

# Business Volatility, Job Destruction and Unemployment

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## Abstract

Unemployment inflows fell from 4 percent of employment per month in the early 1980s to 2 percent or less by the mid 1990s and thereafter. U.S. data also show a secular decline in firm-level employment volatility and the job destruction rate. We interpret this decline as a decrease in the intensity of idiosyncratic labor demand shocks, a key parameter in search and matching models of frictional unemployment. According to these models, a lower intensity of idiosyncratic demand shocks produces less job destruction, fewer workers flowing through the unemployment pool and less frictional unemployment. To evaluate this theoretical mechanism, we relate industry-level unemployment flows from 1977 to 2005 to industry-level indicators for the intensity of idiosyncratic shocks. Unlike previous research, we focus on the lower frequency relationship of job destruction and business volatility to unemployment flows. We find strong evidence that declines in the intensity of idiosyncratic labor demand shocks drove large declines in the incidence of unemployment.

Keywords: business volatility, job destruction, unemployment inflows, job-finding rates  
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## 1. Introduction

Trends in the volatility of economic activity attract considerable attention. Many recent studies examine the “great moderation” in aggregate U.S. fluctuations since the early to mid 1980s.<sup>1</sup> Another recent line of research finds a secular decline in business-level volatility. In this regard, Faberman (2006) documents a decline in the rate at which jobs are reallocated across establishments. Davis, Haltiwanger, Jarmin and Miranda (2006; DHJM) document a decline in the cross-sectional dispersion of business growth rates and in the time-series volatility of business growth rates.<sup>2</sup> DHJM and Davis, Faberman, and Haltiwanger (2006) also point out that the secular decline in business-level volatility roughly coincides with a marked decline in the magnitude of unemployment flows. Unemployment inflows, for example, fell from 4 percent of employment per month in the early 1980s to about 2 percent per month by the mid 1990s.

In this paper, we investigate whether declining business-level volatility drove the large decline in unemployment flows. The theoretical motivation is a basic one – according to search and matching theories of the labor market, a lower intensity of idiosyncratic labor demand shocks produces less job destruction, fewer workers flowing through the unemployment pool and less frictional unemployment. To evaluate the importance of this theoretical mechanism, we relate industry-level movements in the incidence and duration of unemployment to industry-level movements in several indicators for the intensity of idiosyncratic shocks. Unlike previous research, we focus on

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<sup>1</sup> See Kim and Nelson (1999), McConnell and Perez-Quiros (2000), Blanchard and Simon (2001) and Stock and Watson (2002), among others.

<sup>2</sup> In contrast, Comin and Mulani (2006), and Comin and Philippon (2005) find rising volatility among publicly traded firms in recent decades. It turns out, as DHJM show, that the volatility trend for publicly traded firms differs dramatically from the trend for privately held firms and the private sector as a whole. Privately held firms have become less volatile, and they dominate the overall trend.

the low frequency relationship of job destruction and business-level volatility measures to unemployment flows. The central question we pursue is whether longer term changes in the intensity of idiosyncratic shocks explain changes in the extent of frictional unemployment, as implied by canonical search and matching models.

To carry out our empirical investigation, we integrate industry-level data from three sources. We construct annual measures of job creation, job destruction and business-level volatility from 1977 to 2001 using the Longitudinal Business Database (LBD) and quarterly measures from 1990 to 2005 using Business Employment Dynamics (BED). We rely on the Current Population Survey (CPS) for monthly data on unemployment inflows, outflows and escape rates. We average the monthly CPS data to the quarterly and annual frequency with due attention to the within-period timing of observations in the LBD and BED.

The industry-level data provide compelling evidence that changes in the intensity of idiosyncratic shocks drove large changes in the incidence of unemployment. This key result holds in the annual and quarterly data. We estimate, for example, that a decline of 100 basis points in an industry's quarterly job destruction rate lowers its monthly unemployment inflow rate by 28 basis points with a standard error of 5 basis points. This estimate reflects a specification that includes industry and period fixed effects, so it relies entirely on industry-specific time variation. To put the estimate in perspective, the quarterly job destruction rate fell by 157 basis points in the U.S. private sector from 1990 to 2005. Multiplying this drop by its estimated effect yields a decline of 44 basis points in the unemployment inflow rate, which amounts to 48 percent of the drop in the

unemployment inflow rate from 1990 to 2005 and 20 percent of its average value. Our other indicators for the intensity of idiosyncratic demand shocks yield similar results.

The evidence in our study is much weaker with respect to the estimated effects of job destruction and business volatility on the unemployment escape rate. Some specifications imply that lower business volatility raises the unemployment escape rate, contrary to the steady-state implications of basic search models. As we discuss below, however, this implication is likely less robust to factors outside the scope of basic search models. In addition, our industry data are less suitable for testing implications about escape rates, because an unemployed person's opportunities for new jobs are not limited to the industry of his or her most recent employment.

The next section discusses the theoretical motivation for our empirical investigation and a few conceptual issues. Section 3 describes the data and our measurement procedures. Section 4 presents evidence on movements in aggregate volatility, business-level volatility, job destruction rates and unemployment inflows in recent decades. Section 5 carries out our main empirical analysis. Section 6 discusses the implications of our findings for frictional and cyclical unemployment. Section 7 concludes.

## **2. Theoretical Considerations and Conceptual Issues**

The theoretical motivation for our empirical investigation rests on implications of well-known search and matching models. Consider the seminal model of Mortensen and Pissarides (1994). When an employer wants to fill a job opening in this model, it posts a vacancy and searches for an unemployed worker. The meeting rate and the aggregate flow of new hires are outcomes of a matching function defined over the stock of

vacancies and the number of unemployed persons. Given a standard specification for the matching function, a higher ratio of vacancies to unemployment means a higher job-finding rate for unemployed persons and a lower job-filling rate for employers.<sup>3</sup> When employer and job seeker meet, they split the match surplus and commence production. After match formation, employment relationships are subject to exogenous dissolution events and to aggregate and idiosyncratic shocks that can result in endogenous job destruction. These shocks drive fluctuations in the pace of job destruction and the incidence of unemployment.

Mortensen and Pissarides show that an increase in the variance of idiosyncratic shocks raises the job destruction rate and the incidence of unemployment. It also raises the vacancy-unemployment ratio in steady state and, hence, raises the job-finding rate. These model properties imply that unemployment inflows and escape rates respond positively to measured job destruction rates and other empirical indicators for the intensity of idiosyncratic shocks. We test these implications in the empirical work below.<sup>4</sup>

The idea that idiosyncratic labor demand shocks drive the incidence of unemployment predates its particular expression in Mortensen and Pissarides (1994). It is intrinsic to Friedman's (1968) concept of the natural rate of unemployment. Phelps (1968) provides the first formal model of frictional unemployment, and many, many

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<sup>3</sup> See Shimer (2005) for evidence on the behavior of the job-finding rate and Davis, Faberman and Haltiwanger (2007) for evidence on the behavior of the job-filling rate.

<sup>4</sup> We do not explore implications of the MP model for vacancy rates, given our focus on low frequency behavior, because U.S. data on job vacancies are not suitable for drawing inferences about trends. In this connection, see Shimer (2005) for a discussion of spurious trends in the normalized Help Wanted Index, the object of many studies that consider the cyclical behavior of job vacancies. Time series on vacancy rates derived from the Job Openings and Labor Turnover Survey are, as yet, too short to draw inferences about trends.

others follow. Hall (1979) and Pissarides (1985) provide early formalizations that feature idiosyncratic demand shocks as drivers of unemployment inflows and key determinants of the natural rate of unemployment. In light of these remarks, we see our empirical investigation as testing a core idea that inhabits many models of frictional unemployment. We couch our discussion in terms of the MP model because of its central role in recent thinking and research about unemployment. For those already convinced that idiosyncratic labor demand shocks determine the extent of frictional unemployment, our study quantifies the contribution of longer term changes in the intensity of such shocks to movements in unemployment inflows and escape rates.

In taking the theoretical implications to the data, at least three conceptual issues arise. First, the MP model maintains a sharp distinction between common (“aggregate”) and match-specific (“idiosyncratic”) shocks. In reality, the labor demand effects of common shocks differ greatly among employers.<sup>5</sup> Indeed, by allowing for heterogeneity in the impact of common shocks, it is easy to generate a trend decline in firm-level volatility from a decline in the size or frequency of common shocks, as DHJM discuss. Hence, trends in empirical indicators for the intensity of idiosyncratic shocks can reflect changes in the size and frequency of common shocks or changes in firm-level responses to common shocks. We include period fixed effects in our regression specifications to

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<sup>5</sup> Durable goods producers are more sensitive to aggregate income and wealth shocks according to standard theories of consumption behavior. Persistent technology shocks have a bigger impact effect on the capital-producing sector in real business cycle models. Exchange rate movements differentially affect importing and exporting firms (e.g., Revenga, 1992). The effect of changes in the corporate income tax rate on a firm’s investment incentives depend on the composition of its capital stock (Cummins, Hassett and Hubbard, 1994). The impact of changes in the dividend tax rate depends on the firm’s dividend payout rate and its marginal source of investment funds (Auerbach and Hassett, 2005). Kashyap, Stein and Wilcox (1993) and Gertler and Gilchrist (1994) find greater sensitivity to monetary shocks among smaller firms. Davis and Haltiwanger (2001) find that the magnitude of employment responses to oil price shocks rises with energy’s cost share, capital intensity in production and durability of the output good. Many studies consider regional and industry differences in the response to aggregate shocks (e.g., Clark, 1998).

control for the average effect of common shocks in the cross section. The differential effects of common shocks are, for our purposes, the same as idiosyncratic shocks.

Second, the basic MP model allows for only two labor market states, employment and unemployment. In reality, many workers flow in and out of the labor force. If the propensity of job-losing workers to exit the labor force differs among industries or over the course of our sample period, and if the differences are correlated with our empirical indicators for the intensity of idiosyncratic shocks, then we will obtain biased estimates for the effects on unemployment inflows and escape rates. To address this potential source of bias, we rely on industry and period fixed effects as controls.

Third, unemployed persons in the MP model are homogeneous, and they have identical job-finding rates at a given point in time. In reality, unemployed persons differ in search intensity, ability to find a suitable match, willingness to accept a job offer and propensity to exit the labor force – all of which lead to heterogeneity in unemployment escape rates. Changes over time in the composition of unemployed workers potentially affect the unemployment escape rate for reasons outside the MP model. Composition effects can arise because the mix of job losers varies over the business cycle, or because the experience, skill mix and other attributes of the population evolve over time. Since we focus on lower frequency relationships in the empirical work, we do not think cyclical changes in the composition of newly unemployed persons are an important concern for our study.<sup>6</sup> Changes in the composition of the working-age population, which by their

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<sup>6</sup> Cyclical spikes in job destruction rates seldom last more than two quarters in U.S. data, and researchers typically estimate unemployment escape rates in the range of 25 to 40 percent per month. Taken together, these two observations suggest that the impact of job destruction episodes on the composition of the unemployment pool dissipates rather quickly. In addition, Shimer (2005) provides evidence that cyclical movements in the composition of unemployed workers account for only minor changes in the average job-finding rate of unemployed persons.

nature tend to be persistent, are a bigger concern. They could be correlated with empirical indicators for the intensity of idiosyncratic shocks and independently drive changes in unemployment inflows and escape rates. To deal with this issue, we rely on period fixed effects to control for changes in the overall composition of the working-age population and unemployment pool.

In addition to testing implications of the MP model, we investigate whether job destruction has a bigger impact on the incidence of unemployment when the lost jobs reflect exiting businesses, as opposed to those that merely shrink. More generally, we hypothesize that a given amount of job destruction produces greater unemployment inflows when the lost jobs are concentrated at businesses undergoing relatively extreme contractions. This hypothesis is motivated by two previous findings in the empirical literature on labor market flows. First, layoffs are much more likely than quits to result in an unemployment spell. See, for example, Leighton and Mincer (1982) and McLaughlin (1990). Second, Davis, Faberman and Haltiwanger (2006, Figure 7) find that the ratio of layoffs to quits rises in the cross section with the contraction rate of the employer. Combining these two empirical regularities yields the hypothesis that job destruction produces greater unemployment inflows when the lost jobs are concentrated at businesses undergoing extreme contractions. We test whether this link between unemployment inflows and the concentration of job destruction operates on the time-series dimension.

### **3. Data Sources and Measurement Procedures**

#### *3.1 Job Flows, Employer Volatility and Cross-Sectional Dispersion*

The Bureau of Labor Statistics (BLS) and the Census Bureau have recently developed longitudinal business data sets that cover the entire private sector of the U.S. economy.

The BLS Business Employment Dynamics (BED) program produces quarterly job flow statistics from 1992 based on three-month changes in establishment-level employment. We rely on a version of the BED extended back to 1990 by Faberman (2006). The Census Bureau's Longitudinal Business Database (LBD) contains firm-level employment data in March of each year from 1976 to 2001.<sup>7</sup> We exploit the LBD to construct annual statistics on job flows, firm volatility and the cross-sectional dispersion of firm growth rates. Our measurement procedures follow Davis, Haltiwanger and Schuh (1996) for job flow statistics and DHJM for firm volatility and dispersion measures.

To spell out our various indicators for the intensity of idiosyncratic shocks, it is helpful to describe our measurement mechanics. Define the growth rate from  $t - 1$  to  $t$  at employer  $e$  as  $g_{et} = (EMP_{et} - EMP_{e,t-1}) / Z_{et}$ , where  $EMP$  denotes the number of employees and  $Z_{et} = 0.5(EMP_{et} + EMP_{e,t-1})$  is a measure of employer size. This growth rate measure has become standard in work on labor market flows because it is symmetric about zero and bounded, affording an integrated treatment of entering, exiting and continuing units. It also has other attractive properties.<sup>8</sup>

Using these measures, we can write the rate of job destruction from  $t - 1$  to  $t$  as

$$JD_t = \sum_e \left( \frac{Z_{et}}{Z_t} \right) \left| \min \{0, g_{et}\} \right| = \sum_e \left| \min \{0, EMP_{et} - EMP_{e,t-1}\} \right| / Z_t, \quad (1)$$

where  $Z_t = \sum_e Z_{et}$ . Equation (1) says that job destruction from  $t - 1$  to  $t$  is the sum of all employment reductions at shrinking units, and it is expressed as a rate by dividing

<sup>7</sup> See Jarmin and Miranda (2002) for details on the LBD and its creation.

<sup>8</sup> The growth rate measure in the text is identical to log changes up to a second-order Taylor Series expansion. Creation and destruction rates calculated according to (1) aggregate consistently. See Tornqvist, Vartia and Vartia (1985) and the appendix to Davis, Haltiwanger and Schuh (1996) for additional discussion.

through by overall employment. We can partition the set of shrinking establishments by the severity of contractions to obtain, for example, the rate of job destruction at exits and continuers. The job creation rate ( $JC_t$ ) can be expressed by substituting the max for the min operator in (1). Job reallocation ( $JR_t$ ) is defined as the sum of job creation and destruction.<sup>9</sup>

Note that the job reallocation rate is equivalent to the size-weighted mean absolute value of employer growth rates. Hence, it can be interpreted as a measure of cross-sectional dispersion in employer growth rates. We also consider a more conventional measure of cross-sectional dispersion in employer growth rates:

$$\sigma_t(\text{Disp}) = \left[ \sum_e (Z_{et} / Z_t) (g_{et} - \bar{g}_t) \right]^{1/2}, \quad (2)$$

where  $\bar{g}_t$  is the size-weighted mean growth rate from  $t-1$  to  $t$ . Equation (2) is the size-weighted standard deviation of employment growth rates from  $t-1$  to  $t$  in the cross section of employers. We refer to (2) as the dispersion of employer growth rates.

Several previous studies measure business volatility using a moving window of fixed length, say ten years, on the standard deviation of business-level growth rates. The window is centered on the current year, and the standard deviations are averaged across businesses in each period to obtain a time series for average business volatility. This measure has two major drawbacks for our purposes. First, it is truncated at both ends of the sample period, a loss of valuable information. Second, the measure is undefined for employers that operate during only part of the window. Because most firms do not survive ten years and short-lived firms are highly volatile, a measure based on a fixed

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<sup>9</sup> Throughout, we multiply job flow rates by 100 and report them as percentages of employment. We do the same for the volatility and dispersion measures described below.

window length misses much of the action. Moreover, the omitted units are excluded on the basis of characteristics, entry and exit, associated with highly variable growth paths. The nonrandom nature of the selection process raises concerns about the accuracy of the resulting volatility measure as an indicator for the overall intensity of idiosyncratic shocks.

To address these issues, we follow DHJM by considering a volatility measure that incorporates entry and exit and short-lived business units. The measure is defined over all units at  $t$  with a positive value of  $Z_{et}$ , as for the measures in (1) and (2). The basic idea of the DHJM measure is to specify a maximal window length but shorten the window length as needed to handle entry and exit and sample end points. To adjust for differences in the window length across units and over time, the measure applies a standard degrees of freedom correction.

Here are the details. Let  $P_{et}$  denote the number of years from  $t - 4$  to  $t + 5$  for which

$Z_{et} > 0$ . Define the scaling quantity,  $K_{et} = P_{et} / \sum_{\tau=-4}^5 Z_{e,t+\tau}$ , and the rescaled weights,

$\tilde{Z}_{et} = K_{et} Z_{et}$ . By construction,  $\sum_{\tau=-4}^5 \tilde{Z}_{et} = P_{et}$ . Our degrees-of-freedom corrected volatility

measure for firm  $e$  at time  $t$  is

$$\sigma_{et}(\text{Vol}) = \left[ \sum_{\tau=-4}^5 \left( \frac{\tilde{Z}_{e,t+\tau}}{P_{et} - 1} \right) (g_{e,t+\tau} - \bar{g}_{et})^2 \right]^{1/2}, \quad (3)$$

where  $\bar{g}_{et}$  is firm  $e$ 's size-weighted mean growth rate from  $t - 4$  to  $t + 5$ , using the  $Z_{et}$  as weights. We construct this measure for all firms in year  $t$  with  $Z_{et} > 0$ . To obtain the average firm volatility at  $t$ , we calculate the size-weighted cross-sectional mean of (3):

$$\sigma_t(\text{Vol}) = \sum_e \left( \frac{Z_{et}}{Z_t} \right) \sigma_{et}(\text{Vol}). \quad (4)$$

Equations (1), (2), (4) and the job reallocation rate are the four main indicators for the intensity of idiosyncratic shocks considered in the empirical investigation below. We construct these measures at aggregate and industry levels. In some of our analysis, we also distinguish between job destruction for continuers and exits. Sampling error is not a concern for these measures, because the BED and LBD are constructed from comprehensive universe files.

### 3.2 Unemployment Inflows and Escape Rates

We estimate monthly series for the unemployment inflow rate and the unemployment escape rate using Current Population Survey data.<sup>10</sup> Let  $U_{it}^S$  denote the number of persons who report an ongoing unemployment spell of less than five weeks and whose most recent work experience is in industry  $i$ .  $U_{it}^S$  is our estimate for the flow of experienced workers from employment in industry  $i$  to the unemployment pool in month  $t$ .<sup>11</sup> To convert this flow to a rate, we divide by the current month's employment, a departure from the usual practice of dividing by the labor force. We scale by employment because the "labor force" is not well defined at the industry level and because it improves the comparability to our job flow measures.

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<sup>10</sup> The data are publicly available at <http://www.bls.gov/cps/home.htm>. We follow Shimer (2005) in adjusting the job finding rate following the 1994 CPS redesign. Shimer (2005) also makes an adjustment to the separation rate for time aggregation bias. As he notes this adjustment is especially relevant for cyclical volatility. Since the job finding rate exhibits little secular movement, this adjustment will have little impact on our secular inflow measures.

<sup>11</sup> The unemployment inflow rate for experienced workers excludes new entrants to the labor force. The industry- $i$  inflow rate includes persons who flow into the unemployment pool upon re-entry to the labor force, if they previously worked and their most recent job was in industry  $i$ . It would be useful to consider an industry-level unemployment inflow measure that captures only persons who transition directly from employment, but the BLS does not regularly produce such a measure.

To estimate the escape rate at time  $t$  among unemployed workers from industry  $i$ , we calculate  $f_{it} = 1 - (U_{it} - U_{it}^S) / U_{i,t-1}$ , where  $U_{it}$  is the total number of unemployed persons in month  $t$  whose most recent employment experience is in industry  $i$ . This escape rate concept involves no requirement that persons return to employment in industry  $i$  when they exit unemployment, or even that they return to employment.  $f_{it}$  is simply the exit rate from unemployment for persons who last worked in industry  $i$ .

### *3.3 Integrating the Data*

Two main issues arise in integrating the data across the BED, LBD and CPS. First, to deal with changes and differences in industry classification schemes – especially the wholesale changeover from the SIC to the NAICS and the mapping of the SIC and NAICS systems to the CPS system – we aggregate the data to the following broad industry groups: Mining, Construction, Durable Goods Manufacturing, Nondurable Goods Manufacturing, Transportation & Utilities, Retail & Wholesale Trade, FIRE (Finance, Insurance and Real Estate), and Services.<sup>12</sup> Our main analysis is conducted at this level of aggregation.

The second issue involves the within-period timing of employment observations in the BED and the LBD. Employment observations in the BED are for the payroll period covering the 12<sup>th</sup> day of the third month in each calendar quarter. For example, the BED-based job destruction rate for the first quarter of 2000 is calculated from

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<sup>12</sup> Even at this level of aggregation, differences between NAICS and SIC require further data integration work. For the LBD-CPS data integration, we use SIC-based industry classifications because both sources are available on an SIC basis for the 1977-2001 period. For the BED-CPS data integration, we use NAICS-based classifications. The BED data are available on a NAICS basis from 1990 to 2005. The CPS data are available on a NAICS basis from 2000 to 2005 and on an SIC basis through 2002. We use the three-year overlap to splice the CPS data and estimate a NAICS-based series from 1990 to 2005.

establishment-level employment changes from December 1999 to March 2000. We link this job destruction figure to the average value of the monthly unemployment inflow rates in the January, February and March CPS data. Similarly, employment observations in the LBD are for the payroll period covering the 12<sup>th</sup> day of March. Thus, we link the LBD-based job destruction rate for 2000 to the average value of the monthly unemployment inflow rates in the CPS from April 1999 to March 2000.

Tables 1 and 2 report simple means for the BED-CPS integrated data and LBD-CPS integrated data for several measures. Industries with high business volatility also tend to have high unemployment flows. This is an interesting result, but we rely principally on aggregate and within-industry time variation to drive the estimated effects of job destruction and business volatility on unemployment flows.

#### **4. Trends in Volatility, Job Destruction and Unemployment Flows**

##### *4.1. Aggregate Volatility*

The volatility of aggregate U.S. economic activity has diminished in recent decades, as documented by Kim and Nelson (1999), McConnell and Perez-Quiros (2000), Blanchard and Simon (2001), Stock and Watson (2002) and others. Figures 1 and 2 illustrate this development for quarterly and annual data, respectively. The figures show the volatility of growth rates in real GDP and aggregate employment as measured by the moving ten-period standard deviation. For employment, we consider the LBD (a universe) and the BLS payroll survey (a large sample). Figures 1 and 2 show major declines in aggregate volatility, but there are some differences of timing between quarterly and annual data.

#### 4.2. Business Volatility and Dispersion

Several recent studies consider measures of volatility at the level of firms and establishments. Comin and Philippon (2005) and Comin and Mulani (2006) argue that firm-level volatility rose over the past several decades despite the fall in aggregate volatility, and they present evidence of declining volatility among publicly traded firms. Davis, Haltiwanger, Jarmin, and Miranda (2006) show that when privately held firms are included in the analysis, average business volatility actually fell.<sup>13</sup>

Figure 3 shows two measures of firm-level volatility from the DHJM study,  $\sigma_t(\text{Disp})$  and  $\sigma_t(\text{Vol})$ , defined above in equations (2) and (4). The first measure captures movements in the cross-sectional dispersion of employment growth rates, and the second captures movements in the average value of firm-level volatility. As seen in Figure 3, both measures of firm variability drift downward in recent decades, especially since the mid 1980s. Figure 4 shows trend movements in the quarterly job creation and destruction rates, drawing on several data sources. Given our focus on trends, we focus for illustrative purposes on the HP-filtered time series trends. There is a clear pattern of declining job creation and destruction in U.S. manufacturing that dates back to the 1960s. For the U.S. private sector, there is a clear pattern of declining quarterly job creation and destruction rates that from 1990 onwards. On an annual basis, Figure 5 shows the patterns of trend job creation and destruction rates from 1977 to 2001 from the LBD. Consistent with the patterns in Figure 3, the annual rates of job creation and destruction show trend declines over this period especially since the mid 1980s. Note that some

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<sup>13</sup> DHJM also find a convergence in the volatility of publicly traded and privately held firms. Volatility is low and rising among publicly traded firms, high and falling among privately held firms. DHJM show that much of the volatility convergence reflects an influx of volatile new listings among publicly traded firms and a shift towards older (less volatile) businesses in the privately held sector.

caution must be used in comparing the quarterly patterns in Figure 4 with the annual patterns in Figures 3 and 5 given differences in frequency, coverage and sample period. However, the broad picture that emerges is that the secular declines in business volatility, business dispersion and job flow measures all point to a sizable decline in the intensity of idiosyncratic labor demand shocks.

#### *4.3. Unemployment Flows and Escape Rates*

As we have emphasized, our objective is to relate longer term changes in indicators for idiosyncratic shock intensity to frictional unemployment. In light of this objective, Figure 6 shows the evolution of unemployment inflow, outflow and escape rates since 1977. Inflow and outflow rates have very similar patterns; both exhibit a pronounced secular decline, with rates falling from 4 percent of employment per month in the early 1980's to about 2 percent by the mid 1990s and later. It is worth noting that the trend decline for inflow and outflow rates dates to the mid 1980s, which appears to be a critical period for dating the trend declines in aggregate and business volatility discussed above. Escape rates, while strongly cyclical, exhibit little or no secular change.

### **5. The Impact of Business Volatility on Unemployment Flows**

We now examine the relationship of unemployment flows to our empirical indicators for the intensity of idiosyncratic shocks. To begin, we briefly consider how unemployment inflows co-vary with job destruction rates across industries. We then show how unemployment inflows and job destruction evolve over time within industries, highlighting the lower frequency relationship. Next, we fit several regressions designed to estimate the impact of longer term movements in idiosyncratic shock intensity on the

unemployment inflow rate. For reasons explained in Section 2, we rely on within-industry time variation to drive our preferred regression estimates. Lastly, we estimate the effect of idiosyncratic shock intensity on the unemployment escape rate.

### *5.1. Job Destruction and Unemployment Inflows across Industries*

Figures 7 and 8 show the between-industry relationship of unemployment inflows to job destruction in the first and last several years of each sample. The figures deliver a clear message: Regardless of data set and time period, unemployment inflow rates are bigger for industries with higher job destruction rates. For example, Figure 7 says that a between-industry difference of 100 basis points in the average quarterly job destruction rate corresponds to a difference of 20-23 basis points in the average monthly unemployment inflow rate. This result supports the view that industry differences in the intensity of idiosyncratic shocks are a major reason for industry differences in the incidence of unemployment.

### *5.2. Job Destruction and Unemployment Inflows over Time within Industries*

Figures 9 and 10 show the joint evolution of job destruction rates and unemployment inflow rates in each major industry. To highlight the lower frequency movements, we show the HP trend for each series along with the raw data. These figures reveal two noteworthy patterns. First, every industry shows a longer term decline in the unemployment inflow rate, although the timing and magnitude of the decline differs among industries. For example, consider two extremes in Figure 9. The trend component of monthly unemployment inflows fell by nearly one third (150 basis points) from 1990 to 2000 in Construction, whereas it dropped very slightly in FIRE. Second, except for

Nondurable Goods Manufacturing and FIRE in Figure 10, every industry shows that job destruction rates and unemployment inflow rates move together over the longer term.

### *5.3. Estimating the Effect of Job Destruction and Business Volatility*

We now estimate the impact of job destruction and the other indicators for idiosyncratic shock intensity on unemployment inflows. In keeping with our focus on longer term movements, we first compute non-overlapping three-year averages of the industry-level outcomes in each data set. This averaging procedure yields 40 industry-level observations from 1990 to 2005 (5 per industry) and 64 industry-level observations from 1977 to 2001 (8 per industry). Using these data, we then regress unemployment inflows on each of the indicators for idiosyncratic shock intensity. We include industry dummies in all specifications, sweeping out the cross-industry variation highlighted in Figures 7 and 8. Thus, we rely entirely on time variation to estimate the effect of job destruction and business volatility on unemployment inflows. We also include period fixed effects in many specifications to isolate within-industry time variation.

Table 3 reports our main results.<sup>14</sup> The top panel considers BED-CPS data from 1990 to 2005, and the bottom panel considers LBD-CPS data from 1977 to 2001. The chief result in Table 3 – indeed, the main result in the paper – is the large, statistically significant effects of the indicators for idiosyncratic shock intensity on the unemployment inflow rate. This result holds for both data sets and regardless of whether we control for period fixed effects.

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<sup>14</sup> In Tables 3 and 4, we report the R-squared including the contribution of the industry and period fixed effects and the “Within R-squared” which is the R-squared after already absorbing the industry and period fixed effects.

To appreciate the precision and size of the estimated effects, consider column (4) in the top panel as an example. We obtain a  $t$ -statistic of nearly 7, despite a sample of only 40 observations and industry and period fixed effects that absorb 13 degrees of freedom. The estimated slope coefficient in column (4) implies that a longer term drop of 100 basis points in the quarterly job destruction rate lowers the monthly unemployment inflow rate by 28 basis points. Applying this estimate to the actual drop in the private sector job destruction rate of 157 basis points from 1990 to 2005 yields a decline in the unemployment inflow rate of 44 basis points. This implied decline in the inflow rate amounts to just over 48 percent of the observed decline of 90 basis points and to 20 percent of the average inflow rate during the same period.

The LBD-CPS results in the lower panel imply a more modest contribution of long term declines in job destruction to the drop in unemployment inflows but a sizable impact of business volatility and dispersion measures. Repeating the same type of exercise as before, multiplying the estimated effect for the volatility (dispersion) of business growth rates by its observed drop yields an implied decline in unemployment inflows that accounts for 22 (52) percent of the actual decline.

Figure 11 presents the scatter plot corresponding to column (4) in the top panel of Table 3. That is, we first sweep out industry and period fixed effects, then plot the unemployment inflow rate against the job destruction rate. Similarly, Figure 12 presents the scatter plot corresponding to column (6) in the bottom panel of Table 3. Both scatter plots provide strong visual confirmation that industry-specific movements in the job destruction rate drive large industry-specific responses in the unemployment inflow rate.

The results in Table 3 have little power with respect to our hypothesis that job destruction produces greater unemployment inflows when it occurs at exiting plants. In the upper panel, the magnitude of the point estimate for  $JD | Exit$  is larger than that for  $JD | Cont$  but the standard errors are large. In the lower panel, there is also some indication that  $JD | Exit$  has a bigger impact than  $JD | Cont$ , but we cannot reject the null hypothesis of equal coefficients.

As robustness checks, we repeated this analysis using non-overlapping five-year time averages of the industry-level measures. For the BED-CPS analysis, the analogue to column (4) of Table 3(a) yields an estimated coefficient of 0.284 (0.068). For the LBD-CPS analysis, the analogue to column (6) of Table 3(b) yields an estimated coefficient of 0.115 (0.022). These results are nearly identical to those for three-year averages. We also obtained very similar results in regressions that use the trend components of HP-filtered data.

#### *5.4. The Relationship between Unemployment Escape Rates and Firm Volatility*

We now estimate the effects of our indicators for idiosyncratic shock intensity on the unemployment escape rate. As before, we first compute non-overlapping three-year averages of the industry-level outcomes in each data set. We then fit regressions of the unemployment escape rate on the indicators while controlling for certain fixed effects.

Table 4 reports the results. The BED-CPS results in the top panel show no statistically significant effects on the escape rate in the specification with industry effects only. When we also control for period effects, the job destruction and job reallocation rates are negatively related to the escape rate, contrary to the steady-state implication of basic search models. Column (4) of the top panel implies that a decline in the job

destruction rate of 100 basis points raises the escape rate by about 135 basis points. This response is less than 5 percent of the average unemployment escape rate during the 1990 to 2005 sample period. The LBD-CPS data considered in the lower panel show a modest, statistically significant negative response of the escape rate to the job destruction rate, when we control for industry and period fixed effects (column (6)). Some other specifications also show mild evidence of a negative response.

In short, we find little support for the hypothesis that a secular decline in idiosyncratic shock intensity lowers the unemployment escape rate. In fact, we find some evidence against the hypothesis. We obtain similar results when we use the job creation rate as the explanatory variable in the escape rate regressions. What might explain our results for the escape rate? One possibility is that period and industry fixed effects do not adequately control for compositional shifts in the unemployment pool that affect the escape rate and that are correlated with the indicators for idiosyncratic shock intensity. . A more likely explanation, in our view, involves the ambiguous nature of data on unemployment outflows by industry. Recall that the industry-specific escape rates reflect the industry of most recent employment, not the industry to which the unemployed person “escapes.” Perhaps a failure to correctly identify the relevant labor market for unemployed persons accounts for the weak empirical relationship between industry-level measures of idiosyncratic shock intensity and the unemployment escape rate.

## **6. Implications for Frictional Unemployment**

The results in Section 5 show that the trend decline in various measures of business volatility (and in particular job destruction) accounts for a large fraction of the secular decline in the unemployment inflow rate. To appreciate the implications of the

secular decline in unemployment inflows for frictional unemployment, consider a simple representation of unemployment rate dynamics:

$$u_t = l_t + (1 - f_t)u_{t-1}(E_{t-1} / E_t) \quad (5)$$

where  $l_t$ , the inflow rate and  $f_t$ , the escape rate, are defined in the manner consistent with section 3.2,  $E_t$  is employment in period t and  $u_t$  is the number unemployed divided by the number employed in period t.

Shimer (2005) presents evidence that unemployment rate dynamics in a given month are well captured by the implied steady state unemployment rate using the current month inflow and escape rates to measure the steady state. We exploit and confirm this finding as follows. From (5), the steady state unemployment rate consistent with the current month inflow and escape rate is given by:<sup>15</sup>

$$u_t^{SS} = l_t / f_t \quad (6)$$

In Figure 13, we confirm the finding of Shimer (2005) and show that the steady state rate closely mimics the behavior of the actual rate even at high frequencies.

Given this finding, it is useful to use the steady state representation of unemployment rates to consider alternative counterfactual exercises. In particular, we consider the implied steady state using the inflow rate at the beginning of the sample (1976) and the inflow rate at the end of the sample (2005). For these exercises, we use the 5-year average value for the first and last 5 years of the sample.

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<sup>15</sup> This formulation of the steady state differs but is equivalent to from Shimer (2005) in that we are characterizing the steady state unemployment rate where the latter is the number unemployed divided by the the number employed (rather than the labor force). Recall we are using this definition of the unemployment rate given our focus on the experienced unemployed by industry. At the economy-wide level, other than a level shift there is little difference between the steady state and actual unemployment rates defined in these alternative ways.

In Figure 14 we show the steady state under these two counterfactuals. The series labeled “U(SS) First” starts deviating substantially from the actual unemployment rate around 1990 and by 2006 it is about double the actual rate with an implied steady state unemployment rate of around 10 percent. The implication is that steady state unemployment would have been much higher in 2006 had inflow rates stayed at the high trend level back in the late-1970s. This simple exercise thus quantifies the importance of the downward trend in the inflow rate over the last 30+ years for frictional unemployment. Moreover, our findings in this paper suggest that a large fraction of the secular decline in the inflow rates is attributable to the secure declines in business volatility.

In closing this section, we note that the secular decline in unemployment inflows also has important implications for the cyclical behavior of the unemployment rate. To see this, use the SS expression in (6) above to calculate the marginal effect of the job-finding rate on the (SS) unemployment rate:

$$du / df = -l / (f^2) \tag{7}$$

A secular decline in the job-loss rate lowers the magnitude of the marginal effect of the job-finding rate. How big is this effect? Let  $f = .41$  and suppose that  $l$  falls from 0.04 to 0.02 percent, roughly equivalent to what we observe in the data over our sample period. Then, the marginal effect of the job-finding rate falls in magnitude from -0.24 to -0.12. This is an enormous drop, and it helps explain why the last two recessions have involved modest unemployment spikes compared to recessions in the 1970s and 1980s.

This calculation also underscores two related points. First, even if the focus is on cyclical unemployment fluctuations and one takes the view that cyclical movements in

the job-loss rate are unimportant (as in Hall (2005)), then the role of the secular decline in the job-loss rate must still be taken into account. Moreover, our results indicate that in turn the trends in business volatility and job destruction are important for cyclical unemployment volatility since they account for much of that secular decline. Second, the recent attention to quantifying the separate contributions of the job-loss rate and the job-finding rate on fluctuations in the unemployment rate is somewhat problematic. There is an interaction between these two rates in accounting for unemployment movements, and the interaction effect is quantitatively significant.

## **7. Concluding Remarks**

We find compelling evidence that the intensity of idiosyncratic labor demand shocks has a large, positive effect on the incidence of unemployment. This relationship holds at the aggregate level over time in the U.S. economy, across major industry groups at a point in time, and over time within industries. The relationship holds for several different indicators for the intensity of idiosyncratic shocks – the volatility of business-level growth rates, the cross-sectional dispersion in business growth rates, the job reallocation rate and the job destruction rate.

Our preferred estimate for the effect of the idiosyncratic shock intensity exploits industry-level movements in job destruction and unemployment inflow rates. The industry-level data allow us to control for time effects and to rely on lower frequency variation to estimate the relationship. Using this type of variation, we estimate that a decline of 100 basis points in the quarterly job destruction rate lowers the monthly unemployment inflow rate by 28 basis points. Multiplying this estimate by the actual drop in the job destruction rate from 1990 to 2000 implies that the declining intensity of

idiosyncratic shocks reduced the incidence of unemployment by about one-fifth. This reduction amounts to about half of the actual drop in unemployment incidence over the period.

We interpret these results as strongly confirming the importance of a key mechanism in leading search and matching models – namely the link from idiosyncratic shocks to job destruction to unemployment inflows. Our results also suggest that the development of these models could usefully devote greater attention to changes in the intensity of idiosyncratic shocks as a driving force in the evolution of unemployment. With respect to future empirical work, a natural question is whether the strong relationships documented in this paper for the United States hold in other countries as well. Finally, we remark that micro data sources that integrate household and individual data with business data would be extremely valuable for deeper studies into the impact of idiosyncratic shocks and job loss on the incidence of unemployment and its consequences.

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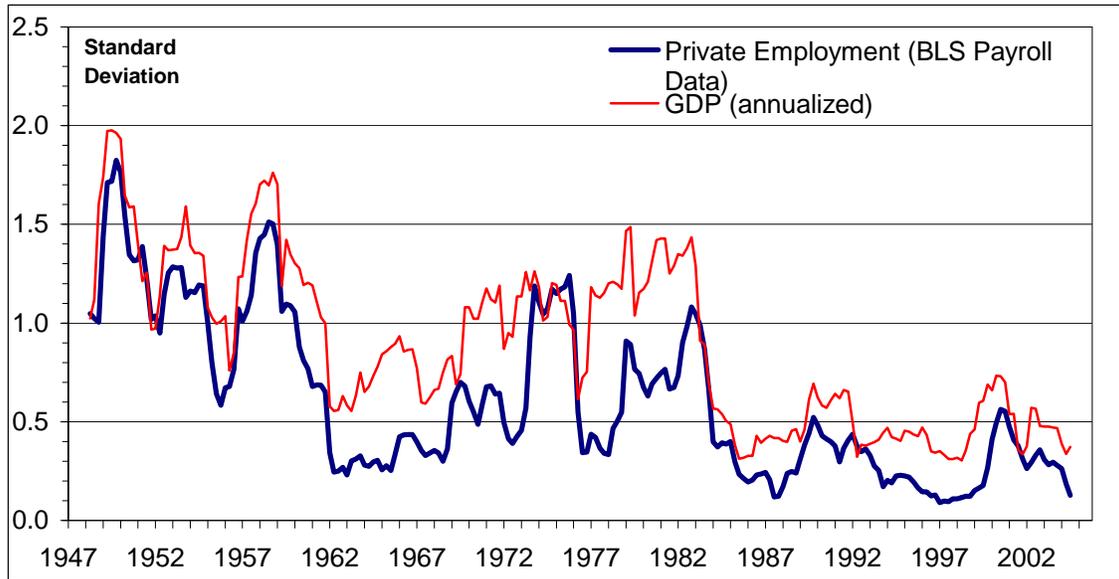
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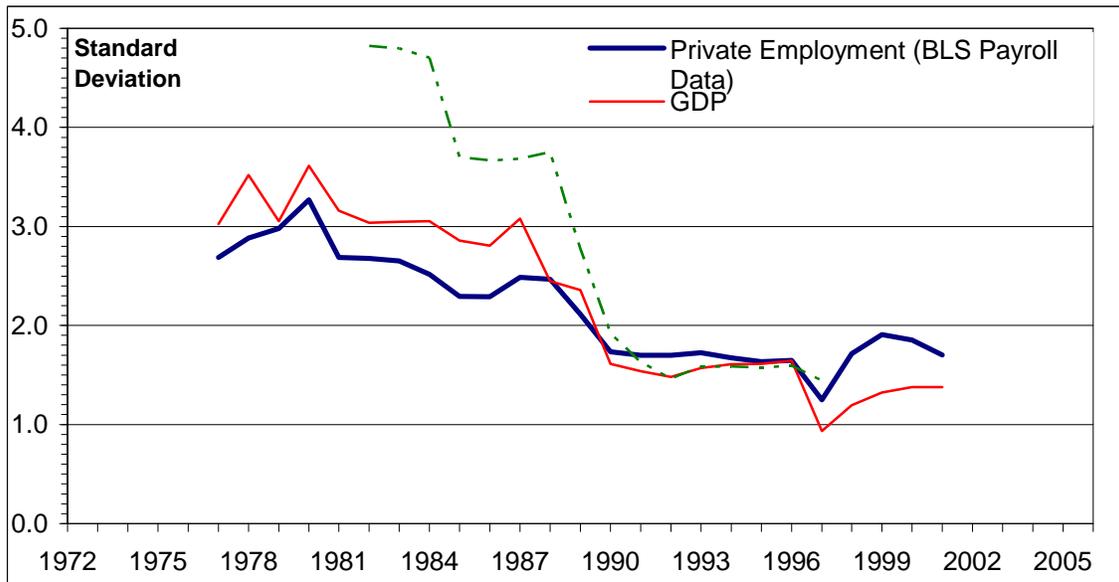
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**Figure 1. Volatility of Quarterly Real GDP and Employment Growth Rates**



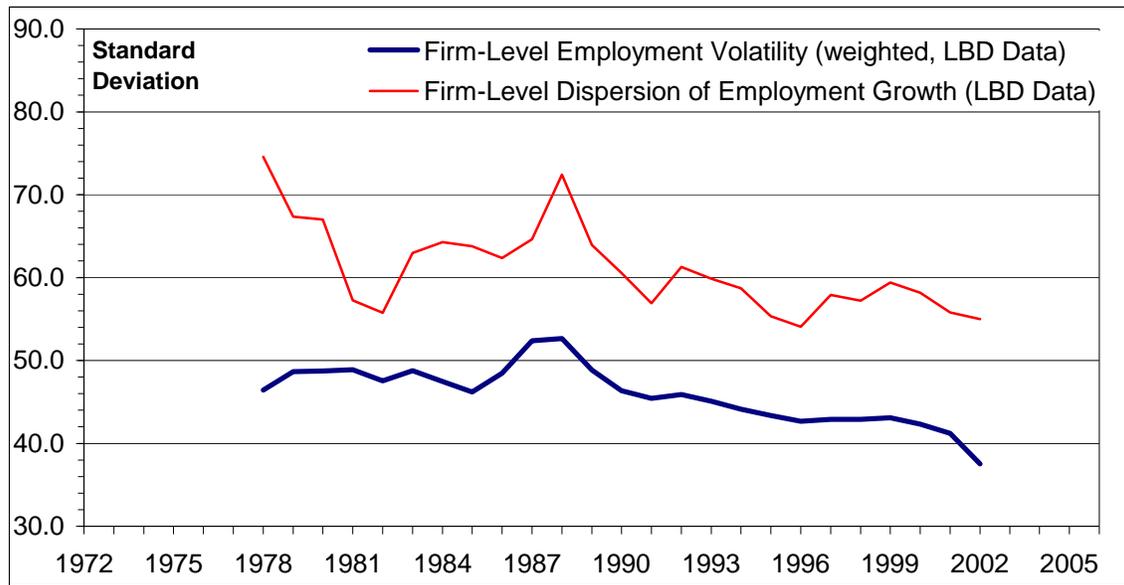
*Notes:* The figure depicts movements in aggregate volatility measured as the standard deviation of the time-series between periods  $t - 4$  and  $t + 5$ . It illustrates the volatility of real GDP and private employment growth measured from the BLS payroll survey. Both are at the quarterly frequency.

**Figure 2. Volatility of Annual Real GDP and Employment Growth Rates**



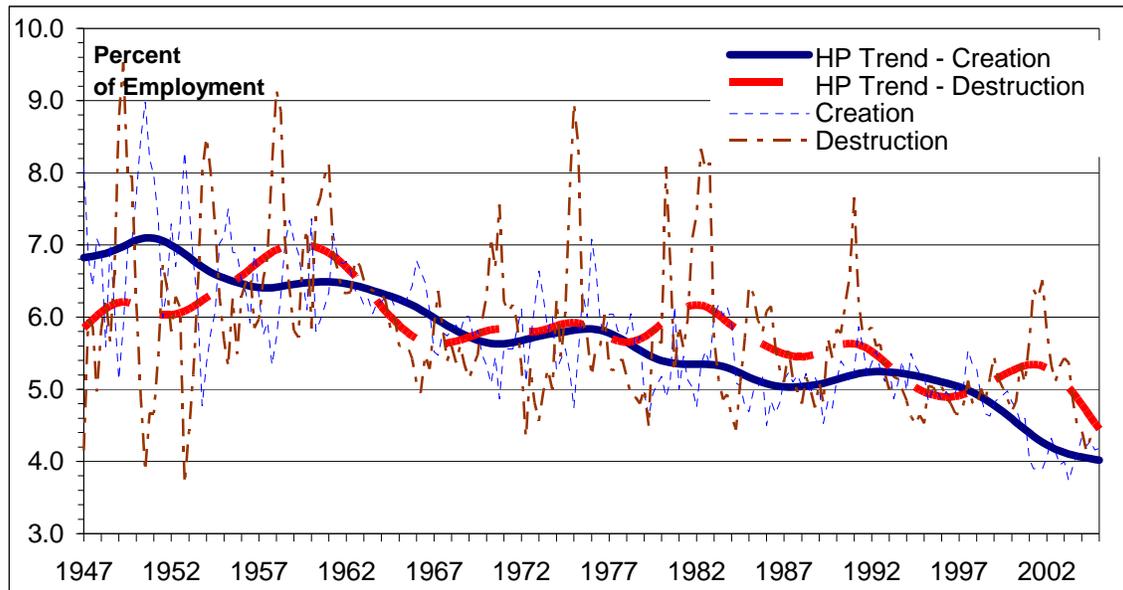
*Notes:* The figure depicts movements in aggregate volatility measured as the standard deviation of the time-series between periods  $t - 4$  and  $t + 5$ . It illustrates the volatility of GDP and private payroll employment growth measured annually. It also includes the volatility of private employment growth measured from the LBD, which unlike the payroll survey, comes from administrative data whose most notable difference is its complete accounting for establishment entry and exit.

**Figure 3. Dispersion and Volatility in Firm-Level Employment Growth Rates**

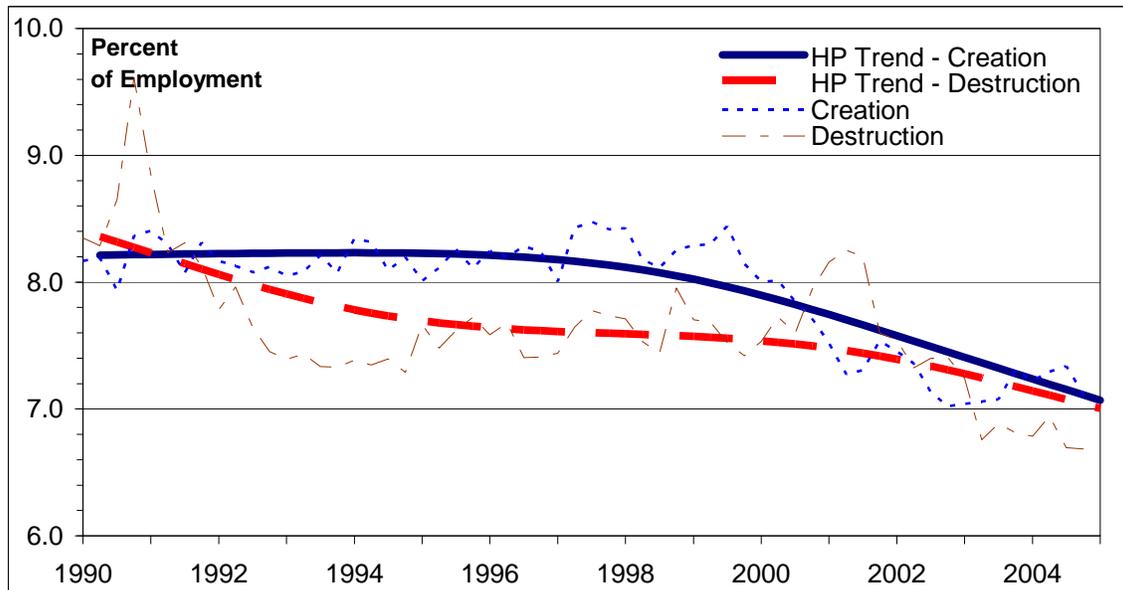


*Notes:* Dispersion and volatility measures from Davis, Haltiwanger, Jarmin, and Miranda (2006). The measures are constructed per equations (2) and (4) in the text using firm-level data in the LBD.

**Figure 4. Movements in Quarterly Job Flows Trends**  
*(a) U.S. Manufacturing, 1947-2005*

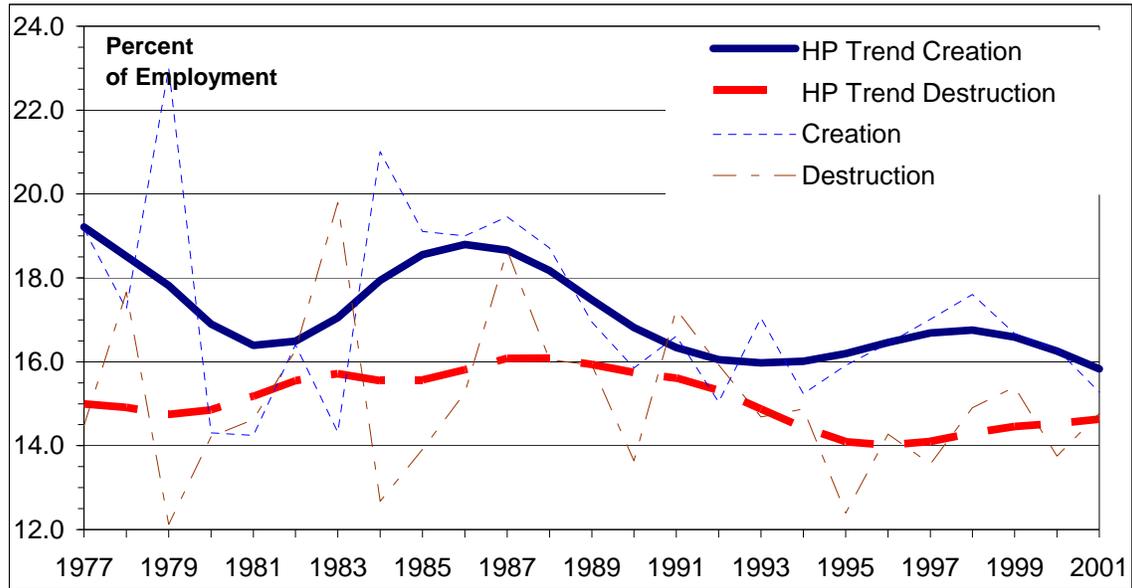


*(b) Nonfarm Private, 1990-2005*



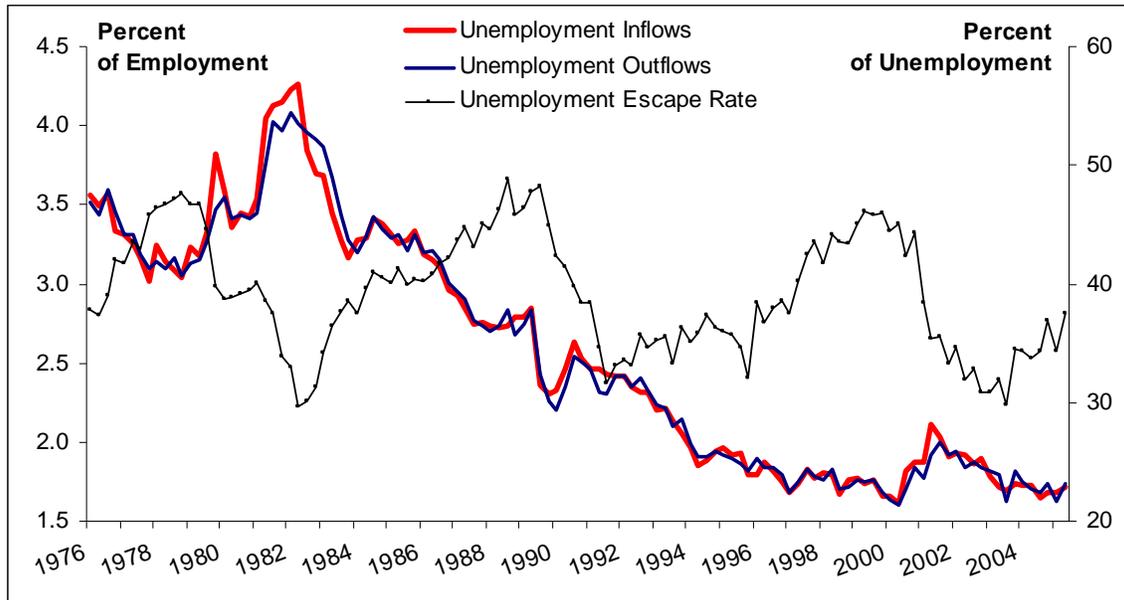
*Notes:* The figures depict the time-series trends in job creation and destruction rates (measured as a percent of employment). The upper panel illustrates quarterly job flow rates from a spliced series of manufacturing data from multiple sources. The lower panel uses series from the BED. The series for both panels come from Faberman (2006) and Davis, Faberman, and Haltiwanger (2006). The HP-filtered trends depicted use a smoothing parameter of  $\lambda = 1600$ .

**Figure 5. Movements in Annual Job Flow Trends, U.S. Nonfarm Business, 1977-2001**



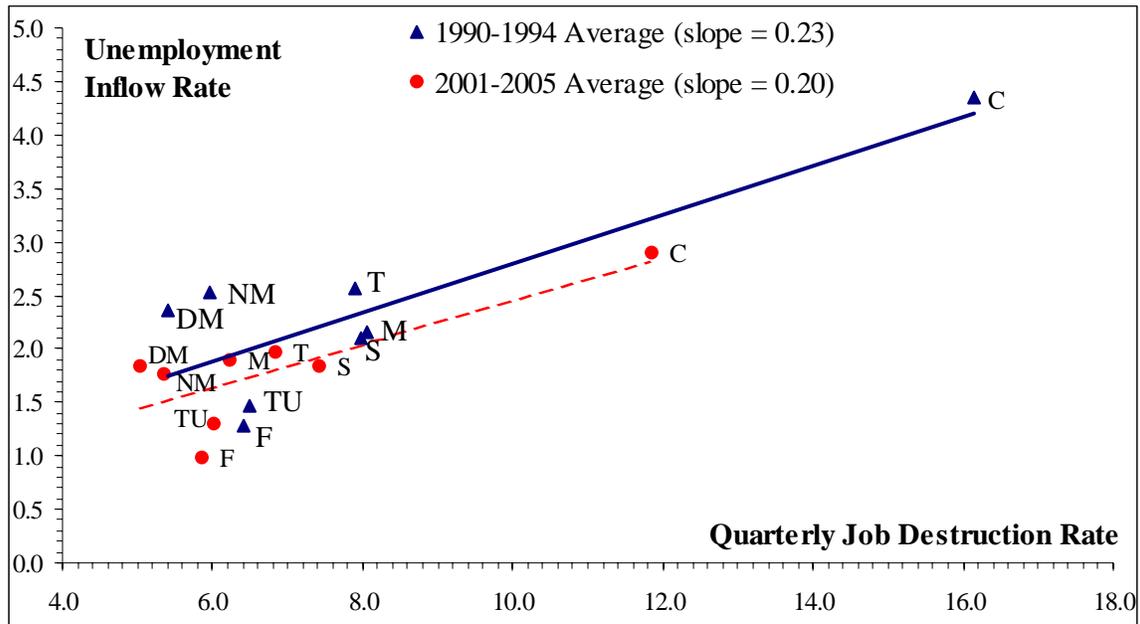
*Notes:* The figure depicts time-series trends of job creation and destruction rates (measured as a percent of employment) using data from the LBD. The HP-filtered annual trends use a smoothing parameter of  $\lambda = 6.25$ .

**Figure 6. Quarterly Unemployment Inflow, Outflow and Escape Rates**



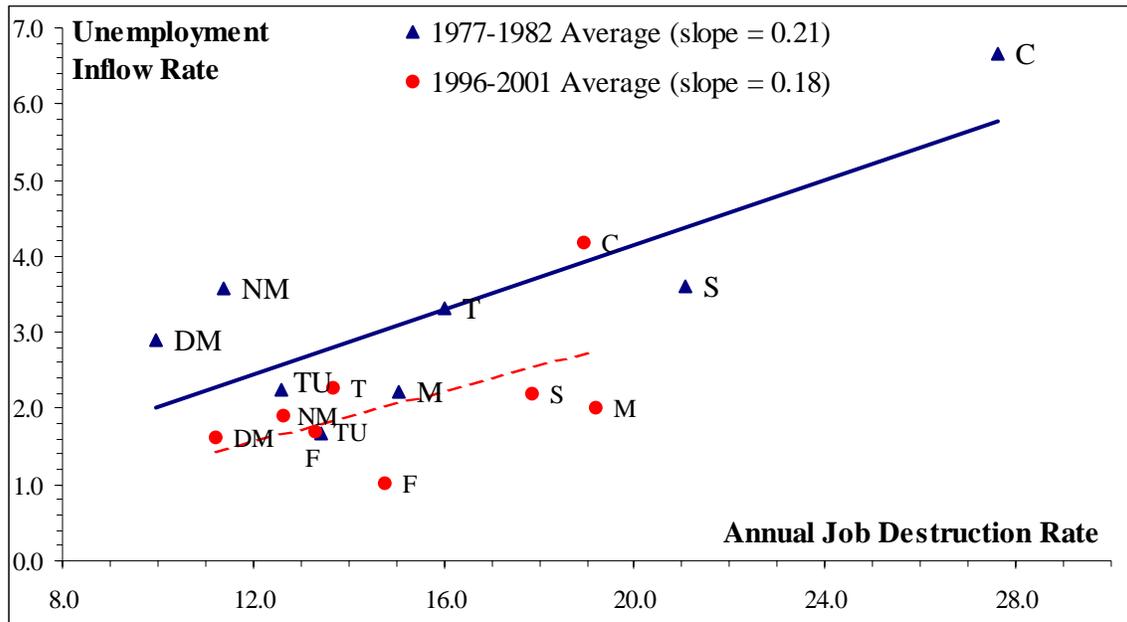
*Notes:* The figure depicts the movements of unemployment inflows and outflows (left axis), and the escape rate out of unemployment (right axis). Estimates are seasonally adjusted and quarterly means of monthly values.

**Figure 7. Job Destruction and Unemployment Inflows by Major Industry Group, Averages of Quarterly Data**



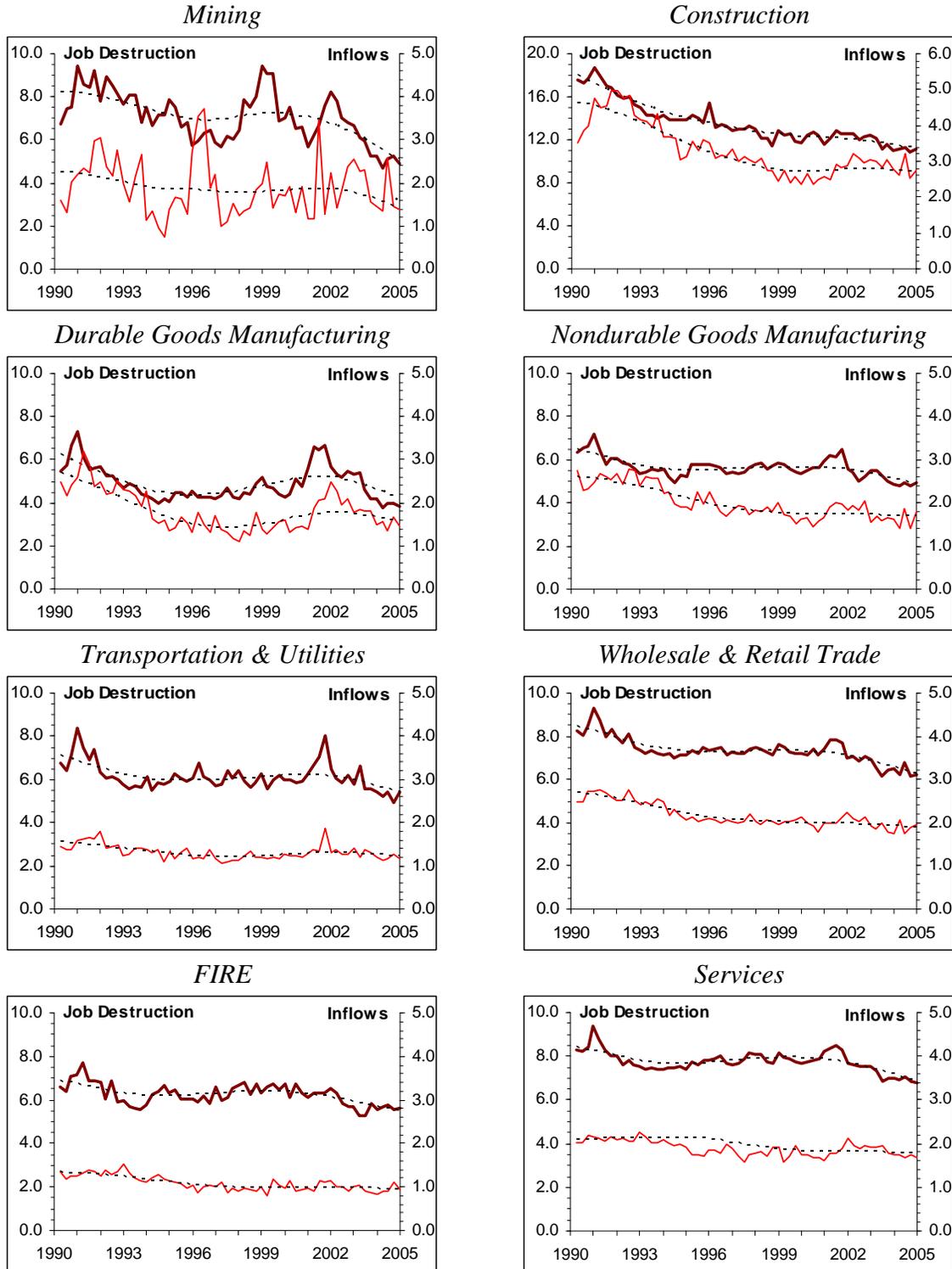
*Note:* Data points are authors' estimates of unemployment inflow rates from the CPS and quarterly job destruction rates from the BED averaged over 1990Q2 – 1994Q1 (triangles), and 2001Q2 – 2005Q1 (circles) and plotted for 8 major industry groups: Mining (M), Construction (C), Durable Manufacturing (DM), Nondurable Manufacturing (NM), Transportation & Utilities (TU), Trade (T), FIRE (F), and Services (S). The solid line is the fitted OLS relation of 1990-94 observations, while the dashed line is the fitted OLS relation of the 2001-05 observations. Slope coefficients are noted in the legend.

**Figure 8. Job Destruction and Unemployment Inflows by Major Industry Group, Averages of Annual Data**



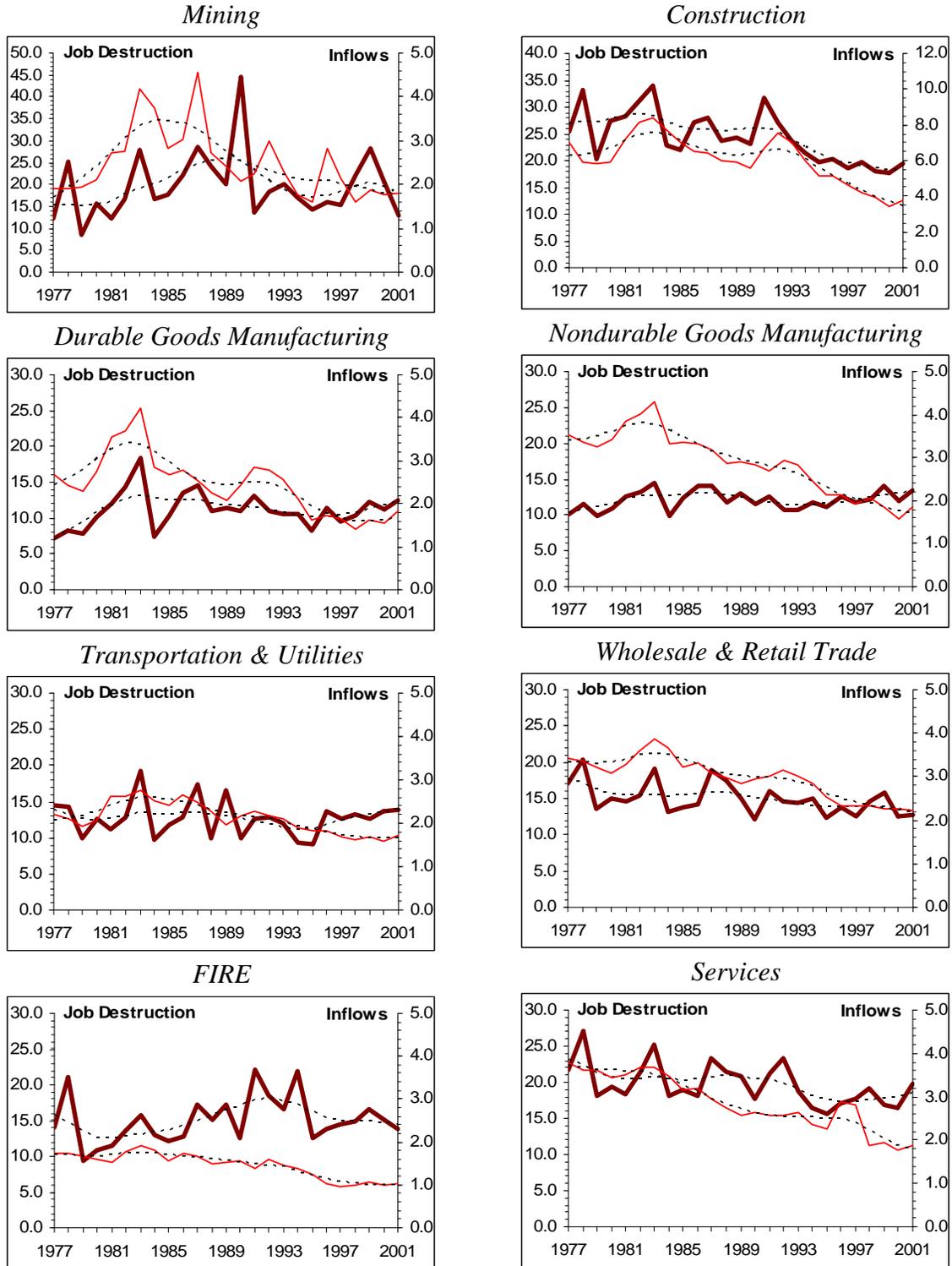
*Note:* Data points are authors' estimates of unemployment inflow rates from the CPS and annual job destruction rates from the LBD averaged over 1977 – 1982 (triangles), and 1996 – 2001 (circles) and plotted for 8 major industry groups (see Figure 9 for notation). The solid line is the fitted OLS relation of 1977-82 observations, while the dashed line is the fitted OLS relation of the 1996-2001 observations. Slope coefficients are noted in the legend.

**Figure 9. Job Destruction and Unemployment Inflows, Quarterly Estimates by Major Industry**



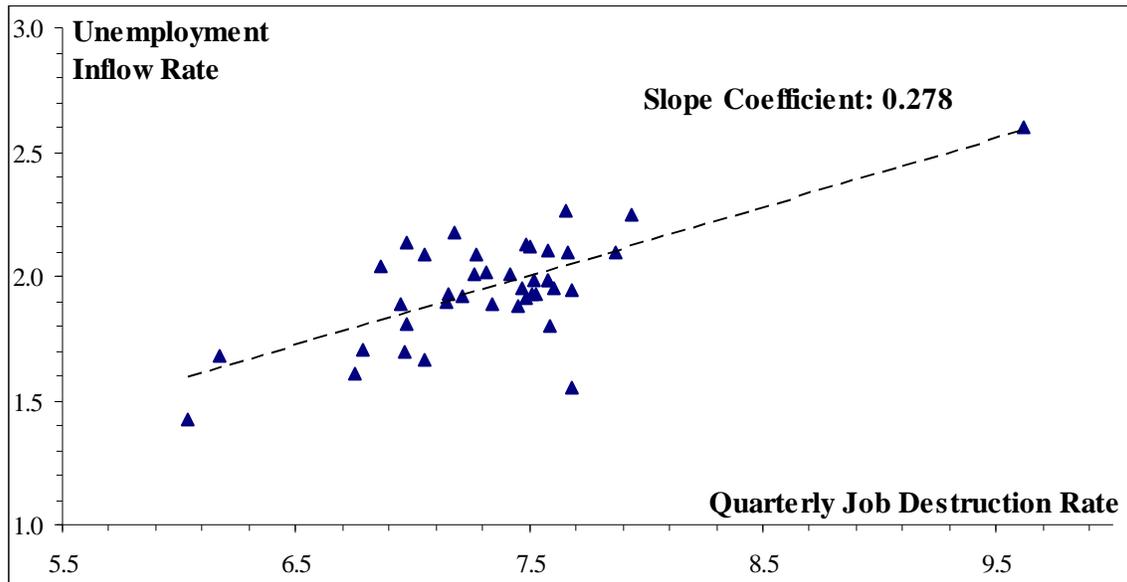
*Notes:* The figures depict the time-series movements of job destruction and unemployment inflow rates (each measured as a percent of employment) for the noted major industries. Job destruction rates come from the BED (private sector) and unemployment inflows come from the CPS. HP-filtered trends are also depicted with a smoothing parameter of  $\lambda = 1600$ .

**Figure 10. Job Destruction and Unemployment Inflows, Annual Estimates by Major Industry**



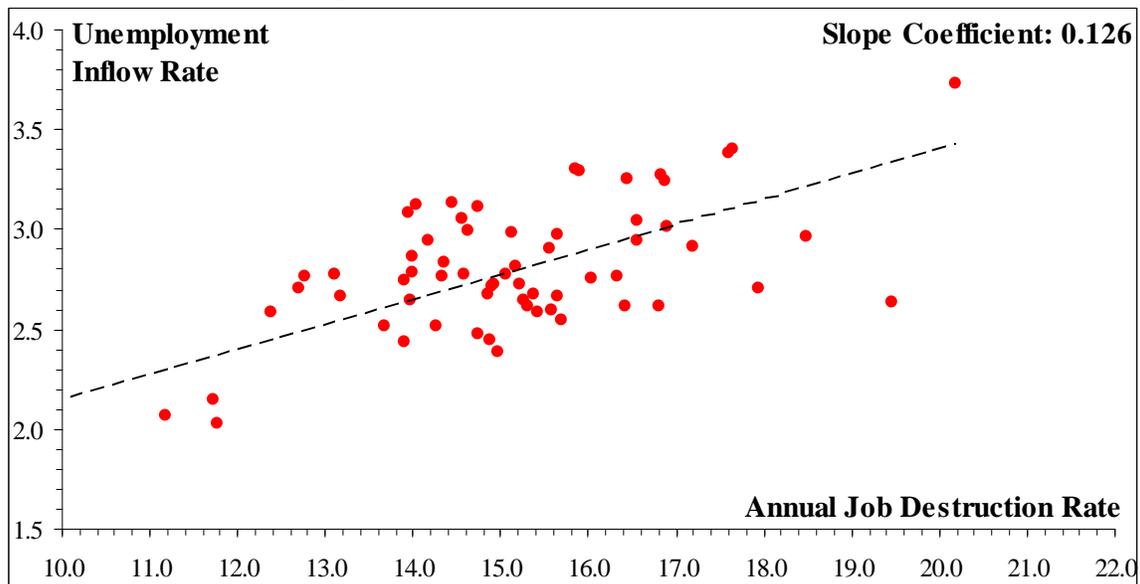
*Notes:* The figures depict the time-series movements of job destruction and unemployment inflow rates (each measured as a percent of employment) for the noted major industries. Job destruction rates come from the LBD (private sector) and unemployment inflows come from the CPS. HP-filtered trends are also depicted with a smoothing parameter of  $\lambda = 6.25$ .

**Figure 11. Job Destruction and Unemployment Inflows by Major Industry Group, Quarterly Data, Controlling for Period and Industry Fixed Effects**



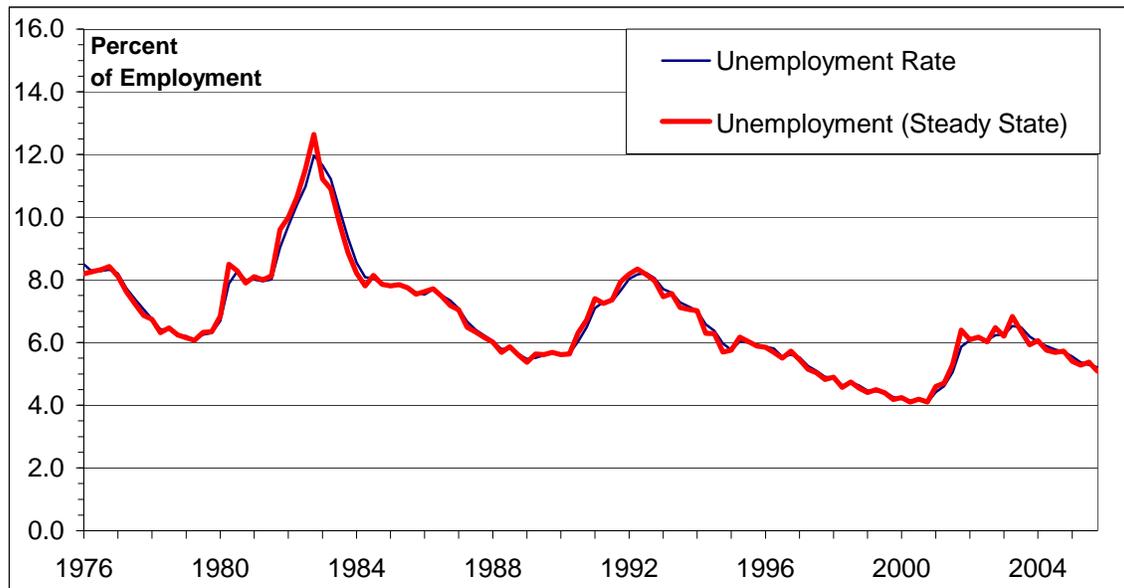
*Note:* Data points are residuals of 3-year mean unemployment inflow rates and 3-year BED job destruction rates from the regression of these rates on period and industry fixed effects (corresponding to Table 3(a), column (4)). The overall mean has been added back into the residuals. The dashed line is the fitted OLS trend, with the slope coefficient noted above.

**Figure 12. Job Destruction and Unemployment Inflows by Major Industry Group, Annual Data, Controlling for Period and Industry Effects**



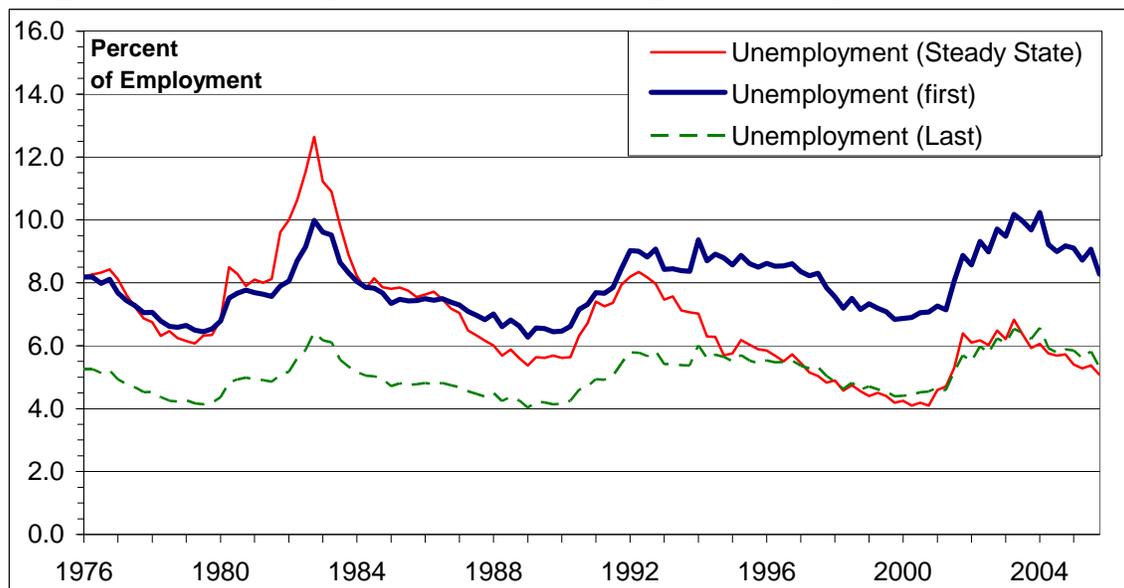
*Note:* Data points are residuals of 3-year mean unemployment inflow rates and 3-year BED job destruction rates from the regression of these rates on period and industry fixed effects (corresponding to Table 3(b), column (6)). The overall mean has been added back into the residuals. The dashed line is the fitted OLS trend, with the slope coefficient noted above.

**Figure 13. A Comparison of the Actual Unemployment Rate and the Steady State Unemployment Rate Using Current Period Inflow and Escape Rates (Averages of monthly values)**



Note: Unemployment rate defined as ratio of unemployment to employment. The steady state unemployment rate in the month (averaged over quarters) is given by equation (6) using current period inflow and escape rates.

**Figure 14. Counterfactual Steady State Unemployment Rates Using Beginning of Sample and End of Sample Inflow Rates (Averages of monthly values)**



Note: The steady state unemployment rate in the month (averaged over quarters) uses equation (6) using current period inflow and escape rates. U (SS) First (Last) uses equation (6) but setting the inflow rate to its 5-year average value for the first (last) 5 years of the sample.

**Table 1. Sample Means of BED and CPS Measures, 1990 to 2005**

	<i>Quarterly Rates (BED)</i>			<i>Monthly Rates (CPS)</i>		
	<b>Job Destruction</b>	<b>Job Destruction, Continuers</b>	<b>Job Destruction, Exits</b>	<b>Job Reallocation</b>	<b>Unemployment Inflows</b>	<b>Unemployment Escape</b>
Mining	7.1	5.5	1.6	13.8	1.9	36.6
Construction	13.5	10.6	2.9	27.4	3.3	39.2
Manufacturing, Nondurable Goods	5.6	4.6	1.0	10.8	2.0	33.5
Manufacturing, Durable Goods	4.9	4.1	0.8	9.4	1.8	33.4
Transportation & Utilities	6.1	4.9	1.3	12.5	1.3	35.1
Retail & Wholesale Trade	7.3	5.9	1.4	14.8	2.2	38.2
FIRE	6.2	4.5	1.7	12.7	1.1	33.3
Services	7.7	6.0	1.7	16.1	1.9	38.9
All, Private Employment	7.6	6.0	1.6	15.6	2.2	38.1

*Notes:* Broad sectors for integrated BED and CPS data are defined on a NAICS basis. All BED statistics are based on establishment-level employment changes from third month of quarter in prior quarter to third month in current quarter. CPS unemployment flows are integrated with BED by taking annual averages of monthly flows for corresponding time intervals. The resulting quarterly integrated series are seasonally adjusted. Job flows and unemployment flows are expressed as percentages. Reported statistics for all series here are simple averages of these measures.

**Table 2. Sample Means of LBD and CPS Measures, 1977 to 2001**

	<i>Annual Rates (LBD)</i>				<i>Monthly Rates (CPS)</i>			
	<b>Job Destruction</b>	<b>Job Dest., Continuers</b>	<b>Job Dest., Exits</b>	<b>Job Reallocation</b>	<b>Firm Volatility</b>	<b>Firm Dispersion</b>	<b>Unemployment Inflows</b>	<b>Unemployment Escape</b>
Mining	19.6	13.4	6.2	36.2	51.4	64.1	2.5	37.0
Construction	24.3	15.1	9.2	51.6	68.8	78.2	6.0	40.6
Manufacturing, Nondurable Goods	12.1	7.7	4.4	24.2	34.1	48.9	2.9	39.3
Manufacturing, Durable Goods	11.1	7.6	3.6	22.7	33.0	46.7	2.4	35.6
Transportation & Utilities	12.7	7.6	5.2	27.8	40.5	55.9	2.1	37.3
Retail & Wholesale Trade	15.0	8.6	6.3	32.2	46.4	61.9	3.0	44.7
FIRE	15.1	8.2	6.9	32.0	46.8	61.9	1.5	38.8
Services	19.7	11.0	8.7	44.3	51.3	66.4	2.9	43.5
All, Private Employment	15.1	8.8	6.3	32.2	45.9	61.1	2.8	41.1

*Notes:* Broad sectors in integrated LBD and CPS data are defined on an SIC basis. All LBD statistics are based on firm level employment changes from March 12 to March 12. CPS unemployment flows are integrated with LBD by taking annual averages of monthly flows for corresponding time intervals. Job flows and unemployment flows are expressed as percentages. Measures of firm volatility and firm dispersion are as described in text. Reported statistics for all series here are simple averages of these measures.

**Table 3. Unemployment Inflows and Firm Volatility**  
**Dependent Variable: Unemployment Inflows (Average of Monthly Rates)**

(a) *BED and CPS Three-Year Averages*

Independent Variables	(1)	(2)	(3)	(4)	(5)	(6)
$JD_{it}$	0.323 (0.047)			0.278 (0.053)		
$JD_{it}/Cont$		0.269 (0.150)			0.264 (0.132)	
$JD_{it}/Exit$		0.483 (0.424)			0.327 (0.424)	
$JR_{it}$			0.187 (0.028)			0.174 (0.031)
Sector Effects?	Yes	Yes	Yes	Yes	Yes	Yes
Period Effects?	No	No	No	Yes	Yes	Yes
R-Squared	0.915	0.916	0.912	0.956	0.956	0.959
Within R-Squared	0.608	0.609	0.589	0.500	0.500	0.540

(b) *LBD and CPS Three-Year Averages*

Independent Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$JD_{it}$	0.163 (0.033)					0.126 (0.022)				
$JD_{it}/Cont$		0.141 (0.039)					0.118 (0.025)			
$JD_{it}/Exit$		0.211 (0.059)					0.148 (0.043)			
$JR_{it}$			0.108 (0.023)					0.063 (0.016)		
$\sigma_{it}(Vol)$				0.093 (0.016)					0.034 (0.015)	
$\sigma_{it}(Disp)$					0.070 (0.016)					0.036 (0.013)
Sector Effects?	Yes									
Period Effects?	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
R-Squared	0.851	0.854	0.846	0.868	0.838	0.964	0.964	0.953	0.944	0.947
Within R-squared	0.309	0.321	0.288	0.388	0.252	0.413	0.418	0.236	0.101	0.138

*Note:* the tables report the regression coefficients and standard errors (in parentheses) of the unemployment inflow rate on the noted business volatility measures. All regressions use a panel of 3-year mean values across 8 major industries. The BED-CPS data (top panel) use  $N = 40$  observations, with 8 major industry and 5 period fixed effects. The LBD-CPS data (bottom panel) use  $N = 64$  observations, with 8 major industry and 8 period fixed effects.

**Table 4: Escape Rates and Firm Volatility**  
**Dependent Variable: Unemployment Escape Rate (Average of Monthly Values)**  
*(a) BED and CPS Three-Year Averages*

Independent Variables	(1)	(2)	(3)	(4)	(5)	(6)
$JD_{it}$	0.498 (0.896)			-1.355 (0.385)		
$JD_{it}/Cont$		-1.835 (2.861)			-1.133 (0.947)	
$JD_{it}/Exit$		7.392 (8.074)			-2.132 (3.052)	
$JR_{it}$			0.340 (0.525)			-0.753 (0.240)
Sector Effects?	Yes	Yes	Yes	Yes	Yes	Yes
Period Effects?	No	No	No	Yes	Yes	Yes
R-Squared	0.281	0.298	0.283	0.946	0.947	0.943
Within R-Squared	0.010	0.034	0.013	0.314	0.315	0.267

*(b) LBD and CPS Three-Year Averages*

Independent Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$JD_{it}$	-0.344 (0.257)					-0.507 (0.170)				
$JD_{it}/Cont$		-0.732 (0.297)					-0.619 (0.196)			
$JD_{it}/Exit$		0.533 (0.448)					-0.174 (0.337)			
$JR_{it}$			-0.101 (0.179)					-0.140 (0.121)		
$\sigma_{it}(Vol)$				-0.283 (0.128)					-0.039 (0.101)	
$\sigma_{it}(Disp)$					-0.035 (0.125)					-0.058 (0.090)
Sector Effects?	Yes									
Period Effects?	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
R-Squared	0.339	0.400	0.321	0.373	0.318	0.839	0.843	0.814	0.809	0.811
Within R-squared	0.032	0.121	0.006	0.082	0.001	0.157	0.180	0.027	0.003	0.009

*Note:* the tables report the regression coefficients and standard errors (in parentheses) of the unemployment escape rate on the noted business volatility measures. All regressions use a panel of 3-year mean values across 8 major industries. The BED-CPS data (top panel) use  $N = 40$  observations, with 8 major industry and 5 period fixed effects. The LBD-CPS data (bottom panel) use  $N = 64$  observations, with 8 major industry and 8 period fixed effects.