit, Houston, Los Angeles, Miami, New York, Philadelphia, and Washington D.C.

[6]To ensure the index accurately reflected weekday and weekend trends both the daily and Sunday rate were collected for the nine major newspapers. Daily prices were weighted by two-thirds and Sunday prices by one-third to reflect the relative quantity of ads appearing in daily and Sunday papers.

Adding these variables results in a better signal of labor market demand because it corrects for advertising information biasing the index.

Table 2:

Nominal Help-Wanted Price Index
Base Year 1982 = 100[a]

Year	Help-Wanted	Year	Help-Wanted
1951	15.6	1971	35.9
1952	16.6	1972	37.0
1953	18.0	1973	38.9
1954	18.7	1974	41.3
1955	18.9	1975	44.4
1956	19.9	1976	50.8
1957	22.0	1977	54.5
1958	22.6	1978	60.7
1959	22.8	1979	70.2
1960	23.6	1980	75.3
1961	24.4	1981	91.5
1962	26.0	1982	100.0
1963	27.6	1983	116.2
1964	28.0	1984	126.6
1965	28.8	1985	136.7
1966	29.4	1986	153.6
1967	30.7	1987	163.6
1968	32.1	1988	175.5
1969	33.2	1989	195.8
1970	34.2		

[a]Note: Based on the cost per line of a help-wanted ad in 9 major U.S. newspapers.

III. Unemployment Insurance Data

UI pays laid-off workers up to 26 weeks of compensation which averages approximately one third of their employed weekly wage.(Dept. Labor 1989) This program, set up to help experienced workers looking for work, has been extensively analyzed by researchers. Researchers doing empirical investigations have a number of different data series to

choose from for their tests. This chapter primarily focuses on real contributions per employee and real benefits per laid-off worker.

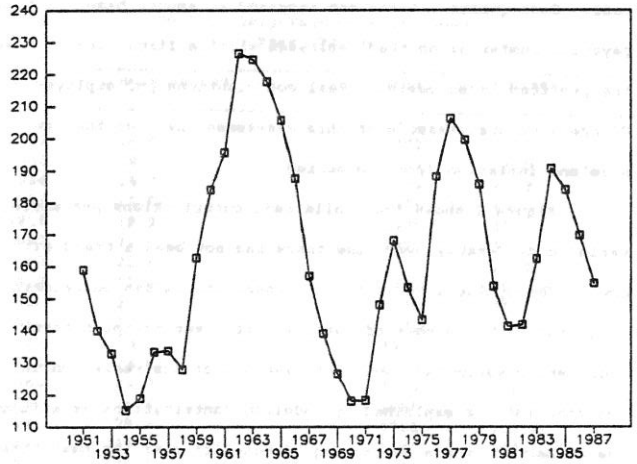
Contributions measure UI's cost to employers during a given year. Each quarter, firms are assessed an amount based on their total payroll, number of covered employees and the firms' layoff history over the previous three years.[7] Real contributions per employee covered by UI are a natural measure of this assessment because they remove firm size and inflation from the series.

Figure 1 shows that while real contributions per employee have varied considerably over time there has not been a trend either up or down. The cyclical variation in contributions can be primarily explained by the number of total layoffs over the past three years. Econometric estimates show that over 85% of the variation in contributions is explained by modeling contributions as a function of the number of people collecting UI benefits over the past three years.

[7]The series contains contributions paid during the year, not contributions owed. This occurs because most states allow a one month grace period causing most December payments to be credited to the next year. This accounting detail should not affect the empirical results.

Figure 1

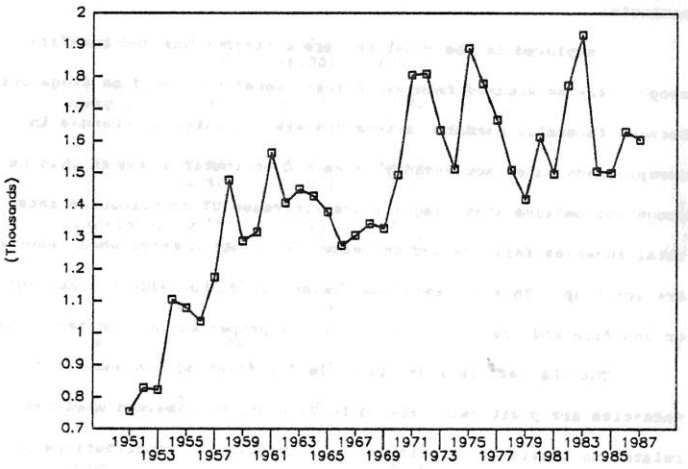
U.S. National Real UI Contributions Per Covered Employee
From 1951 to 1987 In 1982 dollars



Benefit data measure UI's payments to laid-off workers. Real benefits per laid-off worker are computed by dividing total payments, adjusted for inflation, by the number of first-time UI payments during the year. This series, graphed in Figure 2, shows that while benefits trended upwards during the 1950's and 1960's there has been no trend since.

Figure 2

U.S. National Real UI Benefits Per Laid-Off Worker
From 1951 to 1987 In 1982 dollars



IV. National Empirical Tests

Empirical tests using the above data can suggest answers to the question, *What is the effect of unemployment insurance on vacancy rates*? This section, using national data finds that the level of unemployment insurance contributions is positively correlated with the job vacancy rate, holding unemployment rates constant. Additionally, the level of unemployment insurance benefits is negatively correlated with the job vacancy rate.

These results are obtained by using ordinary least square (OLS) to estimate the Beveridge curve shown previously in Equation (3). OLS

is an improper technique if any of the right hand side variables are affected by the vacancy proxy. Chapter Two investigated this question for price and readership data and suggests that neither are affected by vacancies.

Unexplored is the question, *are contributions and benefits exogenously determined from vacancies?* Benefits should be exogenous because federally mandated extensions are triggered by changes in unemployment rates not vacancy rates. Contributions should also be exogenous because state legislatures increase UI contribution rates when total reserves fall low and decrease contribution rates when reserves are built up. This suggests that vacancies do not affect contributions or benefits and indicate that OLS is the proper estimation technique.

The OLS results found in Table 3's first column show that vacancies are positively related to UI contributions and negatively related to benefits. Specifically, increasing UI contributions by $10 per employee increases the vacancy rate by 0.017% while increasing UI benefits by $10 per laid-off worker decreases the rate by 0.005%.

What would be the effect on vacancies of increasing contributions per employee by $10 and giving the money to laid-off workers who are currently receiving UI benefits? In 1987 there were 13.7 workers contributing for every person drawing UI benefits. Holding all other factors constant, if UI contributions increased by $10 per worker, benefits would need to increase by $137 dollars to give all the additional money as benefits. Multiplying these dollar amounts times the respective coefficients suggests this idea would have lowered the national vacancy rate by 0.05 percent in 1987.

Table 3

Regression of National Vacancy Proxy on UI and Other Variables 1951-1987[a]

Dependent Variable: Help-Wanted Index			
Constant	3.76	2.76	5.73
	(14.0)	(8.00)	(7.73)
Unemploy	-0.45	-0.34	-0.42
	(13.4)	(8.12)	(12.2)
Ad Price	-0.02	-0.01	-0.02
	(4.94)	(2.65)	(5.87)
Readership	0.16	0.11	-0.007
	(12.8)	(6.63)	(0.11)
UI Contrib[b]	0.0017	0.0029	0.0017
	(1.60)	(3.07)	(1.73)
UI Benefit[c]	-.0005	0.0	-0.0005
	(2.07)	(0.05)	(2.44)
Coinc Index[d]		0.05	
		(3.83)	
Trend			0.11
			(2.81)
R^2	.91	.94	.92
SSR	1.25	0.84	0.98
D-W	1.90	1.75	2.00
# obs	37	37	37

Note: Column 1 is the base regression.
Column 2 adds index of coincident indicators.
Column 3 adds time trend.

[a] T-Statistics are shown in parentheses.
[b] Real unemployment insurance contributions divided by number of employees covered by UI.
[c] Real unemployment insurance benefits divided by number of individuals who received at least one UI payment.
[d] Index of coincident indicators, U.S. Commerce Dept.

Table 3's first column uses unemployment as the indicator of the state of the economy. Clearly, this is an oversimplification since the economy's health depends on more than just the labor market. One data series designed explicitly to closely follow changes in the U.S. business cycle is the U.S. Commerce Department's Index of Coincident Indicators.

Results of adding this variable to the regression are listed in the second column of Table 3. They show job vacancies are positively and significantly related to this business cycle measure. More importantly, adding this variable reduces the coefficient on UI benefits by a factor of thirty and renders the variable statistically insignificant. The coefficient is reduced because benefits and the coincident index are closely related. During economic downturns benefits are often extended and then revert to normal levels during economic upturns.

Another test is to add a time trend to detect any drift over the four decades. Results in column 3 reveal changes not in the UI coefficients but in readership's. This suggests that readership and a time trend may be tracking the same underlying phenomena.

Together these national regressions suggest that when other factors are held constant, increasing contributions increases vacancies while increasing benefits decreases vacancies. When UI contributions are increased to provide more benefits the overall effect on vacancies is small and negative.

The national outcome may be different from disaggregated state results because no two states have the same UI rules. Thus, aggregated

national data may hide important differences. Unfortunately, meaningful empirical tests can not be run because vacancy proxies are compiled for major U.S. cities, unemployment insurance data are compiled for states and readership data are compiled nationally.

Since the disaggregated data series do not measure the same geographic areas, disaggregated tests can not be meaningfully interpreted. Even though this method is not feasible other tests can check the results sensitivity. The next sections preform tests by adding lagged explanatory variables, adding demographic variables and using different contribution and benefit measures.

V. Lagged Empirical Tests

National data clearly indicate UI contributions and benefits influence vacancies. However, are these results sensitive the datas' timing? Adding lagged vacancy, unemployment and UI contribution and benefit data to the Beveridge curve provide a means to investigate the question. Since none of these lagged variables should be in the *true* model their addition should not significantly affect the empirical results.

The first test adds the HWI lagged one period to the right hand side of the equation to see if the vacancy proxy is better explained by its own past values than by explanatory variables. Examination of Table 4's first column shows that the coefficient on the lagged HWI is small and statistically insignificant. More importantly since adding this variable does not significantly change any of the other coefficients the vacancy proxy is better defined by the explanatory variables.

The second test adds a lagged value of unemployment suggesting that vacancies are affected by current and past values of unemployment. Results, shown in column 2, indicate that only the UI contribution variable is affected. While the contribution coefficient is halved in value and reduced in statistical significance it's correct sign and nonzero magnitude still suggest that UI effects vacancies.

The last test adds two variables, contributions lagged one year and benefits lagged one year suggesting that changes in UI contributions and benefits have both an immediate and lagged effect on the vacancy proxy.

Results in column 3 reveal that the total effect over both years of contributions is 0.009 while the total effect of benefits is -0.0003. Both of these total coefficients have the correct sign and magnitude but are statistically insignificant. The very low t-statistics on each of the lagged UI terms suggests that these additional series are not important explanatory variables.

These tests show that lagged values of the vacancy proxy, unemployment and UI do not significantly affect previous results and bear out the assumption that these additional variables do not belong in the true model.

Table 4

Regression of Vacancy Proxy on Lagged Variables: 1952-1987[a]

Dependent Variable: Help-Wanted Index			
Constant	3.84	3.85	3.71
	(7.26)	(12.8)	(10.99)
Unemploy	-0.46	-0.49	-0.43
	(10.4)	(10.8)	(9.04)
Lag Unemp		0.05	
		(1.13)	
Ad Price	-0.02	-0.02	-0.02
	(4.30)	(4.93)	(4.12)
Readership	0.16	0.16	0.15
	(8.89)	(11.96)	(7.02)
UI Contrib[b]	0.0016	0.0008	-0.0005
	(1.28)	(0.63)	(0.11)
Lag Contrib			0.0014
			(0.40)
UI Benefit[c]	-.0005	-.0004	-.0006
	(1.88)	(1.60)	(1.93)
Lag Benefit			0.0003
			(0.77)
Lag HWI	-0.02		
	(0.17)		
R^2	.91	.92	.91
SSR	1.25	1.19	1.22
D-W	1.90	2.03	1.94

Note: Column 1 adds the HWI lagged one year.
Column 2 adds unemployment lagged one year.
Column 3 adds benefits and contributions lagged one year.

[a] T-Statistics are shown in parentheses.
[b] Real unemployment insurance contributions divided by number of employees covered by UI.
[c] Real unemployment insurance benefits divided by number of individuals who received at least one UI payment.

VI. Alternative Measures of UI

Do the results change when alternative measures of UI are taken into account? Previous sections of this chapter have changed the baseline regression in many ways but have not altered the contribution and benefit measures. Average real contributions and benefits are a natural measure of UI but they are not the only series.

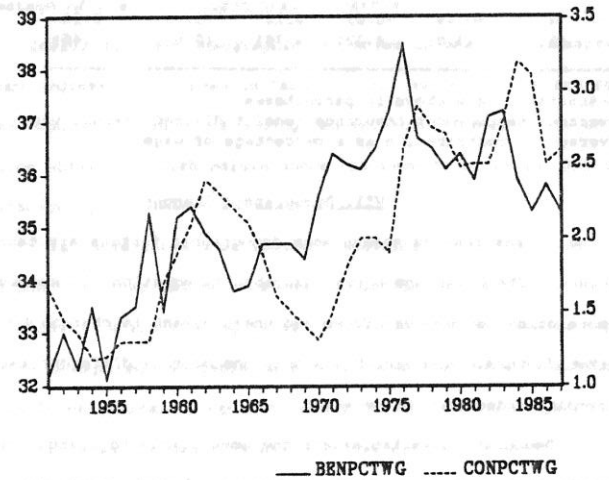
To investigate if other series show different trends two alternative measures of contributions and benefits are analyzed. A commonly used UI indicator of benefits is called the wage-benefit ratio which measures the "earnings" workers receive from UI.[8] This ratio is the result of dividing the average weekly UI benefit by the average weekly wage.

Another commonly used indicator of contributions is contributions as a percentage of total wages. This measure is the average tax rate businesses pay on wages to the UI program. Figure 3 shows how these two indicators have changed over time.

[8] Ishikawa (1980 chap. 2) provides an in-depth examination of the ratio and discusses many reasons why the wage-benefit ratio is a poor "earnings" measure.

Figure 3:

Benpctwg: Benefits As A Percent Of Average Weekly Wage: Left y-axis
Conpctwg: Contributions As A Percent Of Taxable Wages: Right y-axis



Rerunning the baseline regression with the contribution and benefit series replaced by these new indicators supports the previous findings (results are shown in Table 5). The contribution coefficient is positive and roughly seven times larger than the negatively signed benefit coefficient. This is roughly similar to the original regression where the difference was four and a half times.

Table 5

National Vacancy-UI Regressions Using Alternate Measures Of Benefits and Contributions 1951-1987[a]

HWI = Const	Unemp	Price	Reader	Benefits[b]	Contrib[c]
4.62	-0.49	-0.02	0.15	-0.03	0.23
(2.79)	(14.8)	(4.32)	(8.74)	(0.61)	(2.46)

[a]T-Statistics are shown in parentheses.
[b]Average unemployment insurance benefit divided average wage.
[c]Average UI contribution as a percentage of wages.

VII. Demographic Changes

Do the results change when demographic factors are taken into account? The Beveridge curve described by equation (3) suggests that the relation between vacancies and unemployment is changed by labor market factors. However, UI is only one of many different labor market variables affecting the relation.

Demographic variables are the most likely to change the unemployment-vacancy relation because unemployment rates vary widely depending on these characteristics. The three demographic variables most likely to cause changes are age, sex and marriage rates.

Age changes the unemployment-vacancy relation because older workers have lower unemployment rates than teenagers. Changes in the percentage of males and females in the labor force also alters the relation because males have lower unemployment rates than females. Lastly, marriage is important because married workers have lower unemployment rates than single, widowed, divorced or separated workers.

Three national series are constructed to check the previous empirical tests. Age data is constructed for each year by computing the

percentage of labor force participants who are 20 years old or older. Sex data is constructed by computing the percentage of the labor force that is male. Lastly, marriage data is constructed by computing the percentage of the labor force that is married.

Including these demographic variables in the unemployment-vacancy regression is shown in Table 6. The second, third and fourth columns show the results of adding the variables individually to the equation while the fifth column shows the results of adding all of them simultaneously.

This table shows that adding demographic variables does not significantly alter the sign of the UI contribution or benefit coefficients. While the magnitude of the coefficient changes depending on which demographic variable is added, these variables appear to be a relatively unimportant component in explaining the unemployment-vacancy relation because the basic relation is not altered.

Table 6

National Vacancy-UI Regressions Adding Demographic Variables
1955-1987[a]

Dependent Variable: Help-Wanted Index					
Constant	3.98	22.4	24.9	12.38	39.2
	(10.2)	(1.51)	(4.28)	(4.78)	(3.05)
Unemploy	-.449	-0.31	-0.41	-0.58	-0.40
	(11.9)	(2.74)	(12.9)	(11.4)	(4.26)
Ad Price	-0.02	-0.01	-0.02	-0.02	-0.0004
	(4.69)	(0.09)	(4.42)	(5.82)	(0.03)
Readership	0.16	0.10	-0.03	0.09	-0.04
	(11.9)	(2.13)	(0.65)	(4.09)	(0.69)
UI Contrib[b]	0.0015	0.0005	0.002	0.002	0.0014
	(1.30)	(0.34)	(2.51)	(2.10)	(1.09)
UI Benefit[c]	-0.0006	-0.0011	-0.0002	-0.0003	-0.0002
	(2.04)	(2.18)	(2.51)	(0.93)	(0.45)
Age[d]		-19.97			-20.61
		(1.24)			(1.37)
Pcnt Male			-27.8		-12.4
			(3.60)		(1.22)
Pcnt Married				-11.09	-9.02
				(3.27)	(2.13)
R^2	.90	.91	.94	.93	.94
SSR	1.17	1.11	0.78	0.84	0.65
D-W	1.98	1.87	2.03	2.05	2.13
# obs	33	33	33	33	33

Note: Column 1 is the base regression
Column 2, 3, 4 add demographic terms individually.
Column 5 adds all three demographic variables.

[a]T-Statistics are shown in parentheses.
[b]Real unemployment insurance contributions divided by number of employees covered by UI.
[c]Real unemployment insurance benefits divided by number of individuals who received at least one UI payment.
[d]Percent of labor force 20 years old and older.

VIII. Conclusions

This chapter asked, "Does unemployment insurance affect job vacancies?" Empirically, the answer is clearly yes. Increases in UI contributions increase vacancies while increases in UI benefits decrease vacancies.

Originally, UI was designed to provide a safety net for laid-off workers. While economists have uncovered many ways that UI distorts the labor market, the effect of UI on vacancies was previously unexplored. Holding all other factors constant, the effect of increasing UI contributions to give more money as benefits results in a small decrease in vacancies, which is a previously undocumented impact of unemployment insurance on the labor market.

Bibliography

Abraham, K.G. 1983, Structural/Frictional vs. Deficient Demand Unemployment Some New Evidence, American Economic Review #73 pg. 709-724

_____ 1987, Help-Wanted Advertising, Job Vacancies, and Unemployment, Brookings Papers on Economic Activity, 1:1987, pg. 207-243

_____ and Katz, L.F. 1986, Cyclical Unemployment: Sectoral Shifts or Aggregate Disturbances?, Journal of Political Economy, Vol. 94 #3 pg 507-522.

Advertising Research Foundation 1950, The Continuing Study of Newspaper Reading: #139 Montreal Daily Star, Wed. Sept 27, 1950, pg. 51.

Baily, M. and Tobin, J. 1977, Macroecnomic Effects Of Selective Public Employment and Wage Subsidies, Brookings Papers on Economic Activity, 2, pg. 511-544

Barro, R.J., 1977, Unanticipated Money Growth and Unemployment In The United States, American Economic Review, pg. 101-115.

_____, 1978, Unanticipated Money, Output and the Price Level In The United States, Journal of Political Economy, #86 pg. 550-551.

_____ and Hercowitz Z., Money Stock Revisions and Unanticipated Money Growth, Journal of Monetary Economics, #6, April 1980, pg. 257-267.

Becker J. 1972, Experience Rating In Unemployment Insurance: An Experiment in Competitive Socialism, John Hopkins University Press, Baltimore.

Berridge, W. 1955, National Monthly Help-Wanted Advertising Index, American Statistical Association, Business and Economics Section, Annual Proceedings, pg. 262

Beveridge, W.H. 1909, Unemployment: A Problem Of Industry, Longman's, Green and Co., London, 1930 edition

Blanchard, O.J. and Diamond, P. 1989, The Beveridge Curve, Brookings Papers on Economic Activity, 1:1989, pg. 1-76

Boschan, C. 1966, Job Openings and Help-Wanted Advertising, in The Measurement and Interpretation of Job Vacancies, National Bureau of Economic Research. New York: Columbia University Press

Brownlie A., and Hampton P. 1967, An Econometric Study Of Wage Determination In New Zealand, International Economic Review Vol. 8, No. 3, Oct., pg. 327-334.

Bruda, M.C., and Sachs J.D., 1987, Institutional Aspects Of High Unemployment In The Federal Republic Of Germany, Working paper 2241, National Bureau of Economic Research.

Budd, A. Levine P. and Smith P., 1987, Long-Term Unemployment and the Shifting U-V Curve: A Multi-Country Study, European Economic Review, Vol 31 pg 296-305.

Burch, S.W., and Fabricant R.A. 1968, A Further Comment on the Behavior of Help-Wanted Advertising, Review of Economics and Statistics pg. 278-281

Bureau of Labor Statistics 1988, Handbook of Methods, U.S. Department of Labor, Bulletin 2285, pg. 12

Bureau Of Labor Statistics 1980, Estimating State and Local Area Unemployment: A Guide For Data Users, Department of Labor, April 1980, Bulletin 2058

Chavrid, V.D., and Kuptzin H. 1966, Employment Service Operating Data as a Measure of Job Vacancies, in NBER Conference Report "The Measurement and Interpretation of Job Vacancies", pg 373-403

Chazelle J., 1966, The Collection and Utilization of Job Vacancy Data In France, in NBER Conference Report "The Measurement and Interpretation of Job Vacancies", pg 237-264

Cohen, M.S., and Solow R.M. 1967, The Behavior of Help-Wanted Advertising, Review of Economics and Statistics, pg. 108-110

_____ 1970, The Behavior of Help-Wanted Advertising: A Reply, Review of Economics and Statistics, pg. 442-443

Conant E.H. 1966, An Evaluation of Private Employment Agencies as Sources of Job Vacancy Data, in NBER Conference Report "The Measurement and Interpretation of Job Vacancies", pg 519-547

Conference Board 1964, New Index of Help-Wanted Advertising, Conference Board, N.Y.

Department of Labor 1989, Unemployment Insurance, Report of the Secretary of Labor, January 1989

Dickey, D.A. and Fuller, W.A. 1979, Distribution Of The Estimators For Autoregressive Time Series With A Unit Root, Journal of the American Statistical Association, pg 427-431

Dow, J., and Dicks-Mireaux L. 1958, The Excess Demand For Labour. A Study Of Conditions In Great Britain 1946-1956, Oxford Economic Papers, Vol. 10 pg. 1-33

Dunlop J. 1966, Job Vacancy Measures and Economic Analysis, in NBER Conference Report "The Measurement and Interpretation of Job Vacancies", pg 27-47

Fair, R. 1970, The Estimation of Simultaneous Equation Models with Lagged Endogenous Variables and First Order Serially Correlated Errors, Econometrica, Vol 38, pg. 507-516

Feldstein, M.S., 1975, The Importance Of Temporary Layoffs: An Empirical Analysis, Brookings Papers on Economic Activity, 5, pg 725-745

_____, 1976, Temporary Layoffs In The Theory Of Unemployment, Journal of Political Economy, 84 pg 937-957

_____, 1978, The Effect Of Unemployment Insurance On Temporary Layoff Unemployment, American Economic Review, 68 pg 834-846

Gujarati, D. 1969, Cyclical Behavior of Help-Wanted Index and the Unemployment Rate, Review of Economics and Statistics, pg. 482-484

_____ 1972, Behavior of Unemployment and Unfilled Vacancies, Economic Journal, 82 pg 195-201

Hamermesh D.S., 1977, Jobless Pay and the Economy, Baltimore: John Hopkins University Press

Hansen B. 1970, Excess Demand, Unemployment, Vacancies, and Wages, Quarterly Journal of Economics, Vol. 84 pg. 1-23

Holmberg P., 1966, Collection and Uses of Job Vacancy Data In Sweden, in NBER Conference Report "The Measurement and Interpretation of Job Vacancies", pg 265-290

Holt C.C., and David M.H. 1966, The Concept of Job Vacancies in a Dynamic Theory of the Labor Market, in NBER Conference Report "The Measurement and Interpretation of Job Vacancies", pg 73-110

Holzer, H.J. 1989, Unemployment, Vacancies and Local Labor Markets, W.E. Upjohn Institute for Employment Research

Ishikawa, Mamoru. 1980, Unemployment, Insurance, Job Search and Manpower Policy, Unemployment Insurance Technical Staff Paper #2, U.S. Dept. of Labor, Employment and Training Administration.

Jackman R, Layard R, and Pissarides C., 1989, On Vacancies, Oxford Bulletin of Economics and Statistics. Nov. pg 377-394.

Lilien, D.M. 1982, Sectoral Shifts and Cyclical Unemployment, Journal of Political Economy, Vol. 90, pg 777-793

Loungani, P., Rogerson, R. 1989, Cyclical Fluctuations and Sectoral Reallocation: Evidence from the PSID, Journal Monetary Economics, #23 pg. 259-273

_____, Rush, M. and Tave, W,. 1990, Stock Market Dispersion and Unemployment, Journal Monetary Economics, #25 pg. 367-388

Martinez T. 1976, The Human Marketplace: An Examination Of Private Employment Agencies, Transaction Books, New Brunswick, N.J., pgs. 44-50.

McClure L.,and Fulton P. 1964, Advertising in the Printed Media, MacMillan Co. N.Y., pg. 71.

Medoff, J.L. 1983, U.S. Labor Markets: Imbalance, Wage Growth, and Productivity in the 1970s, Brookings Papers on Economic Activity, 1:1983, pg. 87-120

Meyer, H.E. 1978, Jobs and Want Ads: A Look Behind the Words, FORTUNE Magazine, Nov. 20, 1978, Vol. 98 No. 10, pg. 88-96.

Murphy, K.M., and Topel, R, 1987, The Evolution of Unemployment in the United States: 1965-1985, in Stanley Fisher ed., NBER Macroeconomics annual 1987, MIT Press, Cambridge Mass.

Newspaper Advertising Bureau Inc. 1986, Employment Classified: A Study Of Prospect Status, Readership and Interest, NY NY

Newspaper Advertising Bureau Inc. 1987, Key Facts 1987: Newspapers Consumer Advertising, NY, NY.

Niesten L.J., 1966, Collection and Uses of Job Vacancy Data In the Netherlands, in NBER Conference Report "The Measurement and Interpretation of Job Vacancies", pg 291-305

Pissarides C.A. 1987, Search, Wage Bargains and Cycles, Review of Economic Studies, Vol. 54 pg. 473-483

_____ 1985, Short Run Equilibrium Dynamics of Unemployment, Vacancies and Real Wages, American Economic Review, Vol. 75 pg. 676-690

Preston, N.L. 1977, The Help-wanted Index: Technical Description and Behavioral Trends, Conference Board, New York

Schmidt, P. 1990, Dickey-Fuller Tests With Drift, Advances in Econometrics, Vol. 8, JAI Press, pg 161-200.

Schultze, C. 1971, Has The Phillips Curve Shifted? Some Additional Evidence, Brookings Papers on Economic Activity, 2, pg. 452-467.

Shelton W.C. and Neef A., 1966, Foreign Job Vacancy Statistics Programs, in NBER Conference Report "The Measurement and Interpretation of Job Vacancies", pg 145-172

Shleifer A., and Summers L., 1990, The Noise Trader Approach To Finance, Journal of Economic Perspectives, Vol 4 #2, page 19-34

Solow, R.M. 1983, Comments on James Medoff's paper U.S. Labor Markets: Imbalance, Wage Growth, and Productivity in the 1970s, Brookings Papers on Economic Activity, 1:1983, pg. 123-127

Somers G.G and Tsuda M., 1966, Job Vacancies and Structural Change in Japanese Labor Markets, in NBER Conference Report "The Measurement and Interpretation of Job Vacancies", pg 195-236

Thomson W., 1966, Collection and Uses of Job Vacancy Data in Canada, in NBER Conference Report "The Measurement and Interpretation of Job Vacancies", pg 173-194

Topel, R. 1990, Financing Unemployment Insurance: History, Incentives, and Reform, in Hansen and Byers Unemployment Insurance, University of Wisconsin Press.

Topel, R. and Welch F., 1980, Unemployment Insurance: Survey and Extensions, Economica 47 pg 351-379

U.S. Bureau of Census, Census of Manufactures, Various years

U.S. Bureau of Census, Historical Statistics Of The United States: Colonial Time to 1970

U.S. Congress Joint Economic Committee's Subcommittee on Economic Statistics 1966, Job Vacancy Statistics Hearing: May 17 and 18, 1966, U.S. Government Printing Office

Van Ours J.C. 1989, Durations of Dutch Job Vacancies, De Economist, Vol 137 iss. 3 pg 309-327

Wall Street Journal 1990, Labor Letter Column May 1, pg. 1.

Walsh, J., Johnson, M., Sugarman, M. 1975, Help Wanted: Case Studies Of Classified Ads, Olympus Publishing Co. Salt Lake City

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