THE INS AND OUTS OF UNEMPLOYMENT: THE INS WIN

Michael R. Darby

University of California, Los Angeles

National Bureau of Economic Research

John C. Haltiwanger

University of California, Los Angeles

Mark W. Plant

University of California, Los Angeles

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The Ins and Outs of Unemployment: The Ins Win

ABSTRACT

This paper develops a framework for analyzing unemployment in terms of variations in the number and distribution of people becoming unemployed and in individual probabilities of leaving unemployment. Contrary to the emphasis on exit probabilities in the recent macroeconomics literature, we present empirical evidence in support of the proposition that changes in the size and distribution of the inflow into unemployment are the primary determinant of the unemployment rate. Instead of falling at the beginning of a recession, the outflow rate rises (with a lag) in response to the increased inflows which drive the recession. In contrast to normal unemployment, cyclical unemployment is concentrated in groups with low normal exit probabilities; so the observed procyclical variation in the average exit probability may largely be explained by predictable distributional effects.

Michael R. Darby
Department of Economics
University of California, Los Angeles
Los Angeles, CA 90024
(213) 825-3343

John C. Haltiwanger
Department of Political Economy
The Johns Hopkins University
Baltimore, MD 21218
(301) 338-7600

Mark W. Plant
Department of Economics
University of California, Los Angeles
Los Angeles, CA 90024
(213) 825-3847

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Michael R. Darby

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John C. Haltiwanger

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University of California, Los Angeles

To understand changes in the unemployment rate, should we concentrate on the factors that determine inflows into unemployment or outflows from it? Or, are both flow concepts statistical ephemera without any substantial use? This paper attempts to answer those questions and does so in a surprising way: The main proximate determinant of changes in the unemployment rate is variations in the level and distribution of inflows into unemployment. Since the probability of leaving unemployment is primarily determined by the characteristics of those becoming unemployed and is little affected by the business cycle, outflows from unemployment and hence the actual changes in the unemployment rate are primarily determined by the inflows.

Figure 1 provides preliminary evidence in support of the startling hypothesis that the unemployment rate is determined primarily by the inflows. The upper line labeled u is the unemployment rate. The solid line labeled ϕ is the quarterly average of monthly inflows into unemployment measured as a percentage of the labor force. The dashed line labeled ω measures the outflow from unemployment in the same way. The change in the unemployment

FIGURE 1

Inflows (ϕ) into, Outflows (ω) from, and Level (u) of Unemployment

(Quarterly Averages of Monthly Data)

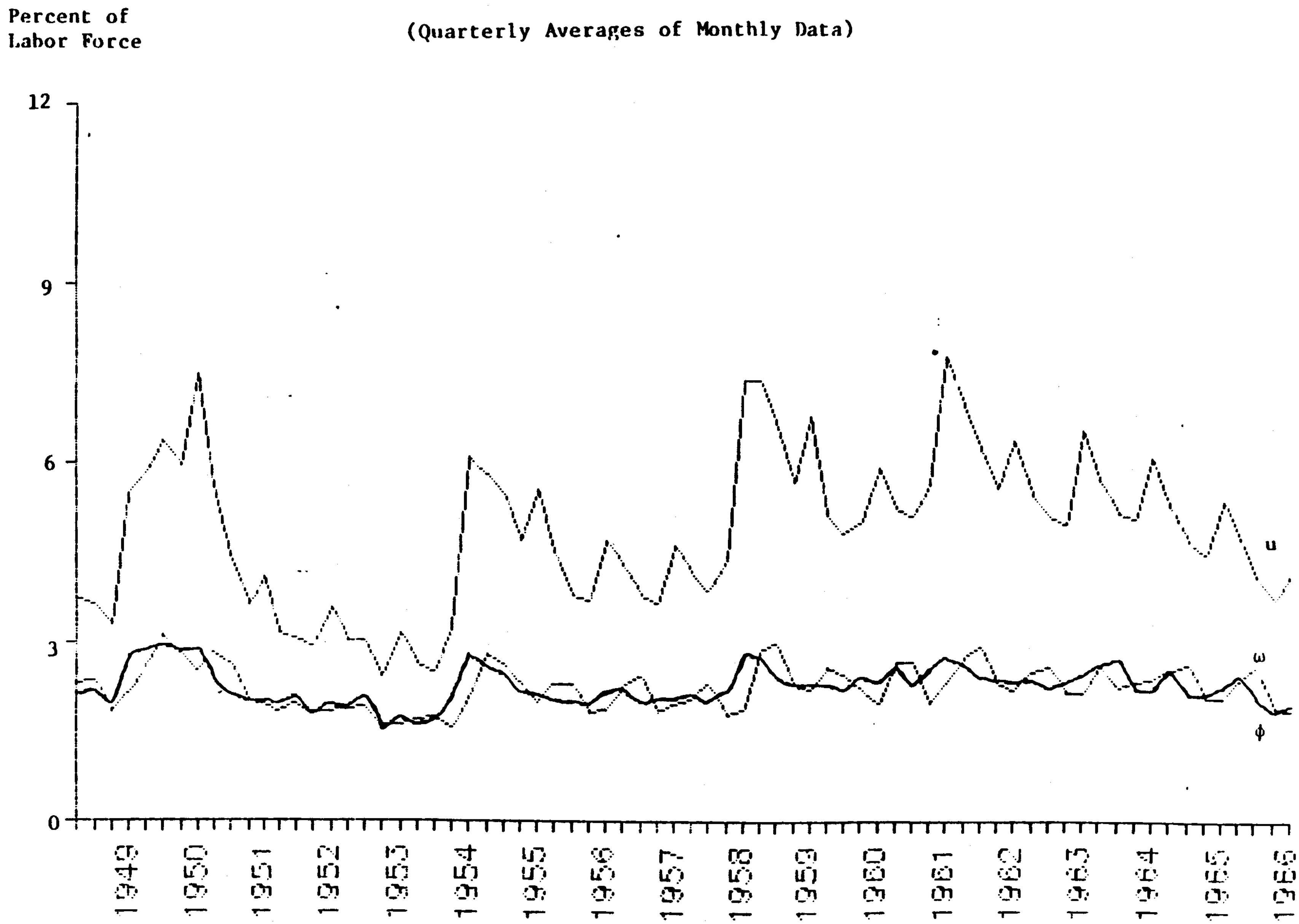
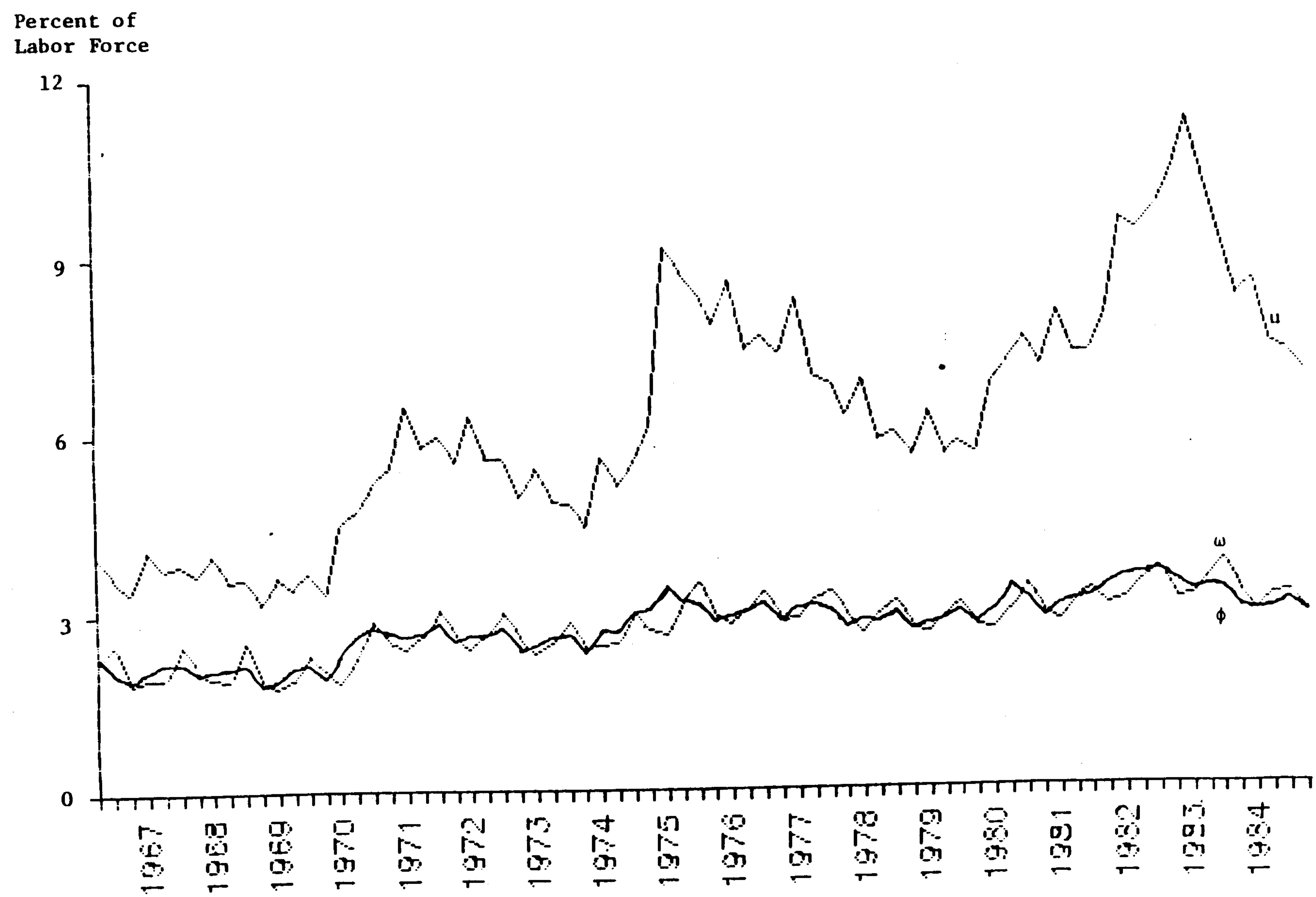


Figure 1 (Concluded)



rate over a quarter is three times the gap between the ϕ and ω lines.[1] Statistical analysis reported below confirms the visual impression that changes in inflows ϕ preceded changes in outflows ω. Note particularly that the onset of a recession is characterized by a sharp increase in ϕ followed quickly by an increase in ω. Unemployment rises so long as the increase in ω lags behind the increase in ϕ and then falls once ϕ falls below ω.

This rise in ω at the beginning of recessions is inconsistent with the predictions of the standard expectational-error/search paradigm in which a recession is characterized by fooling workers into declining job offers which they would take if they were aware of the decline in the offer distribution available. This characterization of the business cycle has played a fundamental role in the macroeconomics literature during the last 20 years and is the primary explanation of business cycles provided in many current intermediate macroeconomics texts (e.g., Dornbusch and Fischer 1984, Gordon 1984). Yet, Figure 1 and our subsequent analysis suggests that business-cycle analysts have placed too much emphasis on workers making expectational errors. Instead, we contend that increases in the unemployment rate primarily reflect more people passing through that state, not each individual spending an abnormally longer time time in it.[2]

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[1]For monthly observations, we have from definitions $\Delta u \equiv \phi - \omega - \gamma u$ where γ is the growth rate of the labor force. Since γu is negligible in magnitude relative to $\phi - \omega$, we have that the cumulative change in u over a quarter will indeed equal 3 times the average values of $\phi - \omega$ over the quarter. Measurement of these variables is discussed below.

[2]Explanations other than the expectational error story have been offered to explain persistent deviations of the probability of escape from unemployment from its normal value, for example duration dependence (e.g., Heckman and Borjus, 1980). We make no judgments about the relative validity of the various explanations for such persistent deviations other than recognizing the importance of heterogeneity.

In our (1985) paper we developed data which showed that the average probability of leaving unemployment does fall during recessions. In this paper, we extend our heterogeneity hypothesis which relates these changes in average probability to the much larger representation of slow searchers in cyclical as opposed to normal unemployment. We demonstrate in this paper that taking into account these distributional effects on average probabilities tends to strengthen the result that it is the level and distribution of the inflows that dominates movements in unemployment.

A useful analogy which clarifies our viewpoint is to think of the number of people traveling by air at a given moment. At major holidays, this number rises both because more people are making trips and their trips cover longer distances on average. While there may be some increase in the time required to make a certain trip, this is secondary to the number and type of trips as a determinant of the number flying at any given time. Even for the average duration of trips, variation in the average length of trips may be a more important explanation than variation in the average duration of a given type of trip.

Our results here do not show that individual outflow probabilities (π_i) are constant. We do show that controlling for such observed characteristics as age, sex, race, reason for unemployment, occupation, and industry reduces the cyclical variability in group-specific average values of π_i. Much future research is needed to determine how much of the remaining cyclical variation is due to unobserved, within-group heterogeneity and how much is to be attributed to variations in the individual π_i values over the cycle for equilibrium or disequilibrium reasons.

Our results bring us closer to the viewpoint of Lilien (1982) than in our (1985) paper. Variations in the rate of industrial change do appear to be an important determinant of the level and distribution of inflows and hence of the unemployment rate. Much future research by us and others is needed to understand exactly what determines the level and distribution of inflows, but the point of this paper is that research focusing on the determinants of the inflows is important if we are to answer Mitchell's (1951) question *What Happens During Business Cycles?* Our working hypothesis is that such research will indicate the importance of cyclical factors (structural change is concentrated in recessions), the real exchange rate (which shifts resources between the tradable and nontradable goods sectors), and wars (which greatly reduce the number of bankruptcies, plant closings, and permanent layoffs).

The first section of this paper develops the analytics of unemployment dynamics and shows that the persistent, hump-shaped fluctuations in unemployment can be explained by these dynamics without necessary recourse to persistent expectational errors. The next section applies these concepts in the empirical analysis of both aggregate data and data disaggregated by individual characteristics. In our final section we summarize the work and propose a program for future research.

I. Theory

In this paper we use the search paradigm to analyze all of unemployment although in principle we would prefer to use this theory to explain the search unemployment rate and model the layoff unemployment rate separately.[3] In future research, we hope to develop data and techniques which would permit us

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[3]Layoff unemployment is used here to refer to those unemployed expecting to be recalled to their previous job while search unemployment refers to all others. A person counted as layoff unemployed this month could remain so next month or become employed at his previous job, employed at a new job, search unemployed, or out-of-the labor force. For reasons to be discussed below, it is likely that the probability of recall from layoff unemployment is affected more by cyclical variables than is the probability that a particular individual will leave search unemployment.

to pursue that strategy. Given the currently available data, we are pleasantly surprised that our model is able to explain changes in total unemployment so well as it does.

I.A. An Unemployment Accounting Paradigm

Let us begin by arranging people into groups indexed by i such that each individual in a particular group has the same probability in any given month of leaving unemployment if they are unemployed at the beginning of the month. This probability may change from month to month with business conditions but it changes in the same way for everyone within the group.[4]

The change in the number unemployed $s_{i,t}$ for each group is found by subtracting the outflows from the inflows $f_{i,t}$:

$$\Delta s_{i,t} \equiv f_{i,t} - \pi_{i,t}\, s_{i,t-1} \tag{1}$$

$$s_{i,t} \equiv f_{i,t} + (1-\pi_{i,t})\, s_{i,t-1}. \tag{2}$$

Repeated substitution of lagged values of $s_{i,t}$ into identity (2) gives us an expression for the number unemployed in terms of only the history of inflows and outflow probabilities of the group:

$$s_{i,t} \equiv f_{i,t} + \sum_{n=1}^{\infty} f_{i,t-n} \left[\prod_{j=1}^{n} (1-\pi_{i,t-j+1}) \right] \tag{3}$$

[4] In our (1985) paper we concentrated on two such groups: a high-turnover and low turnover group. Results reported below suggest at least four major groupings: temporary-layoff unemployed, loosely-attached (to the labor force) workers who have a low probability of getting a job and high probability of leaving the labor force, strongly-attached high-turnover workers who have a high probability of getting a job but a very low probability of leaving the labor force, and strongly-attached low-turnover workers who have a low probability of getting a job (on the rare occasions that they are search unemployed) and a very low probability of leaving the labor force. To fit the strict definition of a group in the text, the number of distinct groups would have to be multiplied by a large number.

The total number unemployed s_t is found by summing over all I groups:

$$s_t \equiv \sum_{i=1}^{I} \{f_{i,t} + \sum_{n=1}^{\infty} f_{i,t-n} [\prod_{j=1}^{n} (1-\pi_{i,t-j+1})]\}. \tag{4}$$

Identity (4) is unwieldy and further simplification is obviously needed in moving from tautology to theory. We propose a decomposition of movements in unemployment into those due to variations in inflows holding exit probabilities constant and those due to variations in exit probabilities holding inflows constant.

I.B. Unemployment Rate Dynamics without Persistent Expectational Errors

Suppose that unemployed individuals are well informed about the state of the labor market so that the expected offer distribution differs from the actual offer distribution only by serially uncorrelated errors. In this environment, it can be demonstrated (see, e.g., Lippman and McCall 1986, Burdett and Ondrich 1985) that fluctuations in a representative searcher's probability of finding a job will be serially uncorrelated as well (at least to a first approximation). The underlying intuition for this result is as follows. An anticipated shift in the offer distribution will primarily result in rational searchers altering their reservation wage. Whether the new reservation wage involves a higher or lower probability of accepting a job depends on the exact nature of the shift, but the presumption is that any such change will be of second order in magnitude.[5]

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[5]Note that Burdett and Ondrich (1985) have developed sufficient conditions to sign the change in π associated with a shift in the offer distribution. However, these sufficient conditions involve technical conditions about the nature of the offer distribution which are not motivated by empirical observation. Further, even if the effect can be signed, it still appears that it is a second order effect relative to the change in the reservation wage itself.

Under this well-informed worker hypothesis, it is reasonable to assume that a representative searcher's outflow probability π_i is roughly constant over time except for random fluctuations. For purposes of empirical testing, we use an extreme characterization and identify this hypothesis with a constant π_i for all individuals at all moments in time.[6] This allows us to address the interesting empirical issue of how much of the variation in observed unemployment can be explained without resorting to any variation in individual π_i's.

Note that under this hypothesis the rate at which firms make offers has little if any effect on the level of unemployment because the reservation wage adjusts as the offer rate changes. The only influence of firms on the current rate of unemployment is through the rate at which different types of people (grouped by their constant π_i) entered unemployment in the past. For government to influence cyclical unemployment, it must work on the rate at which people enter unemployment per se, not the demand of firms for new workers.[7]

Determination of Aggregate Unemployment

The assumption that an individual's outflow probability π_i is constant over time makes the unemployment rate dynamics embodied in (4) quite simple. Use $i = 1,\ldots,I$ to index from the lowest to the highest class of π_i values and identity (4) simplifies to:

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[6] We recognize that asymmetric information may also play an important role in the determination of layoff rates by firms (Grossman and Hart, 1983). Here we concentrate on its alleged role in the determination of π_{it}, not ϕ_{it}.

[7] Again we suspect that this statement is more nearly correct for search than for layoff unemployment. Implicitly we are treating an individual as in one constant π_i group if search unemployed and in another (empirically higher) constant π_i group if layoff unemployed.

(5) $$s_t = \sum_{i=1}^{I} s_{i,t} = \sum_{i=1}^{I} \sum_{n=0}^{\infty} (1-\pi_i)^n f_{i,t-n}$$

We switch to an equality sign to remind us that equation (5) has theoretical content and is no longer true by the way variables are defined.

In our (1985) paper we emphasized that predictable changes in the composition of the unemployed over the business cycle could account for some of the observed movement in the observed average or aggregate outflow probability π_t. Given the current hypothesis, π_t movements are explained entirely by heterogeneity since individual outflow probabilities are constant:

(6) $$\pi_t = \sum_{i=1}^{I} \frac{s_{i,t-1}}{s_{t-1}} \pi_i$$

The large theoretical and empirical literature (e.g., Heckman and Borjas 1980, Topel 1984) on the importance of both observed and unobserved heterogeneity for explaining individual differences in unemployment durations provides considerable guidance for the factors likely to cause variations in π_i. Worker characteristics such as age, sex, race, industry, occupation, education, reason of unemployment have all been shown to be important in microeconomic contexts. Our innovation is to attempt to explain aggregate movements in unemployment with such heterogeneity playing a fundamental role. The difficulty of course is to account for as much of the heterogeneity as possible in the aggregate data.[8]

Business Cycles

In our empirical work we find it useful to distinguish among short-run fluctuations in unemployment which we term business cycles, intermediate-run

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[8]This is made doubly difficult since the micro empirical studies alluded to indicate considerable unobserved heterogeneity even using micro data sets.

movements associated with the pace of structural change in the economy, and longer-term trends associated with gradual changes in the demographic makeup of the labor force.[9] We are interested in demonstrating that the simple partial adjustment model which equation (5) implicitly imposes on each group can in fact explain the type of business cycles which are observed in the United States.

Suppose that there is a constant normal rate $\bar{f}_i$ at which people of groups i flow into unemployment. This abstracts from growth in the labor force, shifts in demographics, and changes in the pace of structural change so that we can concentrate on the business cycle _per se_. The normal level of unemployment of group i is then

$$\bar{s}_i = \sum_{n=0}^{\infty} (1-\pi_i)^n \bar{f}_i = \bar{f}_i/\pi_i \tag{7}$$

The change in unemployment of group i can be most easily derived by setting $\pi_{i,t} = \pi_i$ in equation (1) which yields:

$$\Delta s_{i,t} = \hat{f}_{i,t} - \pi_i \hat{s}_{i,t-1} \tag{8}$$

where $\hat{f}_{i,t} \equiv f_{i,t} - \bar{f}_i$ is the cyclical inflow of group i and $\hat{s}_{i,t-1} \equiv s_{i,t-1} - \bar{s}_i$ is the lagged cyclical unemployment of group i. Equation (8) shows that the assumption of constant π_i indeed implies that $s_{i,t}$ will follow a partial adjustment toward $\bar{s}_i$ at the rate π_i per period in the absence of cyclical inflows.

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[9] Structural change is concentrated during recessions since plant closings which would otherwise occur are accelerated if inventories are high and postponed if inventories are low. However, beyond this bunching phenomenon, we see protracted periods in which the pace of structural change is particularly high or low. As discussed below, we associate these intermediate trends with general changes in tastes and technology, wars, and adjustment to changes in international terms of trade.

It is clear that uncorrelated $\hat{f}_i$ shocks cannot produce the sort of business cycles with which macroeconomists have traditionally concerned themselves.[10] With serially correlated $\hat{f}_i$ shocks, unemployment falls after the first month rather than first building up for 6 to 9 months as in the archetypal hump-shaped business cycle. However, recent inventory based models of persistence (e.g., Blinder and Fischer 1981, Topel 1982 and Haltiwanger and Maccini 1985) suggest that the buffer stock role of inventories may help explain how serially uncorrelated shocks translate into serially correlated inflows into unemployment. In particular, if firms set prices for longer periods than our length of observation (a month), then a single period mistake can lead to growing cyclical inventories over a period of months. Moreover, firms may spread their adjustment to cyclical inventories over time or indeed be hit by an aggregate demand shock at different times. Along these lines, it can be demonstrated that (e.g., Haltiwanger and Maccini 1985) that higher initial inventories in any given period will lead to a higher probability of both permanent and temporary layoffs in the period. Hence, persistent and abnormally high inventories can lead to persistently high probabilities of permanent and temporary layoffs for several periods. Suppose then that cyclical inflows $\hat{f}_{i,t}$ can be described by a first-order autoregressive process:[11]

(9) $$\hat{f}_{i,t} = \eta_{i,t} + \rho_i \hat{f}_{i,t-1}$$

(10) $$\hat{f}_{i,t} = \sum_{j=0}^{\infty} \rho_i^j \eta_{i,t-j}$$

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[10] See Figure 1 in our (1985) paper for a demonstration of this fact.

[11] This is the simplest process for expositional purposes and does surprisingly well at explaining the data as discussed in Section II.

where $\eta_{i,t}$ is white noise. Substituting equation (10) and $f_{i,t} = \hat{f}_{i,t} + \bar{f}_t$ into equation (5) yields

$$\hat{s}_{i,t} = \eta_{i,t} + \sum_{k=1}^{\infty} \eta_{i,t-k} \sum_{j=0}^{k} \rho_i^{k-j}(1-\pi_i)^j \tag{11}$$

So the innovation $\eta_{i,t}$ increases unemployment by its full value in the current period and by an amount which may be more or less than this value in future periods. So long as ρ and π_i lie strictly between 0 and 1, the effect of the innovation must eventually fall to 0 as can be determined by inspection of equation (11). Figure 2 illustrates the effects on $\hat{s}_{i,t}$ of $\eta_{i,t} = 1$ for alternative combinations of ρ and π. (Convenient units are chosen so that a standard shock has size 1.) We see that if cyclical inflows are substantially correlated and the probability of leaving unemployment is not too high, a single period innovation results in a hump-shaped business cycle.[12]

I.C Unemployment Rate Dynamics with Persistent Expectational Errors

An alternative to the well-informed worker hypothesis is the view that workers make persistent expectational errors, particularly over the business cycle. This leads to the characterization of the business cycle found in many of the leading intermediate macroeconomic texts. That is, when a business cycle slump hits, workers make persistent expectational errors which causes the duration and therefore the rate of unemployment to increase. An extreme view of this persistent expectational error hypothesis is that most of the variation

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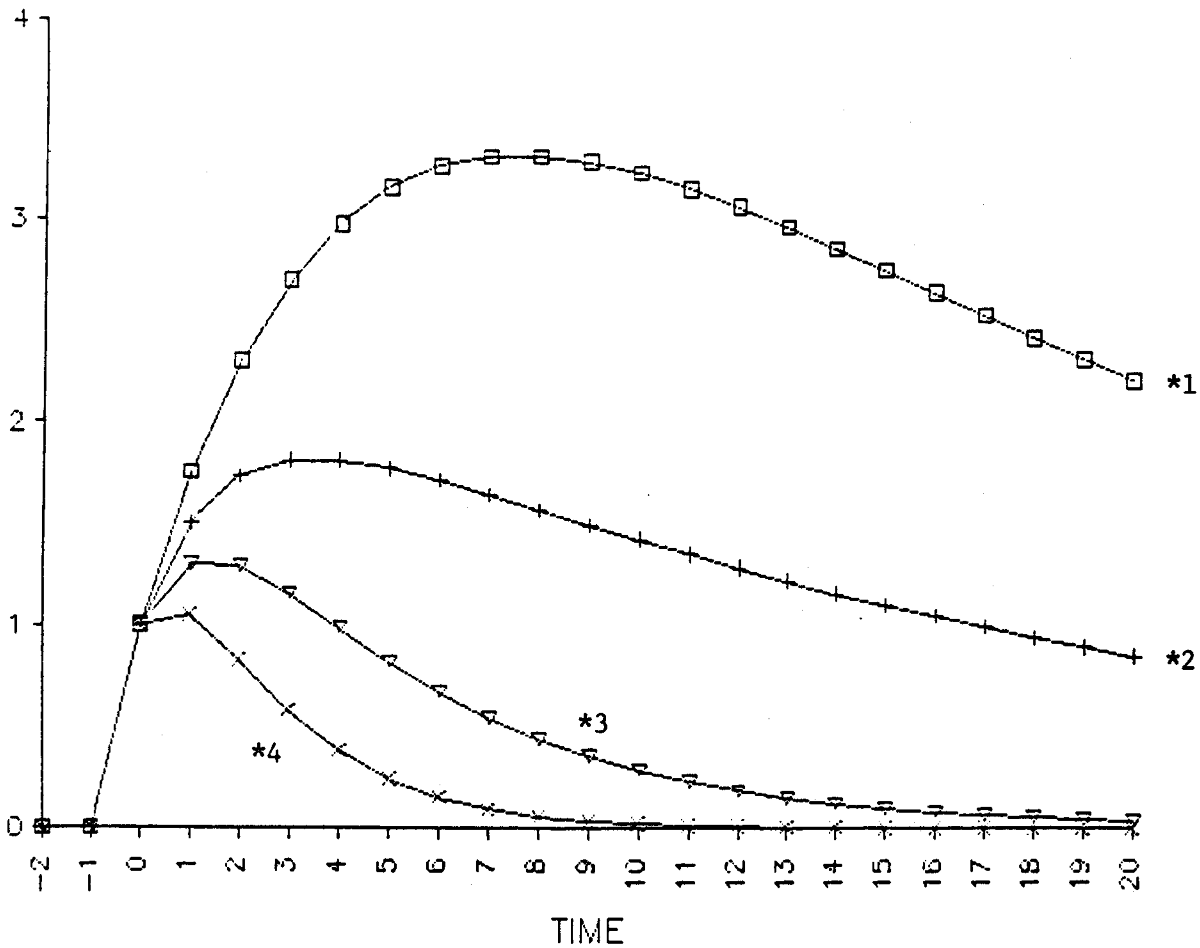
[12] In our earlier paper (1985) we focused on the issue of persistent deviations of the unemployment rate from its steady-state level. In the working paper version of this paper (Darby, Haltiwanger and Plant, 1986), we provide an in-depth analysis of the process underlying Figure 2 which illustrates that this simple process can lead to persistence similar to that observed over the business cycle. A task for future research is to see if such simple AR processes can empirically characterize the business cycle in a succinct way.

FIGURE 2

Cyclical Unemployment from a Unit Innovation in Inflow

Alternative ρ_i, π_i Combinations



Key: *1 $\pi_i = 0.2$, $\rho_i = 0.95$

*2 $\pi_i = 0.45$, $\rho_i = 0.95$

*3 $\pi_i = 0.2$. $\rho_i = 0.5$

*4 $\pi_i = 0.45$, $\rho_i = 0.5$

in unemployment can be accounted for by variations in individual π_i's. While no one seriously argues that inflows will be constant cyclically, it is convenient to use this extreme view to have a corresponding measure of the extent to which changes in unemployment are explained by movements in $\hat{\pi}_{i,t}$ $(=\pi_{i,t}-\bar{\pi}_i)$ alone.

An attractive feature of the unemployment accounting paradigm embodied in equation (4) is that it allows us to separate out how much of the variation in unemployment can be attributed to either inflows or outflows. We obtain our measure of effects of $\hat{\pi}_{i,t}$ variations on s_t by setting $f_{i,t}$ in equation (4) equal to the sample mean $\bar{f}_i$

$$s_t = \sum_{i=1}^{I} s_{i,t} = \sum_{i=1}^{I} \bar{f}_i \left[1 + \sum_{n=1}^{\infty} \prod_{j=1}^{n} (1-\pi_{i,t-j+1})\right] \tag{12}$$

If $\pi_{i,t}$ were always a constant normal value, equation (13) would yield

$$\bar{s}_t = \sum_{i=1}^{I} \bar{s}_i = \sum_{i=1}^{I} \bar{f}_i/\pi_i \tag{13}$$

Since observed $\pi_{i,t}$ values are not strictly constant, the s_t implied by equation (12) generally will deviate from $\bar{s}_t$ according to the history of $\pi_{i,t}$ values.[13]

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[13] To implement either equation (5) or (12) empirically is strictly impossible since we do not have data on $f_{i,t}$ or $\pi_{i,t}$ going back to $-\infty$. However, it is easy to apply their first differenced forms iteratively starting with $s_{i,t-1}$ for the earliest period for which $f_{i,t}$ or $\pi_{i,t}$ data are available. These equations are:

$$\Delta s_t^{\pi} = \sum_{i=1}^{I} \Delta s_{i,t}^{\pi} = \sum_{i=1}^{I} [f_{i,t} - \pi_i \, s_{i,t-1}^{\pi}] \tag{5'}$$

$$\Delta s_t^{f} = \sum_{i=1}^{I} \Delta s_{i,t}^{f} = \sum_{i=1}^{I} [\bar{f}_i - \pi_{i,t} \, s_{i,t-1}^{f}] \tag{12'}$$

where the superscript π (f) denotes values computed assuming π_i (f_i) values are constant at their sample mean starting from $s_{i,0} = s_{i,0}^{\pi} = s_{i,0}^{f}$.

Unfortunately the decomposition of cyclical unemployment into one component which can be attributed to movements in group inflows and another component which can be attributed to movements in group outflow probabilities is imperfect in several ways. First, it is not exhaustive and a remainder term reflecting interaction effects of the two sorts of movements might be substantial. Second, to the extent that available data restrict us to look at groups which are still heterogeneous with respect to individual π_i values (even though more homogeneous than the labor force as a whole), we will attribute too little explanatory power to movements in inflows and too much to movements in individual probabilities.[14] This is particularly true if the marginal π_i values associated with $\hat{f}_i$ differ from average π_i values associated with f_i. (Suppose that group i has a substantial but constant component of loosely attached "churners" in-and-out of the labor market, but marginal inflows relate to firmly attached, low-turnover workers.) We view these limitations as cautions in applying the theory to the exploratory results reported in the remainder of the paper.

II. Empirical Analysis of π, Φ, ω and u

II.A Measurement

To measure unemployment flows, we use the net flow data from the BLS Current Population Survey.[15] The measurement of π_{it} and ϕ_{it} with the net

[14]Basically variations in inflows will induce via sorting the type of effects implicit in equation (5) and explored at length in our (1985) paper.

[15]An alternative would be to use the gross flow data. However, the gross flow data are not published on a regular basis and are known to have some serious measurement problems. Nevertheless, it would be of considerable interest to examine the gross flow data in this context which we plan to do in future research.

flow data follow the procedures identified in our earlier paper. To briefly recount the procedure, we have:

$$\pi_{it} = 1 - (s_{it} - s_{it}^{0-4})/s_{it-1} \tag{14}$$

$$\phi_{it} = s_{it}^{0-4}/n_{it} \tag{15}$$

where s_{it} is the number in group i unemployed in a given month, s_{it}^{0-4} is the number in group i who have been unemployed "0-4" weeks, and n_{it} is the number in the labor force. Note that the inflow level for group i, f_{it}, is simply given by s_{it}^{0-4}. Further, the outflow rate, ω_{it}, is given by $\pi_{it}^{*} s_{it-1}/n_{it}$ where π_{it}^{*} represents the growth-adjusted probability of exiting unemployment. Finally, the unemployment rate for group i is simply s_{it}/n_{it}.

For our analysis in Section II.B on the aggregate behavior of the inflows and outflows, we use monthly data on s_t, s_t^{0-4}, and n_t from 1948:1 to 1985:1. For our disaggregated analysis in Section II.C, computation of π_{it} and ϕ_{it} by demographic group, by reason of unemployment, by industry, and by occupation is possible for 1976:1 to 1985:1.[16]

II.B Aggregate Analysis of π, ϕ, ω and u

We begin our empirical analysis by examining the aggregate data to provide an initial set of stylized facts on the inflows to and the outflows from unemployment and their relative importance in explaining overall movements in unemployment. Our theoretical discussion above indicates that both the level and the distribution of the flows across heterogeneous groups should be

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[16] In this paper, we use data that has not been seasonally adjusted. Given that we are measuring inflows and outflows from unemployment, use of such data makes sense. However the exact role of seasonality needs to be analyzed carefully at a later date with particular attention played to the covariance between seasonal and cyclical factors.

important in this context. As we will see in Section II.C, heterogeneity is very important. However, for the moment we will focus on the aggregate flows ignoring heterogeneity issues. This is intended to establish the broad patterns in the aggregate flows which will be analyzed in detail in the remainder of the paper.

Our empirical analysis of the aggregate inflows and the outflows begins with a simple characterization of the time series properties of these measures. In Table 1, we report F-tests from bivariate vector autoregressions of ω_t and ϕ_t. These results indicate that lagged values of each series are important for explaining the movements in the series itself. More importantly, we find that lagged values of ϕ_t are important in explaining current movements in ω_t, and lagged values of ω_t are important for explaining current movements in ϕ_t, however, the F-statistic in the latter case is the smallest of those reported. We do not wish to place any causal interpretation on these results, but they do re-enforce the visual impression from Figure 1 that increases (decreases) in inflows precede increases (decreases) in outflows.

We close this section by examining a variance decomposition of the overall movement of the unemployment rate. Since we are neglecting measurement of heterogeneity in this section, we cannot directly examine the role of the distribution of the inflows but rather only the level. We are interested in how much of the variance in overall unemployment can be explained by the constant π, variable ϕ_t model and how much can be explained by the constant ϕ, variable π_t model. To accomplish this, we consider the following two different dynamic simulations. Assuming homogeneous workers, we can derive from (2):

$$u_t = \phi_t + \frac{(1-\pi_t)}{1+\gamma_t} u_{t-1} \tag{16}$$

TABLE 1

Time Precedence Tests for ϕ and ω

Test for "Causality" of	By Lagged[b]	Maintained Lag Regressors	Test Statistic[a]	Marginal Significance
ω	ω	ϕ	39.70	0.0001
ω	ϕ	ω	55.36	0.0001
ϕ	ϕ	ω	45.56	0.0001
ϕ	ω	ϕ	11.33	0.0001

Notes: All regressions cover 1948:1 to 1985:1 including twelve lags of each variable as regressors and a linear time trend.

[a]The test statistic is an F-ratio for the null hypothesis that the coefficients for the six lagged values in this column are jointly equal to zero.

where u_t is the unemployment rate and γ_t is the growth rate of the labor force.[17] We simulate the path of u_t under two different assumptions: first, that π_t is constant at its mean level with ϕ_t taking on its actual level; second, that ϕ_t is constant at its mean level with π_t taking on its actual level (in both cases, γ_t takes on its actual level). For the variance decompositions reported in Table 2, we use u_t in the first month of 1948 to initiate the simulation and then perform dynamic simulations under these two alternative hypotheses. Two sets of numbers are reported in Table 2. In column (1) of the first row we report the ratio of the variance of the simulated u_t with π constant to the variance of the actual u_t. If we write u_t as the sum of the simulated value of u_t plus a residual term, then the variance of the actual u_t is equal to the sum of the simulated u_t variance plus the variance of the residual plus twice the covariance of the simulated u_t and the residual. These last two terms are reported in columns (2) and (3) as a fraction of the total variance of u_t. In the second row, we repeat the same procedure except we use the simulated u_t with ϕ_t constant. These results indicate that, even without accounting for heterogeneity, inflows are at least as important factors as outflows in explaining the overall variance. That is, 29.4% of the total variance is accounted for by the constant π, variable inflow model. In contrast, 26.4% of the variance can be explained by the constant ϕ, variable π_t model. We also see that the residuals and associated covariances are quite important. Given that these

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[17] In the empirical analysis that follows, we use the unemployment rate and the associated inflow and outflow rates rather than the levels which were used in the theoretical discussion. Since a substantial portion of the increase in the unemployment level and the inflow level is due to the growth of the labor force, using levels in our analysis will attribute too much of the variance to the inflow level. The use of the unemployment rate normalizes for the size of the labor force.

TABLE 2

Variance Decompositions of Unemployment Rate

Simulation:	(1)	(2)	(3)
π_i constant	0.294	0.300	0.406
ϕ_t constant	0.264	0.333	0.403

Note: Calculated as described in text using not seasonally adjusted data for 1948:1 to 1985:1.

Column (1): Fraction of total variance accounted for by simulated u_t.

(2): Fraction of total variance accounted for by residual.

(3): Fraction of total variance accounted for by twice covariance of simulated u_t and residual.

results are based upon aggregate data ignoring heterogeneity and thus the distribution of the inflows, these results provide preliminary support for the primary hypothesis stated in the introduction. Namely, that the main proximate determinant of changes in unemployment is variations in the inflows into unemployment. We will now explore the role of heterogeneity in this context. As will become apparent, the results on heterogeneity are of interest but we are severely constrained in this effort by the limitations imposed by the available data.

II.C. Heterogeneity

The preliminary empirical results presented in Section II.B assumed that workers were homogeneous with respect to the rate of inflow into unemployment, ϕ_t, and with respect to the probability of leaving unemployment, π_t. However, in our theoretical discussion in Section I we noted that significant heterogeneity in π_{it} would imply that variations in the distribution of the inflows are important for explaining movements in the unemployment rate. In the analysis reported in this section we investigate sources of the heterogeneity in π_{it} and ϕ_{it}. We then use the identified heterogeneity to examine the hypothesis that both the level and distribution of the inflows are fundamental for explaining movements in unemployment.

In Tables 3 through 6 we report values of $\bar{\pi}_i$, $\bar{\phi}_i$ and $\bar{u}_i$ (these are computed using equations (14) and (15) and taking sample means) for various demographic breakdowns of the labor force. The natural rate of unemployment, $\bar{u}_i$, is computed as the ratio of $\bar{\phi}_i$ to $\bar{\pi}_i$. It is difficult to summarize all the information contained in these tables, but there are several patterns that should be noted. In the age-sex breakdown, reported in Table 3, the values of both $\bar{\pi}_i$, $\bar{\phi}_i$ and $\bar{u}_i$ decrease with age until retirement. There is a particularly large decrease between the early teens and the

TABLE 3

Estimated Normal Values of π, ϕ, and u by Age and Sex

Age Group	Males			Females		
	$\bar{\pi}_i$	$\bar{\phi}_i$	$\bar{u}_i$	$\bar{\pi}_i$	$\bar{\phi}_i$	$\bar{u}_i$
16-19	0.500	0.096	0.191	0.547	0.102	0.186
20-24	0.384	0.046	0.119	0.476	0.053	0.112
25-34	0.331	0.022	0.066	0.437	0.034	0.057
35-44	0.310	0.014	0.044	0.413	0.024	0.057
45-54	0.293	0.012	0.040	0.382	0.019	0.049
55-64	0.294	0.012	0.040	0.361	0.015	0.041
65 +	0.353	0.013	0.038	0.390	0.015	0.037

Notes: Calculated as described in text using LABSTAT data (not seasonally adjusted) for 1976:6 to 1985:1.

TABLE 4

Estimated Normal Values of π, ϕ^*, and u^* by Age, Sex, Reason

Age, Sex Reason Group	$\bar{\pi}_i$	$\bar{\phi}^{*}_i$ [a]	$\bar{u}^{*}_i$ [b]
Temporary Layoffs:			
16-19	0.59	0.007	0.0097
Males, 20+	0.45	0.006	0.0140
Females, 20+	0.46	0.004	0.0096
All	0.47	0.005	0.0106
Permanent Layoffs:			
16-19	0.45	0.014	0.0304
Males, 20+	0.25	0.007	0.0305
Females, 20+	0.29	0.006	0.0208
All	0.30	0.007	0.0233
Non-Layoff Unemployment:			
16-19	0.53	0.079	0.1502
Males, 20+	0.39	0.007	0.0180
Females, 20+	0.50	0.020	0.0388
All	0.51	0.018	0.0353

Notes: Calculated as described in text using LABSTAT data (not seasonally adjusted) for 1976:6 to 1985:1.

[a]The values for $\bar{\phi}^{*}_i$ are computed by dividing the number of newly unemployed by the number of labor force participants in the appropriate age-sex group rather than the age-sex-reason group since the latter is ill defined.

[b]Note that the manner used to compute $\bar{\phi}^{*}_i$ changes the interpretation of $\bar{u}^{*}_i$ as well.

TABLE 5

Estimated Normal Values of π, ϕ, and u by Industry

Industry	$\bar{\pi}_i$	$\bar{\phi}_i$	$\bar{u}_i$
Agriculture	0.484	0.058	0.124
Mining	0.349	0.025	0.080
Construction	0.382	0.050	0.137
Manufacturing	0.362	0.028	0.081
Durables	0.338	0.026	0.081
Nondurables	0.396	0.032	0.081
Transportation, Communications & Public Utilities	0.362	0.018	0.050
Trade	0.432	0.035	0.081
Finance, Insurance & Real Estate	0.399	0.015	0.038
Services, excluding Private Households	0.422	0.024	0.058
Public Administration	0.355	0.016	0.046
Non-agricultural Industries, excluding Private Households	0.395	0.028	0.071
Private Households	0.496	0.031	0.063

Notes: Calculated as described in text using LABSTAT data (not seasonally adjusted) for 1976:6 to 1985:1.

TABLE 6

Estimated Normal Values of π, ϕ, and u by Occupation

Occupation	$\bar{\pi}_i$	$\bar{\phi}_i$	$\bar{u}_i$
White collar	0.416	0.017	0.041
Professional & Technical	0.408	0.012	0.029
Professional & Managerial	0.378	0.010	0.026
Managers & Administrative excluding Farm	0.330	0.009	0.027
Sales workers	0.434	0.020	0.046
Clerical & Kindred Workers	0.436	0.025	0.058
Blue Collar	0.388	0.036	0.093
Craft & Kindred	0.375	0.024	0.064
Transport equipment operatives	0.358	0.027	0.075
Operatives excluding transport	0.397	0.044	0.111
Nonfarm Laborers	0.394	0.039	0.099
Service Workers	0.460	0.039	0.085

Notes: Calculated as described in text using LABSTAT data (not seasonally adjusted) for 1976:6 to 1985:1.

mid-20's as young workers become attached to the labor force and gain labor market experience. The decrease in $\bar{u}_i$ reflects the fact that decreases in $\bar{\phi}_i$ are generally larger proportionally than those in $\bar{\pi}_i$.[18] The values of both π_i and ϕ_i are larger for women than for men, given age.

Table 4 shows a breakdown of the labor force by reason of unemployment. The probability of exiting unemployment is highest for those on temporary layoff (except for females) and lowest for those permanently laid off. Both females and teens have a high inflow rate into non-layoff unemployment. Prime-aged males enter into all three unemployment states at approximately equal rates.

In Tables 5 and 6 we report the values of $\bar{\pi}_i$ and $\bar{\phi}_i$ for industry and occupation respectively. The values of $\bar{\pi}_i$ tend to be low in manufacturing and construction, and high in non-industrial sectors of the economy. In construction and agriculture, $\bar{\phi}_i$ is very high as one would expect given the usually temporary nature of the employment contract in these industries. Combined with relatively low values of $\bar{\pi}_i$, the result is a high natural rate of unemployment. In typically white collar sectors of the economy, such as finance, insurance, and real estate $\bar{\phi}_i$ is relatively low. This corresponds to a low $\bar{\phi}_i$ for professionals and managers. Further, $\bar{\pi}_i$ is low for professionals, managers and persons in crafts — all of whom have rather specific human capital.

In these tables we have broken the labor force into various categories to see if any broad patterns emerge. Although a wide variety of types of workers are evident, typically one sees $\bar{\pi}_i$ decrease with any form of attachment to the labor force -- particularly with specificity in human capital due to age

[18]More firmly attached workers spend less time unemployed on average even though each spell tends to be longer.

or occupation. Low values of $\bar{\pi}_i$ are usually accompanied by low values of $\bar{\phi}_i$ except for those workers involved in occupations that have employment arrangements with short-term firm-worker relationships.

Given that these preliminary results do indicate that there is significant heterogeneity in π_{it}, it remains to be seen whether there is significant variation in the distribution of the inflows over time and over the cycle. In Tables 7-9 we present the correlations of the overall unemployment rate with the unemployment shares for various breakdowns of the labor force. The numbers in Table 7 are quite provocative. The groups which tend to increase their share of unemployment when there is an overall increase in the unemployment rate are male workers aged 20-34, female workers of the same age, and females aged 55-64. Popular belief is that teenagers bear the brunt of unemployment, but this table demonstrates that non-teenage young workers who are relatively inexperienced but probably beginning to be strongly attached to the labor force feel the impact most severely, and that experienced workers seem to be relatively protected. It is important to note that these are correlations of shares and so all groups may in fact be increasing in numbers of unemployed and unemployment rates. Those groups with positive correlations are suffering a disproportionate impact of the business cycle. Table 8 presents similar numbers for a partition of the labor force by age, sex, and reason of unemployment. This table indicates that increases in the unemployment rate come through increases in layoffs. The strongest positive correlation is for permanent layoffs of prime-aged men. Temporary layoffs of the same group also play a strong role and another channel for adjustment is permanent layoffs of females. Note that the share of temporary layoffs of females and layoffs of teens have a weak negative correlation with the unemployment rate. Table 9 reports the same correlations for industry and

TABLE 7

Correlations of Unemployment Shares with the

Unemployment Rate by Age and Sex

Age Group	Male	Female
16-19	-0.154	-0.108
20-24	0.642	0.254
25-34	0.592	0.382
35-44	-0.085	-0.341
45-54	-0.311	-0.457
55-64	-0.431	0.258
65 +	-0.598	0.166

Notes: Calculated as described in text using monthly LABSTAT data (not seasonally adjusted) for 1976:6 to 1985:1.

TABLE 8

Correlations of Unemployment Share with the

Unemployment Rate by Age-Sex and Reason

Temporary layoff	
Teenagers	-0.143
Males 20+	0.653
Females 20+	-0.397
Permanent layoff	
Teenagers	-0.424
Males 20+	0.784
Females 20+	0.602
Non-Layoff unemployed	
Teenagers	-0.574
Males 20+	-0.840
Females 20+	-0.772

Notes: Calculated as described in text using monthly LABSTAT data (not seasonally adjusted) for 1976:6 to 1985:1.

TABLE 9

Correlations of Unemployment Shares with the

Unemployment Rate by Industry and Occupation

Industry	
Agriculture	0.232
Mining	0.757
Construction	0.309
Manufacturing, Durables	0.661
Manufacturing, NonDurables	-0.479
Transportation, Communication and Public Utilities	0.335
Trade	-0.502
Finance, Insurance and Real Estate	-0.259
Services, Excluding Private Households	-0.590
Public Administration	-0.567
Private Households	-0.483
Occupation	
Professional and Technical	-0.439
Managers and Administrators	0.029
Sales Workers	-0.455
Clerical Workers	-0.533
Craft	0.656
Transportation Equipment Operatives	0.539
Operatives Excluding Transport	0.515
Non-Farm Laborers	0.093
Service Workers	-0.607

Notes: Calculated as described in text using monthly LABSTAT data (not seasonally adjusted) for 1976:6 to 1985:1.

occupation. The industries that are thought to be cyclically sensitive are those which are disportionately affected -- mining, durable manufacturing, construction, and transportation. Craft workers and operatives are the occupation categories that exhibit a positive correlation between unemployment shares and the overall unemployment rate. The story one is tempted to tell from these three tables is that the business cycle has a disproportionate impact on industries whose labor force is comprised primarily of blue collar workers. Typically the adjustment is made through layoffs, and given the heavily unionized nature of these industries, the youngest workers are first laid off. The older a worker is, the more insulated he is from the business cycle. Thus, we see young workers who are just becoming attached to the labor force to be the most vulnerable to the business cycle. On an age-sex breakdown alone, this runs counter to the intuition that we expect to see a preponderance of low-π workers when the overall unemployment rate is high. However, if we look at the other breakdowns -- by reason, by occupation, and by industry -- it is the low-π workers who have a positive correlation of unemployment share with overall unemployment rate.

As always, however, correlations do not give us any information about causality. We would expect to see a larger share of low-π workers if the recession had a more severe impact on sectors of the economy where those laborers were employed. That is the story we just told. However, as we showed in our (1985) paper, if there were heterogeneity in π_i and if an initial perturbation in ϕ_t resulted in an equiproportionate increase in inflow rates ϕ_{it} for all groups, as the unemployment rate began to return to its natural level, low-π workers would be a larger fraction of the labor force since they take longer to return to normal levels of unemployment. Thus, differential impact of the business cycle is not necessary to cause the correlations that we saw in the last three tables. Nevertheless, independent of causality considerations, we have seen that there exists significant heterogeneity in inflow and outflow rates as well as significant variations in the shares over time.

We now attempt to use this disaggregated data to consider the primary hypothesis of this paper. That is, it is primarily variations in the level and distribution of the inflows which account for the variation in the unemployment rate. Unfortunately, we do not have this data for a long time period, nor do we have cross tabulations simultaneously breaking down the data by age, sex, reason, industry, and occupation.

Our initial analysis using the disaggregated data does not attempt to use all of the information simultaneously but rather uses each breakdown independently. These results are reported in Table 10. Following the same methodology discussed in Section II.B, we ran simulations of disaggregated unemployment rates with the disaggregated data holding π_{it} and ϕ_{it} constant in turn, aggregating by appropriate labor force shares, and then doing a variance decomposition of the movements in the unemployment rate. In the leftmost column of Table 10 we note the type of heterogeneity assumed in each of the separate simulations. These results indicate that the variance decomposition depends critically on the source of the heterogeneity. We do find that the variation in the level and distribution of the inflows is the primary determinant of variations in unemployment for temporary and permanent layoff unemployment as well as for non-layoff unemployment.[19] However, when

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[19]The reason that we separate out these by reason categories is that aggregation of the simulated values by reason involves labor force shares and obviously labor force shares by reason are relatively ill-defined. For example, the share of the labor force that are temporarily laid off is ill defined compared to, say, the share of the labor force who are 16-19 males.

TABLE 10

Variance Decomposition of Unemployment Rates

Type of Heterogeneity	(1)	(2)	(3)
Age-Sex:			
π_i constant	0.238	0.381	0.381
ϕ_i constant	0.276	0.300	0.424
Permanent Layoffs by Age-Sex:			
π_i constant	0.294	0.265	0.441
ϕ_i constant	0.206	0.353	0.441
Temporary Layoffs by Age-Sex:			
π_i constant	0.436	0.152	0.412
ϕ_i constant	0.130	0.522	0.348
Non-Layoff Unemployment by Age-Sex:			
π_i constant	0.965	0.613	-0.576
ϕ_i constant	0.458	0.688	-0.146
Industry:			
π_i constant	0.205	0.462	0.333
ϕ_i constant	0.400	0.238	0.362
Occupation:			
π_i constant	0.212	0.441	0.347
ϕ_i constant	0.353	0.271	0.376

Notes: Calculated as described in text using not seasonally adjusted data.

Column (1): Fraction of total variance accounted for holding π constant.

(2): Fraction of total variance accounted for by residual.

(3): Fraction of total variance accounted for by twice covariance of simulated u_t and residual.

by reason is not taken into account then it appears that variations in the outflow rate are relatively more important. While this may appear puzzling, this is precisely what the constant π_i hypothesis predicts if there is significant heterogeneity which is not taken into account. The reported values for the π_i's by reason and the fluctuations of shares by reason over the cycle indicate that accounting for variation in the composition of unemployment by reason is an important source of heterogeneity. Since the age-sex, industry, and occupation decompositions do not take unemployment by reason into account, it is not surprising that the constant π_i hypothesis does relatively worse under these sources of heterogeneity.[20]

The results in Table 10 take heterogeneity into account, but only in a limited fashion. To take into account all of the available information on heterogeneity, we pursue the following strategy. Recall that aggregate π and aggregate ϕ are determined by:

$$\pi_t = \sum_i \frac{s_{i,t-1}}{s_{t-1}} \pi_{it} \tag{17}$$

$$\phi_t = \sum_i \frac{n_{it}}{n_t} \phi_{it} \tag{18}$$

Equations (17) and (18) indicate that variations in aggregate π and ϕ will depend on both variations in unemployment shares and labor force shares, respectively, as well as factors that induce variations in individual π_i and ϕ_i. Following the specification in our (1985) paper, we estimate regressions

[20]Duration dependence may also be a source of deviations of π_{it} from its natural level. A large statistical literature has been developed regarding the observable distinction between unobserved heterogeneity and state dependence (Heckman and Singer, 1984). Our data does not allow such a distinction.

for aggregate π and ϕ along these lines. In particular, as explanatory variables for π we include lagged unemployment shares by age-sex, by reason of unemployment, by industry, and by occupation and we include a 12 month distributed lag of innovations in the inventory-sales ratio to capture cyclical variations in the individual π_i's. Similarly, as explanatory variables for ϕ we include labor force shares by age-sex, industry, and occupation and the distributed lag of innovations in the inventory/sales ratio. For the sake of brevity, these results are not reported here. However, note that we find that the share variables are significant for explaining variations in aggregate π and ϕ, whereas the distributed lag on inventory/sales innovations are not.[21]

We then used the estimated coefficients from these regressions to produce estimates of π and ϕ that would vary solely due to variations in the composition of unemployment and of the labor force, but not due to variations in individual π_i and ϕ_i. Using these predicted values of π and ϕ based upon share variations alone, we simulated unemployment in two ways in a manner

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[21]That the coefficients on the distributed lag on inventory/sales innovations are insignificant as a group is somewhat puzzling since it contrasts with the results reported in our (1985) paper. However, in that paper, we did not utilize the detailed breakdowns of unemployment by age, sex, reason, industry and occupation and as such we were able to use a data set for a much longer time period (1954:8 to 1983:12). Moreover, we used seasonally adjusted data in that paper in the equivalent regressions (at least partly because the inventory/sales data are available only on a seasonally adjusted basis.) In this paper, we again use seasonally adjusted inventory/sales data but seasonally unadjusted unemployment and labor force series for the regression results (as well as all of the other results) reported in the text. Preliminary regression analysis using seasonally adjusted π's and ϕ's as dependent variables indicates that this is probably the source of the discrepancy. That is, we find that using the same period but seasonally adjusted data yields coefficients on the distributed lag on inventory/sales innovations that are significant at the 0.001 level. A complete analysis of the role of seasonality in this context is beyond the scope of this paper but is obviously worth exploring in future research.

similar to that used above. That is, we first simulated unemployment using actual ϕ and the predicted π based upon share variations alone and then we simulated unemployment using actual π and the predicted ϕ based upon the share variations alone. In this manner, we have incorporated all of the available information on heterogeneity to predict how unemployment would vary for constant π_i and how unemployment would vary for constant ϕ_i.

The resulting variance decompositions from these simulations are reported in Table 11. We find that most of the variance of the actual unemployment rate can be accounted for by the constant π_i model. That is, approximately 90% of the total variance in unemployment can be explained by variations in the level and distribution of the inflows. It is of course interesting that the constant ϕ_i simulated unemployment rate can explain close to 60% of the total variance in unemployment. However, this is not inconsistent with the hypothesis that it is primarily the level and the distribution of the inflows that explains unemployment. We know from the regression results that variations in aggregate π are influenced significantly by variations in the unemployment shares. Since the constant ϕ_i simulated unemployment rate uses the actual aggregate π values, this implies that the distribution of the inflows and the resulting variation in unemployment shares plays a significant role in helping explain the total variance with the constant ϕ_i simulated unemployment rate. Overall, these results provide substantial support for the hypothesis that the main proximate determinant of unemployment is variations in the level and distribution of inflows into unemployment.

IV. Concluding Remarks

Much of the emphasis in explaining unemployment in the macroeconomics literature has focused on the role of expectational errors by workers. In this paper, we develop an unemployment accounting paradigm that allows us to

TABLE 11

Variance Decompositions of the Unemployment Rate

Simulation:	(1)	(2)	(3)
π_i constant	0.8830	0.0235	0.0935
ϕ_i constant	0.5896	0.1136	0.2968

Notes: Calculated as described in text using not seasonally adjusted data 1976:6 to 1985:1.

Column (1): Fraction of total variance accounted for by simulated u_t.

(2): Fraction of total variance accounted for by residual.

(3): Fraction of total variance accounted for by twice covariance of simulated u_t and residual.

quantify how much of the variance in unemployment can be accounted for by the expectational error hypothesis. Our findings suggest that the emphasis on expectational errors by workers has been misplaced. We find that most of the variation in unemployment can be explained by variations in the level and distribution of the inflows into unemployment, while assuming that individual outflow rates are constant. We point out that constant individual outflow rates is precisely the result one would expect from job search theory with well informed workers. Further, we use recent inventory based models of persistence to suggest that even in the face of relatively constant individual outflow rates one may still expect to observe persistent cyclical variations in inflow rates.

Our results are more suggestive than conclusive but they do indicate fruitful directions for future research. We see four main goals for future research: (a) Extend our ability to differentiate between unobserved hetrogeneity and persistent deviations in individual π_{it} values from their normal levels. (b) Develop models to explain the disaggregated behavior of ϕ_{it} values. These models should in principle provide structural linkages to changes in tastes and technology, monetary and fiscal policy, exchange rate movements, and wars. As we showed in our theoretical development, a constant π_{it}, variable ϕ_{it} model can go a long way towards capturing typical hump-shaped cyclical movements in the unemployment rate. Thus, theoretical and empirical models that explain persistent deviations in inflow rates will be quite fruitful in understanding unemployment rate dynamics over the cycle. (c) Develop models to explain the residual movements in π_{it} if they prove significant. (d) Combine these results to produce a structural model which improves our ability to understand and forecast movements in aggregate and disaggregated unemployment rates.

References

Abowd, John M., and Arnold Zellner, "Estimating Gross Labor-Force Flows," Journal of Business & Economic Statistics, July 1985, 3: 254-283.

Blinder, Alan S., and Stanley Fischer, "Inventories, Rational Expectations, and the Business Cycle," Journal of Monetary Economics, November 1981, 8: 277-304.

Burdett, Kenneth, and Jan Ondrich, "How Changes in Labor Demand Affect Unemployed Workers," Journal of Labor Economics, January 1985, 3: 1-10.

Darby, Michael R., John C. Haltiwanger, and Mark W. Plant, "Unemployment-Rate Dynamics and Persistent Unemployment under Rational Expectations," American Economic Review, September 1985, 75: 614-637.

__________, __________, and __________, "The Ins and Outs of Unemployment: The Ins Win," Working Paper, National Bureau of Economic Research, July 1986.

Dornbusch, Rudiger, and Stanley Fischer, Macroeconomics, 3rd ed., New York: McGraw Hill, 1985.

Gordon, Robert, Macroeconomics, 3rd ed., Boston: Little, Brown and Co., 1985.

Grossman, Sanford J. and Oliver P. Hart, "Implicit Contracts Under Asymmetric Information," Quarterly Journal of Economics, Supplement 1983, 98: 123-156.

Haltiwanger, John, and Louis Maccini, "Inventories, Multiperiod Implicit Contracts, and the Dynamic Behavior of the Firm Under Uncertainty," U.C.L.A. Economics Dept. Working Paper No. 374, May 1985.

Heckman, James J., and Borjas, George J., "Does Unemployment Cause Future Unemployment? Definitions, Questions, and Answers from a Continuous Time Model of Heterogeneity and State Dependence," Economica, August 1980, 47:

247-83.

__________, and Burton Singer, "A Method for Minimizing the Impact of Distributional Assumptions in Econometric Models for Duration Data," Econometrica, March 1984, 52: 271-320.

Lilien, David M., "Sectoral Shifts and Cyclical Unemployment," Journal of Political Economy, August 1982, 90: 777-793.

Lippman, Steven A., and John J. McCall, The Economics of Search, Cambridge: Harvard University Press, 1986 in press.

Mitchell, Wesley C., What Happens During Business Cycles: A Progress Report, New York: National Bureau of Economic Research, 1951.

Poterba, James M., and Lawrence H. Summers, "Adjusting the Gross Change Data: Implications for Labor Dynamics," N.B.E.R. Working Paper No. 1436, August 1984.

Topel, Robert H., "Inventories, Layoffs, and the Short-Run Demand for Labor," American Economic Review, September 1982, 72: 769-787.

__________, "Equilibrium Earnings, Turnover, and Unemployment: New Evidence," Journal of Labor Economics, October 1985, 2: 500-22.