Employment growth: Cyclical movements or structural change?

Ellen R. Rissman

Introduction and summary

The Federal Reserve, in its policy analysis, must carefully weigh incoming data and evaluate likely future outcomes before determining how best to obtain its twin goals of employment growing at potential and price stability. It is tempting to regard high or rising unemployment as a sign of a weak economy. And, normally, a weak economy is one with little inflationary pressure and, therefore, room for expansionary monetary policy to stimulate growth. But unemployment is influenced by more than simply aggregate conditions. In a dynamic economy that responds to changing opportunities, some industries are shrinking while others are growing. Labor must flow from declining industries to expanding ones. This adjustment takes time. It takes time for employees in declining sectors to learn about new opportunities in other industries, acquire necessary skills, apply for job openings, and potentially relocate. And during this period of adjustment, the unemployment rate rises as waning industries lay off workers. Thus, the unemployment rate may increase or decrease, even though the aggregate state of the economy remains stable, simply because the labor market adjusts to shifting patterns of production.

For policymakers, it is essential to decipher what portion of a rising unemployment rate is due to a cyclical slowdown in which many sectors of the economy are simultaneously affected, as opposed to a structural realignment in production in which particular sectors of the economy are affected. The two factors ideally should result in different policy responses. If unemployment is rising because of a weak economy, the textbook response is for the Fed to take a more accommodative policy stance. If, instead, the unemployment rate is rising because of underlying compositional shifts in employment, an easing of monetary policy may discourage declining industries from contracting by keeping them marginally profitable, impeding the adjustment process. Furthermore, this policy may also encourage inflation as employers across a broad spectrum of industries compete for scarce labor resources. Thus, comprehending the underlying sources of movements in the unemployment rate is more than just a theoretical exercise: It has practical implications for monetary policy.

As a first step toward evaluating the role of structural change, I need to be able to measure it. Lilien (1982) suggests a dispersion measure that is a weighted average of squared deviations of industry employment growth rates from aggregate employment growth. Abraham and Katz (1986) argue that Lilien's measure does not properly account for cyclical shifts in employment across industries, instead conflating cyclical variation with structural change. When aggregate economic conditions are weak, certain sectors are affected more than others because demand for their products is more cyclically sensitive, but as soon as economic conditions improve, these sectors will also recover more quickly. The Lilien measure more accurately captures both cyclical variation in employment responses and structural changes in the composition of employment across industries, making it impossible to disentangle the importance of the two effects on the measure of dispersion.

The sectoral shifts hypothesis has been revisited more recently by Phelan and Trejos (2000) and Bloom, Floetotto, and Jaimovich (2009). Phelan and Trejos (2000) calibrate a job creation/job destruction model to data from the U.S. labor market to suggest that permanent changes in sectoral composition can precipitate aggregate economic downturns. Bloom, Floetotto, and Jaimovich (2009) examine the effect of what they term "uncertainty shocks" on business cycle dynamics,

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arguing that increases in uncertainty lead to a decline in economic activity in affected industries, followed by a rebound. Increasing uncertainty, in their view, causes firms to be more cautious in their hiring and investment decisions and impedes the reallocation of capital across sectors. Thus, structural change and recessions are simultaneous events, implying that distinguishing structural change from cyclical downturns is problematic.

As noted by Bloom, Floetotto, and Jaimovich (2009), structural realignment (in other words, sectoral reallocation) may be concurrent with economic downturns. Businesses on the brink of downsizing or disappearing altogether may find that they are tipped over the edge during a recession. To the extent that whole industries are affected, the downturn will then occur at the same time as sectoral reallocation. Recessions are followed by expansions, whereas sectoral reallocation tends to have a long-term impact on the composition of employment. Therefore, shifts in production that are cyclical in nature tend to be transitory, but those that are the result of structural realignment are more long lasting.

Previous studies, including Loungani, Rush, and Tave (1990) and Rissman (1993), have employed a variety of techniques to distinguish between sectoral shifts that are driven by structural change and those that are driven by cyclical swings. Loungani, Rush, and Tave (1990), for example, suggest that stock market prices efficiently reflect the future stream of business profits. They employ measures based on stock prices to create a dispersion measure that reflects structural shifts rather than short-term cyclical fluctuations. In Rissman (1993), I note that structural change is long lasting, whereas cyclical swings are of a shorter duration. I use this observation to distinguish between compositional shifts in employment that are due to cyclical fluctuations, which are short term, and those that are due to structural realignment, which are long term. Rissman's (1993) measure cannot be produced in real time because current changes in employment patterns may be either temporary or permanent. Thus, this measure offers little guidance for policymakers who need to make decisions based on current information. In contrast, the Loungani, Rush, and Tave (1990) measure has the benefit of being based on stock price data that are available at high frequency. However, stock prices are noisy, and it may be difficult to disentangle the persistence of shocks from them. In particular, a given decline in a stock price may be a reflection of short-run factors or may instead be interpreted as a small permanent decline in an industry's fortunes. Having a supplementary employment-based measure that does not require the use of leading data, in contrast to Rissman (1993), would provide a useful benchmark.

This problem of optimally inferring the current state has been widely studied in economics and in related statistical literature. Stock and Watson (1989) employ the Kalman filter to create an index of coincident economic indicators. They formally operationalize the idea that the business cycle "refers to co-movements in different forms of economic activity, not just fluctuations in GNP [gross national product]."[1] Stock and Watson (1989) examine several different economic time series, including employment, and try to extract a common factor. I use the same approach here to identify a common factor in the labor market based on how it affects employment in different industries. This common factor is permitted to have different loadings in each industry, giving some context to the notion that some sectors are more cyclically sensitive than others. This framework has the added benefit of creating a common factor that can be interpreted as a measure of the employment cycle, focusing only on the industry cross section of employment growth. This is particularly relevant, since it is widely thought that the labor market typically lags the business cycle. Thus, a measure of the business cycle based only on cross-sectional employment growth helps clarify the relationship between more traditional measures of the cycle, such as real gross domestic product (GDP) growth, and employment growth. This measure of the cycle may help shed light on the phenomenon of the jobless recoveries that we have experienced during the two most recent expansions following the contractions ending in 1991:Q1 and 2001:Q4. Furthermore, the model is based upon quarterly data, giving policymakers a more timely tool for evaluating the relative importance of cyclical and structural factors to the labor market than other measures. There is little reason why the model cannot be estimated on a monthly basis as well. Finally, the model provides some insight into the sources and magnitude of structural change in the economy.

To summarize the results, most industries exhibit cyclical employment growth, which accounts for the majority of the variation in employment in those industries. However, structural shifts are also important and account for most of the variation in employment growth in the finance, insurance, and real estate (FIRE) sector and in the government sector. Perhaps not surprisingly, given the well-chronicled declines in the housing market, the construction industry has undergone a structural reduction in employment after a notably long period of structural expansion. Recent structural employment declines in finance, insurance, and real estate are particularly large when compared with past episodes. Careful measurement of structural change suggests that sectoral reallocation may have been on the rise in the past few quarters. However, structural realignment cannot account for much of the recent increase we have observed in the unemployment rate.

In the next section, I examine employment growth for nine industries comprising most of total nonfarm employment. Then, I introduce the estimation framework. I present my results using this framework. Finally, I develop a measure of sectoral reallocation and investigate its impact on the unemployment rate.

Industry employment growth

The U.S. Bureau of Labor Statistics collects detailed industry employment data for workers on nonfarm payrolls. Over the years the industry classification system has changed to reflect the changing industrial composition of the economy. Because of this, it is difficult to compare earlier industry data, which were collected using the Standard Industrial Classification (SIC) System, with more recent industry data, which were collected using the North American Industry Classification System (NAICS). For example, nine new service sectors and 250 new service industries are recognized in the NAICS data, but they are not in the SIC data. The problem of comparability over time is less of an issue with the broadest industry aggregates. Earlier estimates of sectoral reallocation were computed using SIC data. To facilitate comparison with earlier work, the NAICS data were converted as closely as possible to be consistent with SIC classifications.

Figure 1 shows annualized quarter-to-quarter employment growth from 1950 through the second quarter of 2009 for the following nine sectors: construction; durable manufacturing; nondurable manufacturing; transportation and utilities; wholesale trade; retail trade; finance, insurance, and real estate; services; and government.[2] Business cycle contractions, as determined by the National Bureau of Economic Research (NBER), have been shaded for reference. The figure also shows the average annual industry employment growth rate over this period.

Given the current focus on the housing market as the source of some of our economic problems, it is interesting to examine employment in the construction sector. Employment growth in construction is highly volatile and, not surprisingly, quite cyclical as well. Construction employment growth appears to decline in advance of business cycle peaks and reaches its bottom at or just past the trough of a recession. Although employment growth in construction was above average during the most recent expansion, which peaked in December 2007, the strong employment growth does not appear abnormally large in comparison with earlier recoveries. Nonetheless, the most recent quarters show a very strong drop in construction employment, surpassing even the large declines of the mid-1970s. It is an open question as to what part of this observed decline in construction is structural in nature and what part is cyclical (and will therefore rebound when aggregate conditions improve).

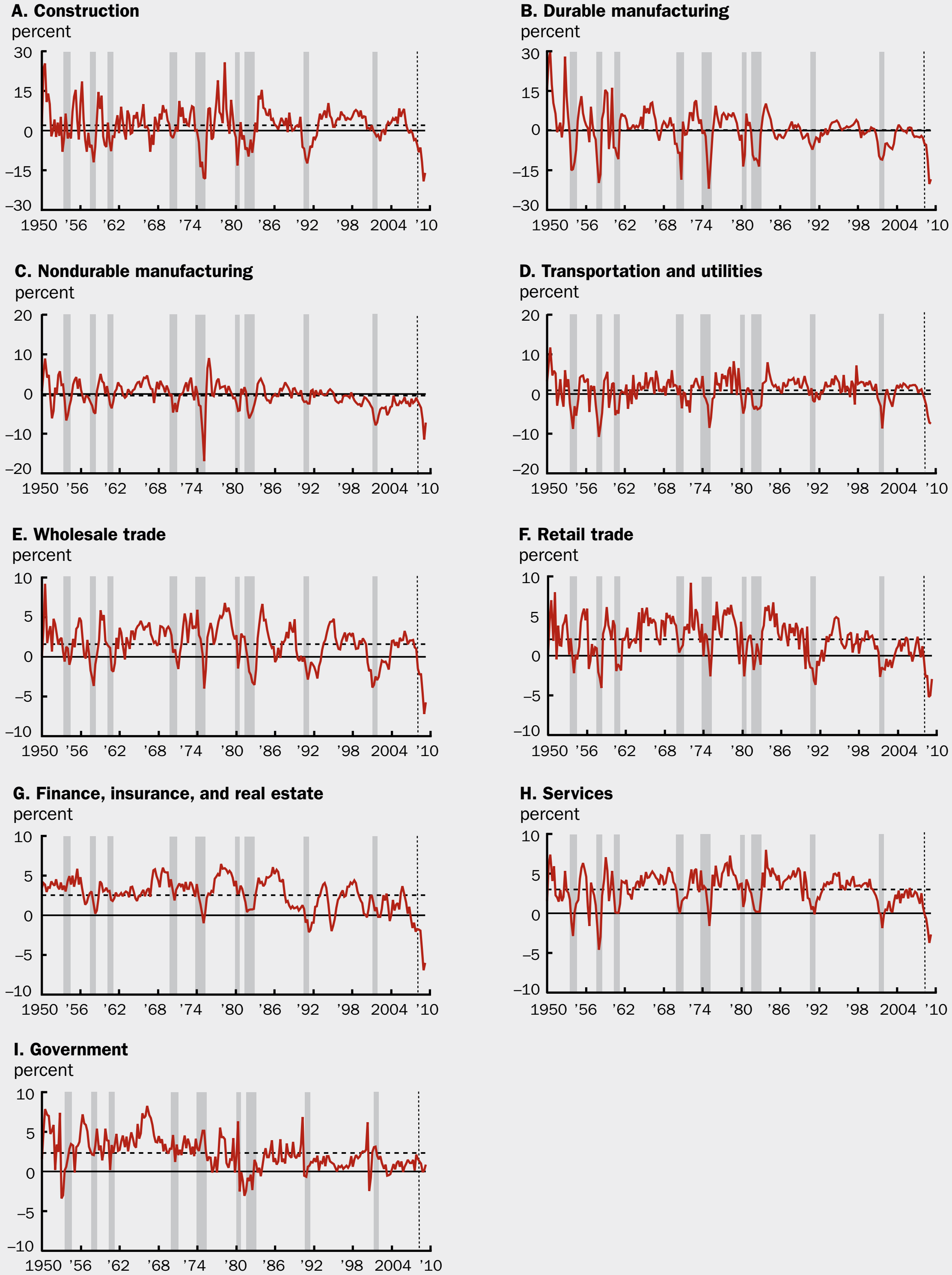
The finance, insurance, and real estate sector tells a somewhat different story. Like most industries, FIRE experiences reduced employment growth during recessions. Yet, while FIRE's employment growth has dipped below average during recessions, historically, employment in this sector has very rarely declined. The steep drop in employment in the early 1990s seems to be the harbinger of a change in employment growth in this sector, with average employment growth falling below the 3 percent growth of earlier decades. Furthermore, the steep job losses of the past few quarters are unprecedented in the past 60 years. The key question is whether the sharp employment declines are cyclical, with employment likely to rebound as the economy moves into the expansionary phase of the business cycle, or structural and, therefore, likely to linger. Later, I will show that employment growth in this industry tends to be highly persistent, suggesting that these declines are likely to last for quite a while. Yet, these job losses in FIRE may not transfer directly into increased unemployment. Since workers in FIRE may have skills that are more easily transferred to other areas, they may be more likely to find employment in expanding sectors; therefore, the adjustment out of this sector may not involve much of an increase in the unemployment rate.

The services sector is also interesting to consider. At one time, this sector was thought to be the engine of employment growth, as can be seen by the high average employment growth rates since the 1950s. Yet, more recently, employment growth here has been weak as well. And employment growth in services over the past couple of quarters is the lowest it has been since the late 1950s.

Taken as a whole, these data suggest several important facts. First, average growth rates differ across industries, with some sectors of the economy barely growing at all, such as durable and nondurable manufacturing, and others exhibiting more robust growth, such as FIRE and services. Second, some industries are far more volatile than others. Construction, durable and nondurable manufacturing, and transportation and utilities have wide swings in employment growth compared with the other industries. Third, unsurprisingly, employment growth is highly cyclical, dropping during contractions and rising during expansions. However, some industries appear more cyclically sensitive than others. Focusing on the period since the onset

FIGURE 1

Employment growth: Selected industries, 1950:Q1–2009:Q2



Notes: These are quarterly annualized growth rates calculated on an SIC (Standard Industry Classification system) conformable basis. The dashed horizontal line in each panel is the average annual industry employment growth rate. The shaded areas indicate official periods of recession as identified by the National Bureau of Economic Research; the dashed vertical line in each panel indicates the most recent business cycle peak.

Source: Author's calculations based on data from the U.S. Bureau of Labor Statistics from Haver Analytics.

of the current recession in the fourth quarter of 2007, employment has declined precipitously in most industries. If most of the recent declines in employment growth are cyclical, then employment growth should rebound and return to normal as the economy moves into the expansionary phase of the business cycle. However, a portion of the recent declines in employment growth may be the result of other factors such as structural realignment in the economy. If this is indeed the case, then it may indicate that some industries will likely experience more permanent reductions in employment or employment growth. An accurate assessment of whether employment data are driven by the business cycle or structural change is important for formulating policy and for projecting the future path of employment growth.

Table 1 shows the same employment growth data for the entire sample in the first row and divided into ten-year increments in the subsequent rows.[3] Construction employment has averaged 2.0 percent annualized quarterly growth over the entire sample period. However, over the past decade the average quarterly growth in construction employment has been –0.42 percent. Durable and nondurable manufacturing have experienced large declines in employment over the past decade, with job losses or stagnant growth since the late 1970s. Employment growth has been weak for the past decade in transportation and utilities, as well as in wholesale and retail trades. In fact, all sectors have exhibited weaker average employment growth over the past decade than they have averaged over the past 60 years.[4]

A model of industry employment growth

The discussion in the previous section suggests that industry employment growth, in addition to having a long-term average, can be described by two additional components: a cyclical component and an idiosyncratic component that reflects other noncyclical factors. Let

$$1)\quad g_{it} = a_i + C_{it} + X_{it},$$

where g_{it} is employment growth in sector i at time t, $i = 1, \ldots, I$, and $t = 1, \ldots, T$; a_i is average employment growth in the industry; C_{it} is the cyclical portion of industry employment growth (and it varies across time and industry); and X_{it} is the idiosyncratic part of industry employment growth (and it also varies across time and industry). This construction is similar to the problem analyzed by Stock and Watson (1989), in which they noted that individual aggregate time series depend upon a common cyclical component and an idiosyncratic component.

TABLE 1

Average annualized quarterly employment growth, in total and by decade

	Construction	Durable manufacturing	Nondurable manufacturing	Transportation and utilities	Wholesale trade	Retail trade	Finance, insurance, and real estate	Services	Government
	(percent)								
Total	2.00	0.37	−0.40	1.00	1.63	2.06	2.53	3.00	2.29
2000s	−0.42	−3.82	−3.41	−0.29	−0.41	−0.18	0.18	1.16	1.04
1990s	2.42	−0.04	−0.78	1.76	1.20	1.44	1.56	3.24	1.28
1980s	1.63	−0.90	−0.25	1.32	1.57	2.52	2.97	3.72	1.13
1970s	2.64	0.98	0.09	1.30	2.97	3.33	3.59	3.62	2.65
1960s	2.08	2.50	1.23	1.30	2.42	3.03	3.38	3.70	4.15
1950s	3.54	3.31	0.58	0.52	1.93	2.08	3.37	2.45	3.41

Note: Data are seasonally adjusted.
Source: Author's calculations based on data from the U.S. Bureau of Labor Statistics from Haver Analytics.

As currently specified, equation 1 cannot be estimated because there is no way to distinguish between the cyclical and idiosyncratic components. To address this issue, I assume that the cycle is a common component affecting all industries. However, the cycle may have a differential impact across sectors. Specifically,

2) $C_{it} = b_i^1 C_t + b_i^2 C_{t-1}$,

where b_i^1 and b_i^2 are parameters indicating the sensitivity of the i-th sector to current and lagged values of the business cycle. Furthermore, it is assumed that the cycle itself follows a second-order autoregressive process with:

3) $C_t = \phi_1 C_{t-1} + \phi_2 C_{t-2} + u_t$.

Here u_t is independent and identically normally distributed with unit variance. The ϕ_1 and ϕ_2 are unknown parameters that are to be estimated. Setting $\sigma_u^2 = 1$ determines the scale of the business cycle. For example, an alternative estimate of the cycle $C_t^* = \delta C_t$ would result in estimates of the b_i values scaled by 1/δ. Two sets of estimates are possible, both C_t and $-C_t$, depending upon the initial values of the parameters. For ease of interpretation, it is assumed that the business cycle has a positive impact on durable manufacturing employment growth.

The idiosyncratic component of industry employment growth X_{it} is assumed to follow an AR(1) process. Specifically,

4) $X_{it} = \gamma_i X_{it-1} + \varepsilon_{it}$,

where γ_i is a sector-specific parameter that indicates the degree of persistence of sectoral shocks. It is assumed that the ε_{it} values are uncorrelated over time and across industries. Note that $E(\varepsilon_{it}) = 0$ and $E(\varepsilon_{it}^2) = \sigma_i^2$ for all i, t. Furthermore, the ε_{it} values are assumed to be uncorrelated with the cyclical shock u_t for all i, t. This specification allows for a common unobserved cycle that has a differential impact across industries. It also permits structural change to occur through the idiosyncratic component X_{it}. Thus, changes in an industry's employment growth are due to either cyclical factors or factors that are specific to that particular industry.

Estimation is accomplished using the Kalman filter, details of which are discussed in box 1. The state vector $\underline{z}_t$ is given by $\underline{z}_t = [C_t, C_{t-1}, C_{t-2}, X_{1t}, X_{2t}, \ldots, X_{It}]'$. The Kalman filter algorithm enables estimates of the state vector $\underline{z}_t$ and the underlying parameters to be estimated. These parameters include the values for a_i, b_i^1, b_i^2, γ_i, σ_i, and ϕ_1 and ϕ_2. The shocks u_t and ε_{it} can also be obtained for $i = 1, \ldots, I$ and $t = 1, \ldots, T$. The Kalman filter is a way of optimally updating the underlying state vector as new information becomes available each quarter. A Kalman smoothing algorithm is used to optimally backcast for final estimates of the state vector and model parameters.

Estimation results

The estimate of the cycle $\hat{C}_t$ obtained from the Kalman filter exercise is shown in figure 2.[5] The 2× standard error bands are also shown. These standard error bands indicate whether the estimate is significantly different from zero. Defining a recession as the period during which the estimated employment cycle is significantly below zero, the estimate indicates that we are currently in the midst of a deep recession. The cyclical point estimate in 2009:Q1 measures the recession to be the most severe since 1950. However, because of parameter uncertainty, this point estimate is not significantly worse than earlier recessions in a statistical sense. The estimate for 2009:Q2 indicates that aggregate employment continues to deteriorate, albeit at a slower pace.

Employment failed to rebound as quickly as other sectors of the economy during the two most recent recoveries following the NBER-dated recessions of 1990–91 and 2001. This lack of improvement in the labor market, termed the "jobless recovery," drew commentary from both the popular press and economists. As computed here, the employment-based measure of the cycles indicates that the contractions lasted seven and eleven quarters, respectively—significantly longer than the length of the NBER's contractionary periods of three and four quarters, respectively—indicating that the labor market experienced a delayed recovery relative to other measures of economic activity that the NBER's Business Cycle Dating Committee examines in determining business cycle peaks and troughs. Shortly after the 2001 recession, Groshen and Potter (2003) suggested that the abnormally slow recovery was the result of sectoral reallocation (in other words, structural factors) rather than cyclical factors. The evidence provided here shows that the slow growth in employment was likely attributable to weak cyclical activity.[6] Using a similar methodology, Aaronson, Rissman, and Sullivan (2004) reach a similar conclusion. Furthermore, findings presented in the next section regarding the role of X_{it} appear to show that sectoral shocks do not play a major role in accounting for unemployment. Recall that the employment cycle is defined by co-movement in employment growth rates across many industries simultaneously. As such, the model interprets the lengthy employment contraction during these two episodes as broad-based; that is, a wide spectrum of industries are negatively affected,

BOX 1

The Kalman filter

The Kalman filter is a statistical technique that is useful in estimating the parameters of the model specified in equations 1–4 (pp. 44–45). In addition, the Kalman filter enables the estimation of the processes u_t and ε_{it} and the construction of the unobserved cyclical variable C_t and the idiosyncratic components X_{it}. The Kalman filter consists of a state equation and a measurement equation. The state equation describes the evolution of the possibly unobserved variable(s) of interest, $\underline{z}_t$, while the measurement equation relates observables $\underline{g}_t$ to the state. The vector $\underline{g}_t$ is related to the $m \times 1$ state vector, $\underline{z}_t$, via the measurement equation:

B1) $\underline{g}_t = B\underline{z}_t + D\underline{\eta}_t + H\underline{w}_t,$

where $t = 1, \ldots, T$; B is an $N \times m$ matrix; $\underline{\eta}_t$ is an $N \times 1$ vector of serially uncorrelated disturbances with mean zero and covariance matrix I_N; and $\underline{w}_t$ is a vector of exogenous (possibly predetermined) variables with H and D being conformable matrices.

In general, the elements of $\underline{z}_t$ are not observable. In fact, it is this very attribute that makes the Kalman filter so useful to economists. Although the $\underline{z}_t$ elements are unknown, they are assumed to be generated by a first-order Markov process as follows:

B2) $\underline{z}_t = A\underline{z}_{t-1} + F\underline{u}_t + G\underline{w}_t,$

for $t = 1, \ldots, T$, where A is an $m \times m$ matrix, F is an $m \times p$ matrix, and $\underline{u}_t$ is a $p \times 1$ vector of serially uncorrelated disturbances with mean zero and covariance matrix I_g. This equation is referred to as the state or transition equation.

The definition of the state vector $\underline{z}_t$ for any particular model is determined by construction. In fact, the same model can have more than one state-space representation. The elements of the state vector may or may not have a substantive interpretation. Technically, the aim of the state-space formulation is to set up a vector $\underline{z}_t$ in such a way that it contains all the relevant information about the system at time t and that it does so by having as small a number of elements as possible. Furthermore, the state vector should be defined so as to have zero correlation between the disturbances of the measurement and transition equations, $\underline{u}_t$ and $\underline{\eta}_t$.

The Kalman filter refers to a two-step recursive algorithm for optimally forecasting the state vector $\underline{z}_t$, given information available through time $t - 1$, conditional on known matrices B, D, H, A, F, G. The first step is the prediction step and involves forecasting $\underline{z}_t$ on the basis of $\underline{z}_{t-1}$. The second step is the updating step and involves updating the estimate of the unobserved state vector $\underline{z}_t$ on the basis of new information that becomes available in period t. The results from the Kalman filtering algorithm can then be used to obtain estimates of the parameters and the state vector $\underline{z}_t$ by employing traditional maximum likelihood techniques.[1]

The model of employment growth proposed here can be put into state-space form, defining the state vector $\underline{z}_t = [C_t, C_{t-1}, C_{t-2}, X_{1t}, X_{2t}, \ldots, X_{It}]'$. The Kalman filter technique is a way to optimally infer information about the parameters of interest and, in particular, the state vector $\underline{z}_t$, which in this case is simply the unobserved cycle, C_t, and its two lags and the unobserved structural components X_{it}. The cycle, as constructed here, represents that portion of industry employment growth that is common across the industries while allowing the cycle to differ in its impact on industry employment growth in terms of timing and magnitude through the parameters b_i^1 and b_i^2. The model is very much in the spirit of Burns and Mitchell's (1946) idea of cycles entailing co-movement, but the estimation technique permits the data to determine which movements are common and which are idiosyncratic.[2]

[1]The interested reader may obtain further details in Harvey (1989) and Hamilton (1994).

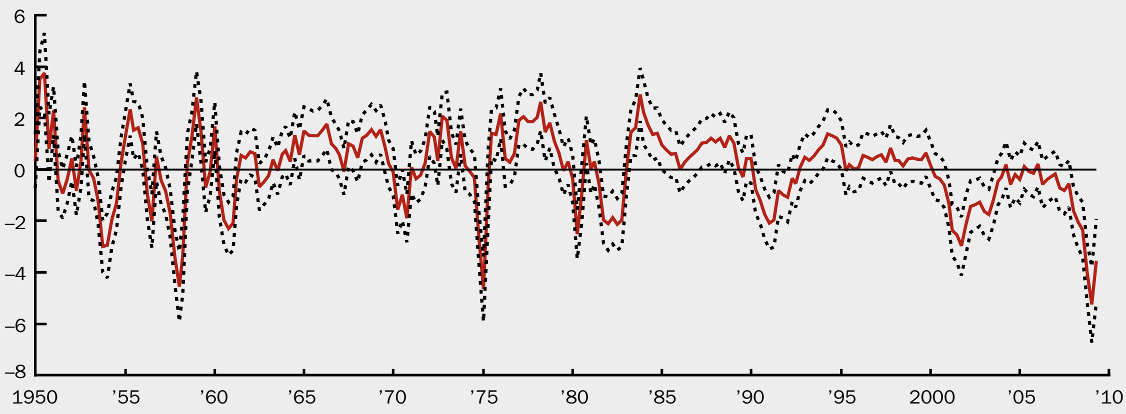
[2]Stock and Watson (1989) employ the Kalman filter in constructing leading and current economic indicators.

and the contraction is not concentrated in only a few industries, as would be the case if sectoral reallocation were the underlying cause of low aggregate employment growth.

Table 2 provides parameter estimates with associated standard errors. Focus on the coefficient estimates of the $\hat{b}_i^1$ values (second column): All sectors of the economy are affected by cyclical variation, as constructed here. However, the degree of cyclical sensitivity varies across industries, with durable manufacturing employment being the most contemporaneously cyclically sensitive, followed by construction. The estimated intercept term $\hat{a}_i$ (first column) is not significantly different from zero in construction, durable manufacturing, nondurable manufacturing, and transportation and utilities. The estimated parameter $\hat{\gamma}_i$ (fourth column) gives the degree of persistence of the idiosyncratic component. There is a great deal of variation in the persistence of these idiosyncratic shocks ε_i, with finance, insurance, and real estate exhibiting the most persistence.

FIGURE 2

Estimated employment cycle, 1950:Q1–2009:Q2



Note: The dashed lines indicate the 2× standard error bands, indicating whether the estimate is significantly different from zero.
Source: Author's calculations based on data from the U.S. Bureau of Labor Statistics from Haver Analytics.

TABLE 2

Parameter estimates, 1950:Q1–2009:Q2

	$\hat{a}_i$	$\hat{b}_i^1$	$\hat{b}_i^2$	$\hat{\gamma}_i$	$\hat{\sigma}_i$
Construction	1.8435 (1.1963)	1.8695*** (0.3407)	1.5357*** (0.4730)	0.4240*** (0.0741)	20.1902*** (1.8060)
Durable manufacturing	0.2714 (1.5350)	3.7417*** (0.3549)	0.8463 (0.6397)	0.612*** (0.0552)	9.9197*** (0.9951)
Nondurable manufacturing	−0.4657 (0.6295)	1.5231*** (0.1537)	0.4054 (0.2385)	0.6461*** (0.0479)	1.9574*** (0.2371)
Transportation and utilities	0.9105 (0.5921)	1.2185*** (0.2354)	0.7769** (0.3036)	0.0933 (0.0883)	3.8068*** (0.4611)
Wholesale trade	1.5546*** (0.4448)	0.8004*** (0.1135)	0.6365*** (0.1888)	0.5516*** (0.0673)	1.2072*** (0.1134)
Retail trade	1.9921*** (0.4377)	1.2430*** (0.1589)	0.2449 (0.2255)	0.1727* (0.0818)	1.7845*** (0.2004)
Finance, insurance, and real estate	2.3220*** (0.6162)	0.2073* (0.0913)	0.2340*** (0.0862)	0.8978*** (0.0361)	0.7583*** (0.0786)
Services	2.9343*** (0.4061)	1.0738*** (0.0994)	0.3221 (0.1661)	0.1728 (0.1119)	0.4891*** (0.0804)
Government	2.2712*** (0.3532)	0.0890 (0.1280)	0.1438 (0.1031)	0.5748*** (0.0639)	2.9139*** (0.2494)

*Significant at the 5 percent level.
**Significant at the 2 percent level.
***Significant at the 1 percent level.
Note: Standard errors are in parentheses.
Source: Author's calculations based on data from the U.S. Bureau of Labor Statistics from Haver Analytics.

BOX 2

Calculating the variance

Rewriting the model as a vector AR(1) process, define

B3) $\underline{y}_t = [g_{1t}, g_{2t}, \ldots, g_{It}, C_t, C_{t-1}, C_{t-2}, X_{1t}, X_{2t}, \ldots, X_{It}]'.$

Then

B4) $\underline{y}_t = \Pi \underline{y}_{t-1} + \underline{\nu}_t,$

which has a variance

B5) $\Omega = \Pi\Omega\Pi' + \Sigma.$

This can be solved as:

B6) $\mathrm{vec}(\Omega) = [I - \Pi \otimes \Pi]^{-1}\mathrm{vec}(\Sigma),$

where $\otimes$ is the Kronecker product of Π with itself and vec(x) is the vector constructed by stacking the columns of an $n \times m$ matrix into a single column vector. The matrix Π is given by

B7) $\Pi = \begin{bmatrix} 0_{I\times I} & B_{I\times 3} & \Gamma_{I\times I} \\ 0_{3\times I} & A_{3\times 3} & 0_{3\times I} \\ 0_{I\times I} & 0_{I\times 3} & \Gamma_{I\times I} \end{bmatrix},$

and the submatrices are given by

B8) $B = \begin{bmatrix} b_1^1 & b_1^2 & 0 \\ b_2^1 & b_2^2 & 0 \\ \vdots & \vdots & \vdots \\ b_I^1 & b_I^2 & 0 \end{bmatrix},$

B9) $A = \begin{bmatrix} \phi_1 & \phi_2 & 0 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix},$

and

B10) $\Gamma = \begin{bmatrix} \gamma_1 & 0 & \ldots & 0 \\ 0 & \gamma_2 & & 0 \\ \vdots & & \ddots & \\ 0 & \ldots & 0 & \gamma_I \end{bmatrix}.$

The error term $\underline{\nu}_t$ is given by

B11) $\underline{\nu}_t = [\varepsilon_{1t}, \varepsilon_{2t}, \ldots, \varepsilon_{It}, u_t, 0, 0, \varepsilon_{1t}, \varepsilon_{2t}, \ldots, \varepsilon_{It}]'.$

Shocks to both services and transportation and utilities are not statistically persistent. Furthermore, variation in these shocks differs across industries, reflecting in part the variation in employment growth noted in figure 1 (p. 43). Shocks to the idiosyncratic portion of industry employment growth are more variable in construction, durable manufacturing, and transportation and utilities than in other sectors of the economy (fifth column).

Using the model, it is straightforward to calculate the portion of the variation in an industry's employment growth that is attributable to cyclical activity and that which is attributable to industry-specific factors. Details of the calculations are found in box 2, and the results are presented in table 3. As noted previously, some industries exhibit much more variation in employment growth than others. Construction and durable manufacturing are the two most volatile sectors of the economy, exhibiting large swings in employment growth. By comparison, the variance of employment growth in nondurable manufacturing and transportation and utilities is about one-fifth that of the most volatile industries, and the least volatile sectors have about one-tenth the variance. The model attributes this volatility to either cyclical variation or the idiosyncratic structural component. Within construction, for example, about half the total variance in employment growth stems from the structural component and half is the result of cyclical variation. The cyclical component accounts for most of the variation in employment growth in durable manufacturing, nondurable manufacturing, transportation and utilities, wholesale trade, retail trade, and services. In contrast, the structural component carries the most weight in two sectors—FIRE and government.

In addition to examining the estimated cycle, it is also useful to consider the idiosyncratic portion of employment growth. Figure 3 shows the idiosyncratic component X_{it} for each of the nine industries from 1950:Q1 through 2009:Q2. Positive values suggest that employment growth is stronger in these industries than explained by either normal cyclical variation C_{it} or long-term averages a_i. Note that the scale differs

TABLE 3

Effect of cyclical and structural components on variation, 1950:Q1–2009:Q2

	Total variance	Fraction of total variance due to C	Fraction of total variance due to X_i
Construction	46.9245	0.4754	0.5246
Durable manufacturing	58.7445	0.7300	0.2700
Nondurable manufacturing	10.8692	0.6909	0.3091
Transportation and utilities	11.5470	0.6674	0.3326
Wholesale trade	5.7097	0.6961	0.3039
Retail trade	6.3833	0.7119	0.2881
Finance, insurance, and real estate	4.2831	0.0874	0.9126
Services	4.4125	0.8857	0.1143
Government	4.4569	0.0236	0.9764

Source: Author's calculations based on data from the U.S. Bureau of Labor Statistics from Haver Analytics.

from one industry to the next. Upon closer inspection of the construction sector (figure 3, panel A), the estimates suggest that employment growth in this industry was higher than could be explained from the business cycle or sectoral trends over most of the 1990s through the first half of 2006, when the trend abruptly reversed, reflecting the unfolding crisis in the housing market. The sharp drop in X_{it} shows that construction employment seems to be taking a bigger hit in the current episode than can be explained based on the usual prior cyclical patterns for this sector. Perhaps even more noteworthy is the recent experience in finance, insurance, and real estate (figure 3, panel G) that shows a marked decline in recent years, suggesting this sector is in the midst of a restructuring that is unexplained by either the normal cyclical pattern or long-term trends. How this downsizing of FIRE affects the unemployment rate is an open question.

As table 1 (p. 44) suggested, the parameters of the model may change over time. A test of parameter stability can be done using a likelihood ratio test. The test statistic compares the log likelihood of the model estimated using the full sample, from 1950:Q1 through 2009:Q2, with the sum of the log likelihoods from the model estimated on two smaller samples—the 1950:Q1–1983:Q4 period and the 1984:Q1–2009:Q2 period. The resulting test statistic is distributed $X^2(46)$, and its value is 498.22, rejecting the hypothesis that at normal confidence levels the parameter vector is the same for the two smaller sample periods.

Table 4 presents parameter estimates from the 1984:Q1–2009:Q2 sample period. In comparing the estimates found in table 2 (p. 47) and table 4, there is some evidence of "The Great Moderation,"[7] with most of the coefficients on the contemporaneous estimate of the cycle, $\hat{b}_i^1$, being smaller in magnitude for the 1984:Q1–2009:Q2 sample period than for the entire sample. For example, in the full sample a one standard deviation increase in the cycle increased durable manufacturing employment growth by 3.7 percent per annum, whereas in the 1984:Q1–2009:Q2 sample, the impact was a much smaller 1.2 percent (see second row, second column of tables 2 and 4, respectively). Furthermore, generally, estimates of the variance of the idiosyncratic shocks in each industry, $\hat{\sigma}_i$, are much smaller for the 1984:Q1–2009:Q2 sample, with the exception of finance, insurance, and real estate (compare the fifth column in tables 2 and 4). For example, the estimate of the standard deviation in the shock to construction is 20.2 for the entire sample, but a much smaller 4.3 for the 1984:Q1–2009:Q2 sample. There is also evidence that for the 1984:Q1–2009:Q2 sample, industry shocks are more persistent, as can be seen by comparing the estimated $\hat{\gamma}_i$ values for the entire sample and those for the 1984:Q1–2009:Q2 sample, with government being a notable exception (see the fourth column in tables 2 and 4). Nonetheless, the interpretation of the results seems to hold. In particular, when estimated on the 1984:Q1–2009:Q2 sample, X_{it} in construction shows the run-up in construction employment starting in the mid-1990s and the abrupt decline in 2006 that cannot be explained by the typical cyclical patterns of the past. The estimated X_{it} values are shown in figure 4 for the two samples.

Sectoral reallocation

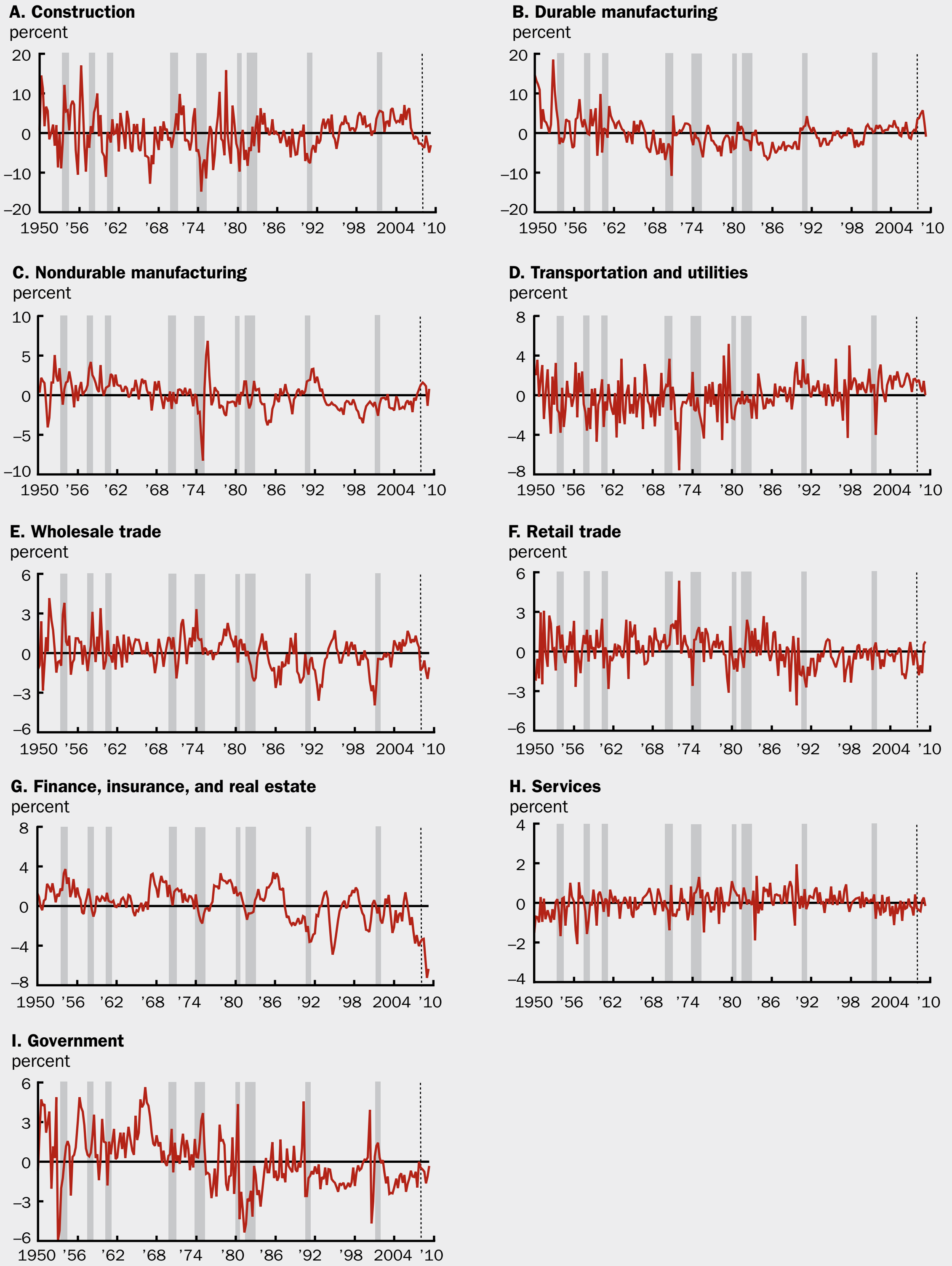
In his original paper, Lilien (1982) presented a dispersion measure as a way to quantify the degree of sectoral reallocation occurring in the economy at any given time. His measure is given by

$$5)\quad \sigma_{Lt} \equiv \left[\sum_i s_{it}(g_{it} - g_t)^2\right]^{1/2},$$

where s_{it} is industry i's employment share at time t; g_{it} is employment growth in i at time t; and g_t is total employment growth at time t. Abraham and Katz (1986) demonstrate that this dispersion measure will increase even if no sectoral reallocation is present, simply because some industries are more cyclically sensitive than others.

FIGURE 3

Noncyclical employment growth: Selected industries, 1950:Q1–2009:Q2



Notes: The panels show the estimated X_{it} values. The shaded areas indicate official periods of recession as identified by the National Bureau of Economic Research; the dashed vertical line indicates the most recent business cycle peak.
Source: Author's calculations based on data from the U.S. Bureau of Labor Statistics from Haver Analytics.

TABLE 4

Parameter estimates, 1984:Q1–2009:Q2

	$\hat{a}_i$	$\hat{b}_i^1$	$\hat{b}_i^2$	$\hat{\gamma}_i$	$\hat{\sigma}_i$
Construction	1.1703 (5.8890)	2.0239*** (0.4471)	0.1505 (0.7041)	0.7837*** (0.1066)	4.3028*** (1.5117)
Durable manufacturing	−2.0404 (5.8171)	1.2233*** (0.3697)	0.9706*** (0.3687)	0.7809*** (0.1028)	1.4940*** (0.3755)
Nondurable manufacturing	−1.7455 (2.8657)	0.6885*** (0.2296)	0.3827 (0.2630)	0.7261*** (0.1025)	0.8580*** (0.2103)
Transportation and utilities	0.9551 (2.8641)	0.6666* (0.3072)	0.4383 (0.3680)	0.0793 (0.1213)	2.0082*** (0.3299)
Wholesale trade	0.5980 (2.6710)	0.7366*** (0.1784)	0.2876 (0.2258)	0.7551*** (0.0807)	0.6228*** (0.1714)
Retail trade	1.0153 (2.5684)	0.7983*** (0.2299)	0.1708 (0.3379)	0.3190* (0.1487)	1.0826*** (0.2504)
Finance, insurance, and real estate	1.1042 (1.5869)	0.2289 (0.1927)	0.2021 (0.1860)	0.8818*** (0.0883)	0.9104*** (0.2466)
Services	2.5218 (2.2840)	0.6012*** (0.1699)	0.2775 (0.1683)	0.0339 (0.2188)	0.3434*** (0.0882)
Government	1.3070*** (0.4682)	−0.1437 (0.2637)	0.2893 (0.2858)	0.2061* (0.1003)	1.4475*** (0.2520)

*Significant at the 5 percent level.
**Significant at the 2 percent level.
***Significant at the 1 percent level.
Note: Standard errors are in parentheses.
Source: Author's calculations based on data from the U.S. Bureau of Labor Statistics from Haver Analytics.

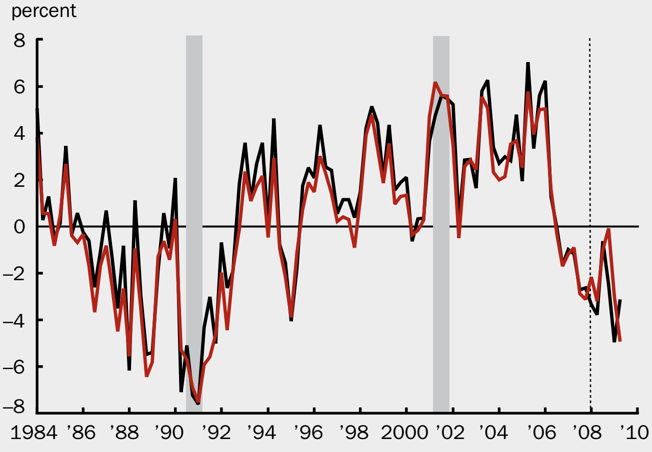
Keep in mind the Abraham and Katz (1986) criticism that Lilien's (1982) dispersion measure reflects cyclical movements: The framework presented previously provides a way to eliminate the impact of the cycle on employment shares, industry employment growth, and aggregate employment growth so as to create a dispersion measure that is purged of cyclical variation. This measure is given by

$$6)\quad \tilde{\sigma}_t \equiv \left[\sum_i \tilde{s}_{it} (\tilde{g}_{it} - \tilde{g}_t)^2 \right]^{1/2},$$

where $\tilde{x}$ indicates that the variable x is purged of the cycle. To create the purged series, first, let $\tilde{g}_{it} = X_{it}$. Then, assuming that the cycle was zero in some reference year, taken here to be 1964, it is simple to calculate $\tilde{e}_{it}, \tilde{e}_t, \tilde{s}_{it}$, and $\tilde{g}_t$, where $\tilde{e}_{it}$ is noncyclical employment in industry i at time t and $\tilde{e}_t$ is total noncyclical employment at time t. Figure 5 shows the results of these calculations. The red line is Lilien's (1982) measure as given in equation 5, and the black line is calculated as in equation 6. The noncyclical measure of dispersion is far less volatile than the original measure, as Abraham and Katz (1986) argued. Nonetheless, there has been a modest uptick in this measure of structural realignment over the past couple of quarters. Figure 6 shows the noncyclical measure in panel A and another measure that is based only on the shocks ε_{it} in panel B. In this figure you can see the recent uptick more clearly. The most recent quarter shows a decline in these dispersion measures, reflecting industry shocks that are smaller in magnitude than those of the previous few quarters. However, while it suggests a potential role for industrial realignment in explaining recent increases in unemployment, this simple summary measure may not be too informative in explaining recent changes in the unemployment rate. To put it more succinctly, structural realignment in and of itself may have little impact on the unemployment rate. Workers laid off in one sector may be readily absorbed into other industries, particularly if real wages adjust to encourage the flow of workers from declining industries to expanding ones.

FIGURE 4

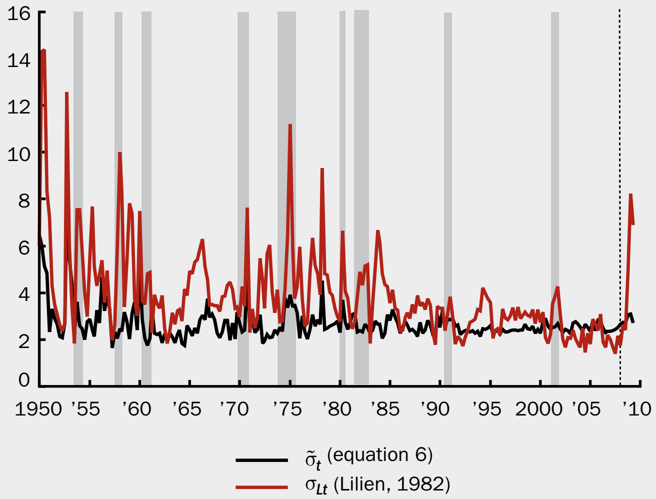
Estimated idiosyncratic component in construction: Full sample versus 1984:Q1–2009:Q2 sample



Notes: See the text for further details on the idiosyncratic component (X_{it}) of industry employment growth, which is estimated on the two samples. The shaded areas indicate official periods of recession as identified by the National Bureau of Economic Research; the dashed vertical line indicates the most recent business cycle peak.
Source: Author's calculations based on data from the U.S. Bureau of Labor Statistics from Haver Analytics.

FIGURE 5

Dispersion measures, 1950:Q1–2009:Q2



Note: The shaded areas indicate official periods of recession as identified by the National Bureau of Economic Research; the dashed vertical line indicates the most recent business cycle peak.
Source: Author's calculations based on data from the U.S. Bureau of Labor Statistics from Haver Analytics.

In order to determine whether the structural component of employment growth plays a role in unemployment dynamics, I ran regressions of the following form:

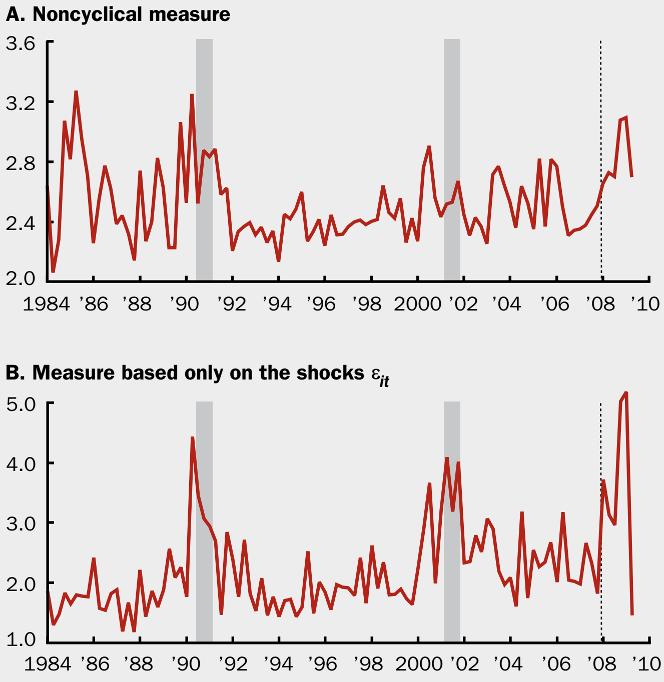
$$7)\quad \Delta ur_t = \alpha(L)\Delta ur_{t-1} + \delta(L)Cycle_t + \lambda(L)\Sigma_t + cW_t + \upsilon_t,$$

where $\alpha(L)$, $\delta(L)$, and $\lambda(L)$ are polynomials in the lag operator L; Δur_t is the change in the unemployment rate at time t; $Cycle_t$ is a measure of the cycle at time t; Σ_t is a measure of sectoral reallocation at time t, including the constructed dispersion measures or, more broadly, the individual estimated X_{it} and ε_{it} values; and W_t is other variables that potentially influence changes in the unemployment rate. The variable υ_t is a random shock assumed to be independent and identically normally distributed.

Two separate measures of the cycle were examined, namely, deviations of real GDP growth from its long-term average $(gGDP_t - \overline{gGDP})$ and $\hat{C}_t$. Several different measures of Σ_t were considered, including the two noncyclical measures computed as in equation 6, as well as the estimated X_{it} values and the ε_{it} values individually. Regression results are shown in table 5. Three lags of changes in the unemployment rate are included in each regression, as is a demographic variable that is calculated as the change in the female labor force participation rate of white women aged 20 and above. (Other demographic variables that reflected changes in the age, race, and sex composition of the labor force were also investigated but were statistically insignificant and are not reported in these results.) Of the two cyclical variables considered, the measure of the employment cycle $\hat{C}_t$ performed better than deviations of real GDP growth from its long-term average, in that those regressions had higher $\bar{R}^2$ values. Generally, the two dispersion measures of sectoral reallocation did poorly in explaining changes to the unemployment rate. The third and fourth columns examine the impact of adding dispersion measures of sectoral reallocation to the regressions. These

FIGURE 6

Noncyclical measures of sectoral reallocation, 1984:Q1–2009:Q2



Note: The shaded areas indicate official periods of recession as identified by the National Bureau of Economic Research; the dashed vertical line indicates the most recent business cycle peak.
Source: Author's calculations based on data from the U.S. Bureau of Labor Statistics from Haver Analytics.

dispersion measures are statistically significant, but enter with the opposite sign anticipated by the sectoral reallocation hypothesis; that is, increasing reallocation, as measured here, tends to reduce the unemployment rate.[8] The last two regressions omit the cyclical variable, $\hat{C}_t$, and include the two dispersion measures. Only in the results of the sixth column, in which the cyclical variable is omitted, does dispersion enter significantly positive. The weak results suggest that sectoral reallocation as measured here may be positively associated with changes in the unemployment rate. However, once cyclical effects are properly accounted for, the impact disappears or changes sign.

One possibility is that these dispersion measures, being summary statistics, are not very good at capturing the effects of reallocation in the labor market. The dispersion measure treats all employment shifts of the same magnitude as identical, regardless of the industry. This ignores the possibility that human capital may differ across industries, suggesting that unemployment responses should differ across sectors as well. Specifically, some industries may require industry-specific human

TABLE 5

Regression results: Dependent variable is Δur_t, 1984:Q1–2009:Q2 sample

	1	2	3	4	5	6
3 lags Δur_{t-1}	Yes	Yes	Yes	Yes	Yes	Yes
Current and two lags of $gGDP_t - \overline{gGDP}$	−0.0433*** (0.0074)	—	—	—	—	—
Current and two lags of $\hat{C}_t$	—	−0.1674*** (0.0264)	−0.1771*** (0.0264)	−0.1980*** (0.0291)	—	—
Change in female participation rate	0.1126 (0.0749)	0.0690 (0.0652)	0.1240 (0.0696)	0.1270 (0.0686)	0.0639 (0.0950)	0.0362 (0.0911)
$\tilde{\sigma}$ based on $\hat{X}_{it}$	—	—	−0.0131* (0.0065)	—	0.0073 (0.0077)	—
$\tilde{\sigma}$ based on $\hat{\varepsilon}_{it}$	—	—	—	−0.0175* (0.0077)	—	0.0182* (0.0079)
$\overline{R}^2$	0.6714	0.7904	0.7970	0.7993	0.5987	0.6162

*Significant at the 5 percent level.
**Significant at the 2 percent level.
***Significant at the 1 percent level.
Notes: Estimating over the full sample did not materially change the results. The full sample was estimated from 1954:Q2 through 2009:Q2, since the female labor force participation rate data are not available prior to 1954:Q2. The estimate of the employment cycle employed in the analysis is from the 1950:Q1–2009:Q2 Kalman filter exercise. Standard errors are in parentheses.
Sources: Author's calculations based on data from the U.S. Bureau of Labor Statistics and U.S. Bureau of Economic Analysis from Haver Analytics.

TABLE 6

Effect of idiosyncratic components and shocks on changes in the unemployment rate, 1954:Q2–2009:Q2

	X_{it}			ε_{it}		
	Coefficient and standard error	$\bar{R}^2$	Coefficient and standard error	Coefficient and standard error	$\bar{R}^2$	Coefficient and standard error
Construction	−0.0111*** (0.0025)	0.7910	−0.0117*** (0.0027)	−0.0093*** (0.0027)	0.7836	−0.0093*** (0.0027)
Durable manufacturing	−0.0174*** (0.0044)	0.7876	−0.0191*** (0.0045)	−0.0156** (0.0050)	0.7818	−0.0102 (0.0062)
Nondurable manufacturing	−0.0022 (0.0076)	0.7718	−0.0013 (0.0082)	0.0010 (0.0105)	0.7718	0.0074 (0.0129)
Transportation and utilities	−0.0146* (0.0065)	0.7770	−0.0041 (0.0070)	−0.0119 (0.0062)	0.7756	−0.0043 (0.0064)
Wholesale trade	0.0161 (0.0104)	0.7743	0.0180 (0.0103)	0.0159 (0.0125)	0.7735	0.0166 (0.0126)
Retail trade	0.0242** (0.0098)	0.7781	0.0108 (0.0103)	0.0212* (0.0099)	0.7766	0.0132 (0.0111)
Finance, insurance, and real estate	0.0001 (0.0074)	0.7718	0.0031 (0.0072)	0.0171 (0.0139)	0.7734	0.0201 (0.0130)
Services	0.0596*** (0.0212)	0.7799	0.0228 (0.0252)	0.0508*** (0.0192)	0.7790	0.0448 (0.0243)
Government	0.0126* (0.0062)	0.7761	0.0146** (0.0059)	0.0224*** (0.0076)	0.7806	0.0227*** (0.0072)
			$\bar{R}^2 = 0.8179$			$\bar{R}^2 = 0.8064$

*Significant at the 5 percent level.
**Significant at the 2 percent level.
***Significant at the 1 percent level.
Notes: Dependent variable is Δur_t. Also included in the regressions are three lags of the dependent variable, one current and two lags of the estimated employment cycle, and changes in the labor force participation rate of white women aged 20 and above. See the text for further details.
Source: Author's calculations based on data from the U.S. Bureau of Labor Statistics from Haver Analytics.

capital. Sectoral reallocation away from those industries will take time and cost more for those who have become displaced. To examine this possibility, I have entered the idiosyncratic components both individually and together. The results are found in tables 6 and 7, which differ only in their sample periods. Table 6 provides results for the period from 1954:Q2 through 2009:Q2, and table 7 provides results from 1984:Q1 through 2009:Q2.[9]

The first two columns of table 6 examine the effect of including each idiosyncratic component separately in a regression having both cyclical and demographic variables. The $\bar{R}^2$ values are reported from each of these regressions in the second column. The sectors of the economy in which the idiosyncratic component of employment growth is statistically significant are construction, durable manufacturing, transportation and utilities, retail trade, services, and government. The signs of these effects are also interesting to consider. Specifically, as noncyclical employment grows above trend in construction, durable manufacturing, and transportation and utilities, it reduces the unemployment rate. However, it has the opposite effect in retail trade, services, and government, in that shifts toward these industries tend to raise the unemployment rate. The third column reports the coefficients from a single regression in which all idiosyncratic industry components are included, in addition to current and lagged employment cycle and demographic variables. Noncyclical shifts in construction, durable manufacturing, and government are still statistically significant, entering with the same sign as in the single variable regressions. However, transportation and utilities, retail trade, and services are no longer statistically significant.

TABLE 7

Effect of idiosyncratic components and shocks on changes in the unemployment rate, 1984:Q1–2009:Q2

	X_{it}			ε_{it}		
	Coefficient and standard error	$\bar{R}^2$	Coefficient and standard error	Coefficient and standard error	$\bar{R}^2$	Coefficient and standard error
Construction	−0.0101* (0.0045)	0.7990	−0.0129* (0.0063)	−0.0085 (0.0055)	0.7935	−0.0125* (0.0059)
Durable manufacturing	−0.0025 (0.0070)	0.7884	−0.0054 (0.0087)	−0.0128 (0.0110)	0.7912	−0.0123 (0.0132)
Nondurable manufacturing	0.0130 (0.0101)	0.7919	0.0031 (0.0145)	0.0152 (0.0175)	0.7898	0.0139 (0.0208)
Transportation and utilities	−0.0254*** (0.0090)	0.8048	−0.0272** (0.0108)	−0.0246*** (0.0086)	0.8050	−0.0243** (0.0094)
Wholesale trade	0.0108 (0.0113)	0.7987	−0.0001 (0.0137)	0.0007 (0.0162)	0.7881	−0.0024 (0.0172)
Retail trade	0.0252* (0.0117)	0.7981	0.0206 (0.0143)	0.0239 (0.0121)	0.7966	0.0221 (0.0146)
Finance, insurance, and real estate	−0.0048 (0.0070)	0.7892	−0.0043 (0.0079)	0.0130 (0.0139)	0.7901	0.0107 (0.0137)
Services	0.0025 (0.0305)	0.7882	0.0102 (0.0376)	0.0003 (0.0274)	0.7881	0.0149 (0.0346)
Government	0.0087 (0.0099)	0.7997	0.0019 (0.0099)	0.0005 (0.0101)	0.7881	−0.0023 (0.0099)
			$\bar{R}^2 = 0.8153$			$\bar{R}^2 = 0.8104$

*Significant at the 5 percent level.
**Significant at the 2 percent level.
***Significant at the 1 percent level.

Notes: Dependent variable is Δur_t. Also Included in the regressions are three lags of the dependent variable, current and two lags of the estimated employment cycle, and changes in the labor force participation rate of white women aged 20 and above. See the text for further details.

Source: Author's calculations based on data from the U.S. Bureau of Labor Statistics from Haver Analytics.

The fourth, fifth, and sixth columns of table 6 repeat the regression exercise but instead employ idiosyncratic shocks ε_{it} as explanatory variables. The results are consistent with the results using X_{it}. Shocks to construction and durable manufacturing tend to reduce unemployment, whereas shocks to retail trade, services, and government tend to raise unemployment (fourth column). The transportation and utilities industry does not meet the 5 percent significance criterion. However, its marginal significance level is close to 10 percent. Table 7 reestimates the equations of the preceding table, but with the 1984:Q1–2009:Q2 sample period. Most of the results disappear for this sample period.

To obtain estimates of the effect of sectoral reallocation on the unemployment rate, I assume that the economy was in equilibrium in 2007:Q4, with an unemployment rate of 4.8 percent. Furthermore, I assume that the cycle is set equal to its expected value from 2007:Q4 through 2009:Q2. In this analysis, that implies that $C_t = 0$. I also assume that there are no demographic changes in the female labor force participation rate over this period.

Table 8 provides estimates of the effect of X_{it} on the civilian unemployment rate as estimated from the equation used in the third column of table 7, using the 1984:Q1–2009:Q2 sample period. The first column gives the estimated total effect of the X_{it} on the unemployment rate, given the assumptions in the preceding paragraph. The impact of sectoral reallocation in this model is negligible. The remaining columns compute the impact on the equilibrium unemployment rate of having idiosyncratic employment growth shocks in the specified industry given by the estimated shocks. For example, although equilibrium employment remained

TABLE 8

Estimated impact of idiosyncratic industry employment growth on unemployment, 1984:Q1–2009:Q2

	All X_{it}	Construction	Durable manufacturing	Nondurable manufacturing	Transportation and utilities	Wholesale trade	Retail trade	Finance, insurance, and real estate	Services	Government
	(- - - - -	- - - - -	- - - - -	- - - - -	- - - - percent	- - - - -	- - - - -	- - - - -	- - - - -	- - - - -)
2007:Q4	4.80	4.80	4.80	4.80	4.80	4.80	4.80	4.80	4.80	4.80
2008:Q1	4.79	4.84	4.78	4.80	4.76	4.80	4.79	4.82	4.80	4.80
2008:Q2	4.76	4.89	4.76	4.81	4.72	4.80	4.75	4.83	4.79	4.80
2008:Q3	4.71	4.91	4.73	4.81	4.69	4.80	4.73	4.85	4.79	4.80
2008:Q4	4.69	4.94	4.70	4.82	4.68	4.80	4.69	4.87	4.79	4.79
2009:Q1	4.73	5.01	4.68	4.81	4.64	4.80	4.70	4.90	4.79	4.79
2009:Q2	4.82	5.06	4.68	4.82	4.63	4.80	4.71	4.94	4.79	4.79

Notes: Results are for the regression in table 7, third column. Calculations assume that the equilibrium unemployment rate was equal to its value of 4.8 percent in 2007:Q4 and that the employment cycle is in equilibrium from 2007:Q4 through 2009:Q2, so that $X_{it} = 0$ from 2007:Q4 through 2009:Q2. The first column calculates the unemployment rate that would have occurred had the industry idiosyncratic components been as estimated from 2007:Q4 through 2009:Q2 and the employment cycle been in equilibrium. The second through tenth columns reflect the impact of the idiosyncratic components in each of the individual industries. For example, in the second column the estimated impact of idiosyncratic shifts in construction on the unemployment rate in 2009:Q2, assuming all other industry components to be as given by the estimated X_{it} values, is to raise the unemployment rate by 0.24 percentage points (calculated by subtracting the value in the last row, first column, from the value in the last row, second column, 5.06 – 4.82). Results differ if the unemployment rate regression is estimated using the entire sample period.

Source: Author's calculations based on data from the U.S. Bureau of Labor Statistics from Haver Analytics.

largely unchanged, by 2009:Q2 the shocks to construction raised the unemployment rate by approximately 25 basis points (see the notes in table 8). This rise was offset by declines elsewhere.

As a whole, these models suggest that idiosyncratic shifts in industry employment growth account for very little of the observed increase in the unemployment rate over the past several quarters. On its own, this would imply that there is room for accommodative policy as a response to the current increase in unemployment, but bringing to bear additional evidence on dispersion would help us gain a better sense of whether the conclusions implied by the empirical model discussed here are robust. There is a great deal of uncertainty surrounding the estimates presented here. As noted before, the parameters of the state-space model appear to differ between the 1950:Q1–1983:Q4 period and the 1984:Q1–2009:Q2 period. Because of parameter and model uncertainty, these estimates of the impact of sectoral reallocation on the unemployment rate must be viewed somewhat skeptically. To underscore this fact, results of the same exercise that estimate the unemployment equation using the full sample suggest a decline in unemployment since 2008:Q1 attributable to sectoral reallocation.

Conclusion

The labor market appears to have a cycle that is well described by co-movements in employment growth. The estimate of the employment cycle that results from my model seems to agree with anecdotal evidence about jobless recoveries. The model also does a good job of capturing turning points in the business cycle, suggesting that it may be a useful tool for understanding labor market dynamics and may help in predicting future employment. The idiosyncratic component that the methodology yields may also provide some additional insight into the impact of structural realignment on changes in the unemployment rate. Structural change favoring construction, durable manufacturing, and transportation and utilities seems to be associated with decreasing unemployment; this suggests that there may be some impediments to displaced workers in these sectors finding jobs in other industries. Even with the downsizing of finance, insurance, and real estate, the overall impact on the unemployment rate is not statistically significant. One possibility is that employees from finance, insurance, and real estate are better able to find alternative employment in other sectors of the economy because the skills they possess are more readily transferable to employment in other industries. Conversely, employees in construction, durable manufacturing, and transportation and utilities may be less readily absorbed into other sectors.

NOTES

[1]Stock and Watson (1989), p. 353.

[2]The services sector includes information services, professional and business services, education and health services, leisure and hospitality, and other services. Mining has been omitted from the analysis for two reasons. First, because of the incidence of strikes, employment growth in this industry is quite volatile. Second, mining accounts for a small fraction of total employment.

[3]Averages for the current decade are based on data through 2009:Q2.

[4]The only exception, unreported here, is the mining sector.

[5]The hat symbol (^) indicates an estimate.

[6]There is another notable discrepancy when comparing the NBER business cycle recession dates with those estimated here. The two NBER recessions in the early and mid-1970s were longer by two and three quarters, respectively, than those proposed here. Instead, the employment-based measure of the cycle shows a labor market that was quick to return to more normal activity during those times.

[7]The Great Moderation is a term used to describe the period usually thought to have begun in 1984 and lasting through the present, during which many economic time series exhibited less volatility than in previous years. The validity of this concept as a permanent shift has been called into question by the recent financial crisis.

[8]The coefficients reported here are for contemporaneous measures of dispersion. Including a number of leads and lags did not substantively change the results. Altering the specification so that the dispersion measure was in changes or log changes had no bearing on the results either.

[9]The full sample period is slightly shortened by starting in 1954:Q2 because earlier data for female labor force participation were not available.

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