# Business Volatility, Job Destruction, and Unemployment[†]

*By* Steven J. Davis, R. Jason Faberman, John Haltiwanger, Ron Jarmin, and Javier Miranda*

*Unemployment inflows fell from 4 percent of employment per month in the early 1980s to 2 percent by the mid 1990s. Using low frequency movements in industry-level data, we estimate that a 1 percentage point drop in the quarterly job destruction rate lowers the monthly unemployment inflow rate by 0.28 points. By our estimates, declines in job destruction intensity account for 28 (55) percent of the fall in unemployment inflows from 1982 (1990) to 2005. Slower job destruction accounts for similar fractions of long-term declines in the rate of unemployment.* (*JEL* E24, E32, J64)

Trends in the volatility of economic activity attract considerable attention. Many recent studies examine the "great moderation" episode in aggregate US fluctuations.[1] Another recent line of research finds a secular decline in the variability of business-level changes. In this regard, Faberman (2008) documents a decline in the rate at which jobs are reallocated across establishments. Davis, Haltiwanger, Ron S. Jarmin, and Miranda (2007; hereafter DHJM) document a decline in the cross-sectional dispersion of business growth rates and in the time-series volatility

of business growth rates.[2] The secular decline in business-level variability measures roughly coincides with a marked decline in the magnitude of unemployment flows. 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 quantify the empirical relationship between the decline in business variability and job destruction and the decline in unemployment flows. To do so, we relate industry-level movements in the incidence and duration of unemployment to industry-level movements in several indicators of variability and job destruction. Unlike previous research on unemployment flows, we focus on low frequency outcomes and relationships. We motivate and interpret our study in terms of steady-state relationships that link job destruction and business variability to unemployment flows.

To carry out our empirical investigation, we integrate industry-level data from three sources. We construct annual measures of job destruction, job reallocation, business volatility, and cross-sectional dispersion in establishment growth rates from 1977 to 2005 using the Longitudinal Business Database (LBD), and quarterly measures from 1990 to 2005 using the 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 strong evidence that changes in business volatility, dispersion, job reallocation, and job destruction account for big changes in the incidence of unemployment. This key result holds in the annual and the 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 4 basis points. This estimate reflects a specification that includes industry and time fixed effects. Ignoring time aggregation, the estimate indicates that the response of unemployment inflows over a quarter is 84 percent (three months times 28 basis points per month) as large as the movement in the number of jobs destroyed.

To put the estimate in perspective, the quarterly job destruction rate for the US private sector fell by 174 basis points from 1990 to 2005. Multiplying this drop by its estimated effect yields a decline of 48 basis points in the unemployment inflow rate, which amounts to 55 percent of the drop in the unemployment inflow rate from 1990 to 2005, and 22 percent of its average value. Analogous calculations based on our estimates with annual data imply that falling job destruction rates account for 28 percent of the larger drop in unemployment inflow rates from 1982 to 2005.

Canonical models of frictional unemployment posit a tight relationship between job destruction and unemployment inflows. The seminal model of Dale T. Mortensen and Christopher A. Pissarides (1994) assumes a one-for-one response of unemployment

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[2] In contrast, Diego Comin and Sunil Mulani (2006), and Comin and Thomas Philippon (2006) find rising volatility among publicly traded firms in recent decades. 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.

inflows to job destruction, and many calibrations of MP-type models rely on a tight relationship between these two objects. One of our contributions is to investigate the relationship empirically using low frequency variation in industry-level data.

An interesting question raised by our results is what drives the secular declines in business variability, job destruction and unemployment inflows. Our study does not provide a definitive answer to this question, but we show that the basic pattern holds across major industries in the US economy. We interpret this pattern as reflecting a secular decline in the intensity of idiosyncratic labor demand shocks. Given such a decline, the MP model predicts the patterns we find in the data. Other interpretations of the same basic patterns are also possible, as we briefly discuss.

We also develop some implications of our findings for the unemployment rate and its cyclical behavior. Simple approximations and decompositions along the lines of those used by Robert Shimer (2007); Michael W. L. Elsby, Ryan Michaels, and Gary Solon (2009); and Shigeru Fujita and Garey Ramey (2009) establish three results. First, the steady-state unemployment rate fell by 43 log points from the period 1976–1985 to the period 1996–2005. Second, nearly the entirety of this decline reflects a drop in the unemployment inflow rate. This result, when combined with our estimates, implies that the secular fall in job destruction accounts for about a quarter to one-half of the long-term decline in the unemployment rate. Third, while we focus on low frequency behavior, our findings also have implications for cyclical dynamics. In particular, the big secular decline in unemployment inflows implies a fall by half in the sensitivity of the unemployment rate to cyclical movements in the job-finding rate. More generally, our results highlight the dependence of short-run unemployment dynamics on the background level of business volatility and job destruction.

The next section provides theoretical motivation for our study and presents some initial evidence based on cross-sectional relationships in establishment-level data. Section II describes the industry-level data and our measurement procedures. Section III presents evidence regarding movements in job flows, business volatility and dispersion, and unemployment inflows in recent decades. Section IV carries out our main empirical analysis on the industry-level data. Section V discusses the implications of our findings for unemployment and its cyclical behavior. Section VI concludes.

## I. Theoretical Motivation and Some Cross-Sectional Evidence

To help fix ideas, consider the seminal model of Mortensen and Pissarides (1994). When an employer wants to fill a job opening in this model, the employer 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.[3]

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[3] See Shimer (2007); Elsby, Michaels, and Solon (2009); and Fujita and Ramey (2009) for evidence on the behavior of the job-finding rate and Davis, Faberman, and Haltiwanger (2009) for evidence on the job-filling rate.

When employer and job seeker meet, they split the match surplus and commence production. After match formation, employment relationships are subject to aggregate and idiosyncratic shocks that can result in endogenous job destruction. These shocks drive the pace of job destruction and the incidence of unemployment.

Mortensen and Pissarides (1994) show that an increase in the variance of idiosyncratic shocks raises the job destruction rate and the incidence of unemployment in steady-state equilibrium. 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 explore these implications in the empirical work below.[4] The Appendix provides a more precise statement of the MP model and these implications.

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 Milton Friedman's (1968) concept of the natural rate of unemployment. Edmund S. Phelps (1968) provides the first formal model of frictional unemployment, and many, many others follow. Robert E. 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 more recent work, Russell Cooper, Haltiwanger, and Jonathan L. Willis (2007) estimate an MP-style model with multiple jobs per employer. Using their estimated model, they show that the variance of idiosyncratic shocks has powerful effects on the overall incidence of unemployment and the unemployment response to aggregate shocks. Thus, we see our empirical study as investigating a core idea that inhabits many models of frictional unemployment.

The basic MP model postulates an iron link from job destruction to worker separations and from separations to unemployment inflows. These two iron links imply that job destruction and unemployment inflows move in lockstep. Richer models can include features that weaken one or both links, and the strength of these links in practice is an empirical question. In Section IV, we use industry-level time-series data to estimate how closely job destruction (and related measures) moves with unemployment inflows. Here, we report cross-sectional evidence that throws some light on each of the two links, and that provides some additional motivation for our time-series study.

Micro data from the JOLTS confirm that the link between job destruction and worker separations is indeed very tight in the cross section of employers. Drawing on JOLTS data, Figure 1 shows that separations rise approximately one-for-one with job destruction at the establishment level. Hires rise approximately one-for-one with job creation. Figure 1 also helps understand why a decline in the intensity of idiosyncratic shocks leads to lower job destruction and fewer separations. Smaller shocks generate a less dispersed growth rate distribution, which in turn yields smaller job

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[4] We do not explore implications for vacancy rates, because the available US data are not suitable for drawing inferences about vacancy 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 (JOLTS) are, as yet, too short to draw inferences about trends.
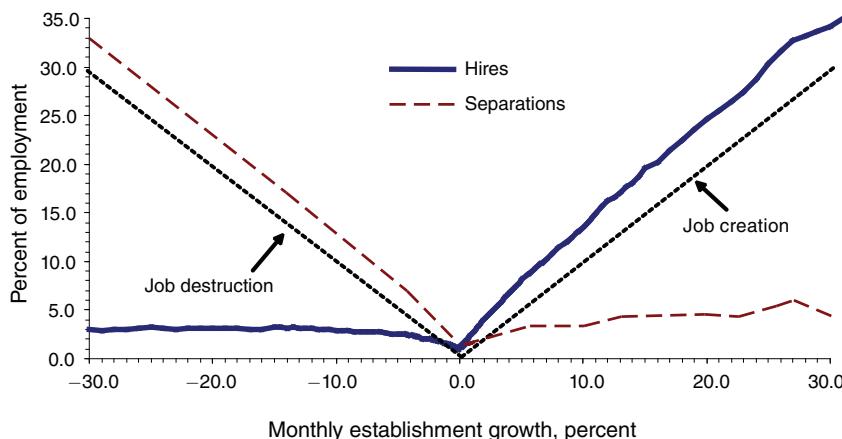
FIGURE 1. THE RELATIONSHIP OF HIRES AND SEPARATIONS TO ESTABLISHMENT GROWTH

*Source:* JOLTS micro data from 2001 to 2006

flows (job creation and destruction) and smaller worker flows (hires and separations). Of course, any factor that reduces the dispersion in establishment-level growth rates leads to smaller job and worker flows. For example, if compensation becomes more flexible, then employers can more readily respond to lower demand with wage cuts instead of job destruction and layoffs.

Figure 2 shows how job destruction and layoffs are linked in the cross section. Drawing again on JOLTS micro data, the figure shows that layoffs are the main margin of adjustment at high rates of job destruction. Quits are the more important margin of adjustment for establishments undergoing moderate contractions. Other studies find, not surprisingly, that layoffs are much more likely than quits to result in unemployment spells.[5] The lower unemployment propensity for quits coupled with the evidence in Figure 2 suggests that the real-world link between separations and unemployment inflows is weaker than the iron link in the basic MP model. This slippage between model and data is one reason why unemployment inflows might not move in lockstep with job destruction.

Figure 2 also motivates an additional hypothesis considered below. The figure shows that the layoff-quit ratio rises strongly in the rate at which employers contract. Given that layoffs are relatively likely to result in an unemployment spell, Figure 2 yields the following hypothesis. A given amount of job destruction produces greater unemployment inflows when the lost jobs are concentrated at businesses that contract more sharply. We consider a simple form of this hypothesis by testing whether job destruction has a bigger impact on the incidence of unemployment when the lost jobs reflect business closures, as opposed to those that merely shrink.

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[5] See Linda Leighton and Jacob Mincer (1982) and Kenneth J. McLaughlin (1990) as well as the discussion in Davis, Faberman, and Haltiwanger (2006).
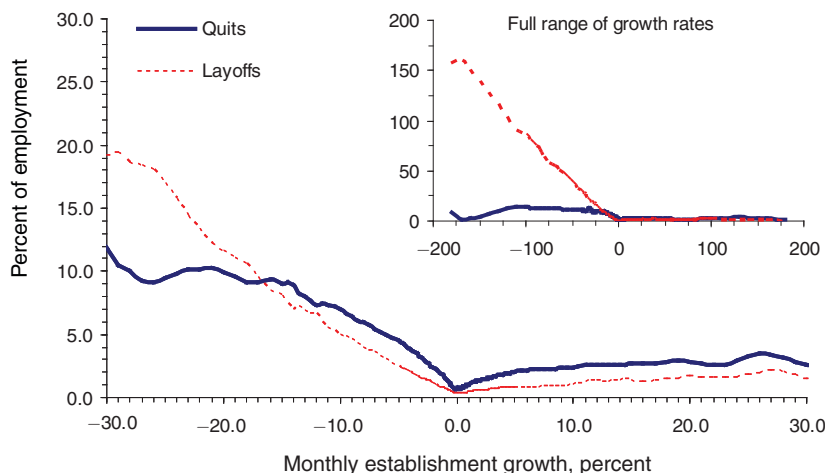
FIGURE 2. THE RELATIONSHIP OF LAYOFFS AND QUITS TO ESTABLISHMENT GROWTH

*Source:* JOLTS micro data from 2001 to 2006

## II. Data Sources and Measurement Procedures

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

The Bureau of Labor Statistics (BLS) and the Census Bureau have recently developed longitudinal business datasets that cover the entire private sector of the US 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 (2008). The Census Bureau's Longitudinal Business Database (LBD) contains establishment data in March of each year from 1976 to 2005.[6] We exploit the LBD to construct annual statistics on job flows, establishment-level employment volatility and the cross-sectional dispersion of establishment growth rates. Our measurement procedures follow Davis, Haltiwanger, and Scott Schuh (1996) for job flow statistics and DHJM for volatility and dispersion measures. Unlike DHJM, however, we focus entirely on establishment-based rather than firm-based measures of volatility and dispersion. We think establishments are the more relevant unit of analysis for a study of unemployment flows.

To carefully define our empirical indicators, it is helpful to spell out our measurement mechanics. Define the growth rate from $t - 1$ to $t$ at establishment $e$ as $g_{et} = (EMP_{et} - EMP_{e,t-1})/Z_{et}$, where $EMP$ denotes the number of employees and

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[6] See Jarmin and Miranda (2002) for details on the LBD and its creation. Miranda (2006a, 2006b) describes updates and improvements to the LBD over time. The quality and availability of source data used to construct the LBD are not uniform across industries and over time. In particular, the first Economic Census of Finance, Insurance and Real Estate (FIRE) took place in 1992. Because the Economic Censuses are important tools for identifying and properly classifying business firms and establishments, LBD data for FIRE are probably of lower quality prior to 1992. As reported in the Web Appendix, our main LBD-based results are essentially unaffected by the exclusion of FIRE observations for 1992 and earlier years.

$Z_{et} = 0.5(EMP_{et} + EMP_{e,t-1})$ 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.[7]

We can write the rate of job destruction from $t - 1$ to $t$ as

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

where $Z_t = \sum Z_{et}$. 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 through by total employment. We 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 the sum of job creation and destruction. 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.

The job reallocation rate is equivalent to the size-weighted mean absolute value of employer growth rates. Thus, 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:

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

where $\overline{g}_t$ 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.

To construct a business volatility measure, we follow recent practice by first computing a rolling time-series standard deviation of growth rates for each employer and then averaging over employers at each point in time. As stressed by DHJM, it is important to perform the first step in a way that captures entry and exit and short-lived business units. Our volatility 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 is to specify a maximal window length for computing the time-series standard deviation in the first step, 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.

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[7] It also has other attractive properties. It is identical to log changes up to a second-order Taylor Series expansion, and the creation and destruction rates calculated according to (1) aggregate consistently. See Leo Tornqvist, Pentti Vartia, and Yrjo Vartia (1985) and the appendix to Davis, Haltiwanger, and Schuh (1996) for additional discussion.

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 establishment $e$ at time $t$ is

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

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

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

To see how the volatility measure (4) differs from the dispersion measure (2), consider an economy with two sets of establishments—one that persistently grows at rate $g$, and another that persistently shrinks at rate $g$, i.e., grows at rate $-g$. The heterogeneity in growth rates yields a positive value for $\sigma(\text{Disp})$, while the constant growth rate over time for each employer implies $\sigma(\text{Vol}) = 0$. For given weights, $\sigma(\text{Disp})$ rises with $g$. In contrast, $\sigma(\text{Vol})$ remains unchanged despite greater hires and separations. We think dispersion and reallocation measures are more suitable for our purposes, because they relate more closely to worker flows than the volatility measure. However, volatility measures figure prominently in recent research, so we consider them as well.

In summary, equations (1), (2), and (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 comprehensive universe files with millions of records per year. As remarked above, all of our job destruction, job reallocation, business dispersion, and business volatility measures are constructed from establishment-level data. An earlier version of this study obtained very similar results using firm-based measures from the LBD.

## B. Unemployment Inflows and Escape Rates

We estimate monthly series for the unemployment inflow rate and the unemployment escape rate using Current Population Survey data.[8] Let $U_{it}^S$ denote the number

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[8] The data are publicly available at http://www.bls.gov/cps/home.htm. To adjust for the 1994 CPS redesign, we follow Shimer (2007, footnote 27) and multiply $U_{it}^S$ by 1.1 from 1994 onward. Shimer (2007) also makes an adjustment to the inflow rate for time aggregation bias. As he notes, this adjustment is especially relevant for cyclical movements. Since this adjustment depends on time series variation in the escape rate, which exhibits little secular movement, it has little impact on secular changes in our inflow measures.

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 $t$.[9] 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 enhances comparability to our job flow measures.

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 $i$.

While the primary focus of our analysis is the relationship of job destruction, business volatility, and dispersion to unemployment inflows, we are also interested in implications for the unemployment rate. Secular changes in the latter depend on both the inflow rate and the escape rate, and we consider both in what follows.

### C. *Integrating the Data Sources*

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.[10] Our main empirical investigation 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 twelfth 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 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 twelfth

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[9] 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.

[10] Even at this level of aggregation, differences between NAICS and SIC require further data integration work. For the BED-CPS data integration, we use NAICS-based classifications. The BED data are available on an NAICS basis from 1990 to 2005. The CPS data are available on an 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. 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. We use a similar splice method (but reversed) to convert the 2001–2005 LBD-based data to SIC.

TABLE 1—SAMPLE MEANS OF BED AND CPS MEASURES, 1990–2005

| | Quarterly rates (BED) | | | | Monthly rates (CPS) | |
|---|---|---|---|---|---|---|
| | Job destruction | Job destruction, continuers | Job destruction, exits | Job reallocation | Unemployment inflows | Unemployment escape |
| 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 quarterly 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, 1977–2005

| | Annual rates (LBD) | | | | | | Monthly rates (CPS) | |
|---|---|---|---|---|---|---|---|---|
| | Job destruction | Job destruction, continuers | Job destruction, exits | Job reallocation | Firm volatility | Firm dispersion | Unemployment inflows | Unemployment escape |
| Mining | 19.9 | 12.9 | 7.0 | 38.6 | 56.2 | 67.6 | 2.4 | 38.0 |
| Construction | 23.3 | 16.1 | 7.2 | 48.8 | 65.2 | 74.0 | 5.8 | 41.0 |
| Manufacturing, nondurable goods | 11.9 | 8.0 | 3.9 | 23.2 | 34.7 | 48.4 | 2.7 | 38.2 |
| Manufacturing, durable goods | 12.3 | 8.7 | 3.6 | 24.4 | 35.3 | 47.6 | 2.4 | 35.0 |
| Transportation & utilities | 15.7 | 10.4 | 5.3 | 33.1 | 49.5 | 63.1 | 2.1 | 36.9 |
| Retail & wholesale trade | 16.5 | 10.0 | 6.5 | 35.1 | 51.6 | 64.7 | 2.9 | 44.0 |
| FIRE | 15.9 | 10.0 | 5.9 | 34.3 | 51.5 | 65.1 | 1.4 | 38.0 |
| Services | 14.4 | 9.3 | 5.1 | 33.0 | 47.6 | 61.9 | 2.7 | 42.3 |
| All, private employment | 15.3 | 9.8 | 5.5 | 30.3 | 47.9 | 61.7 | 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 establishment-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 establishment volatility and establishment dispersion are as described in text. Reported statistics for all series here are simple averages of these measures.

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 industry means for the key variables in the integrated BED-CPS and LBD-CPS datasets.
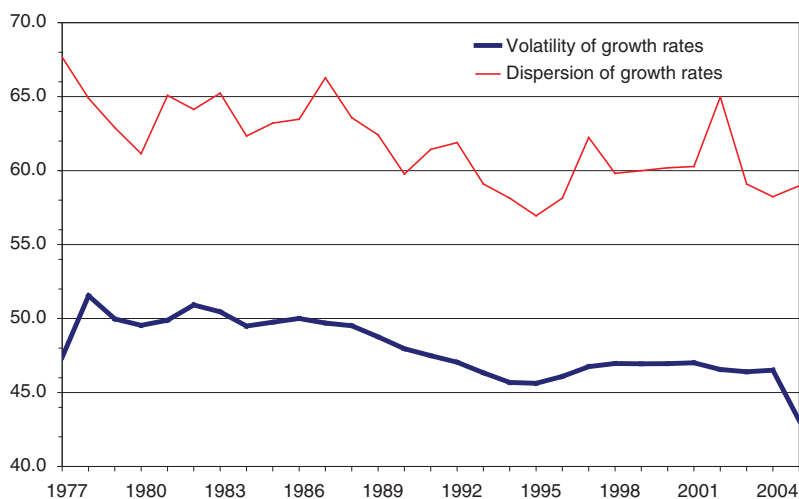
Figure 3. Employer Volatility and Dispersion, Nonfarm Private Sector, 1977–2005

*Note:* Dispersion and volatility measures constructed per equations (2) and (4) in the text using annual establishment-level data from the LBD.

## III. Trends in Business Variability, Job Destruction, and Unemployment Flows

### A. *Business Volatility, Dispersion, and Job Flows*

Figure 3 shows two LBD-based measures of establishment-level variability, $\sigma_t(\text{Disp})$ and $\sigma_t(\text{Vol})$, from 1977 to 2005. The first measure captures movements in the cross-sectional dispersion of employment growth rates; the second captures movements in the average value of establishment-level volatility. Both measures of variability drifted downward in recent decades. DHJM find a similar downward drift using firm-level measures of dispersion and volatility. Figure 4 shows annual LBD-based creation and destruction rates from 1977 to 2005. Consistent with the pattern in Figure 3, annual job flow rates trended downward over the period covered by our data.

Figure 5 shows quarterly job creation and destruction rates, drawing on several data sources. For the manufacturing sector, a clear pattern of declining job creation and destruction dates back to the 1960s. For the US private sector, the available data show a decline in quarterly creation and destruction rates since the early 1990s. Some caution is appropriate in comparing the quarterly patterns in Figure 5 with the annual patterns in Figures 3 and 4 because of differences in frequency, coverage, sample period, and measure. However, the broad picture is clear: multiple sources and various measures point to secular declines in the pace of job destruction, the volatility of establishment growth rates, and the cross-sectional dispersion of establishment growth rates.

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

Our chief objective is to relate longer term changes in measures of business variability and job destruction to unemployment flows. In light of this objective, Figure 6
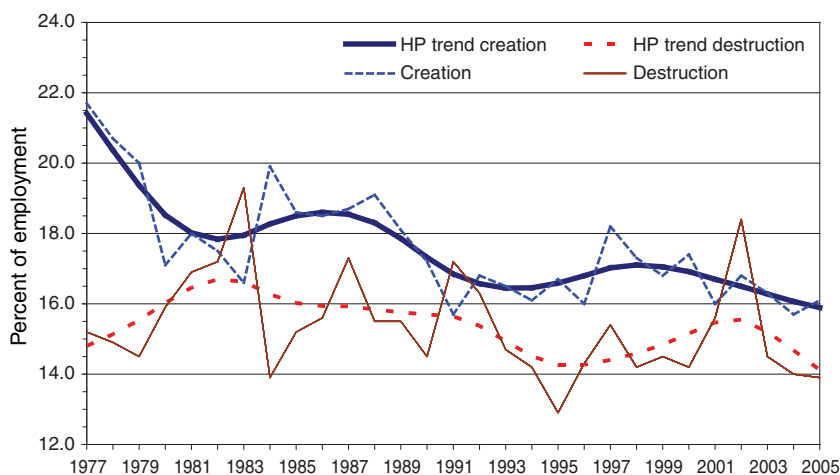
FIGURE 4. ANNUAL JOB FLOWS, NONFARM PRIVATE SECTOR, 1977–2005

*Notes:* Annual job creation and destruction rates constructed using establishment-level data from the LBD. The HP trends reflect a smoothing parameter of $\lambda = 6.25$.

shows the evolution of unemployment inflow, outflow, and escape rates since 1977. Unlike the industry-level measures analyzed in Section IV, the measures reported in Figure 6 include inexperienced workers (i.e., new entrants to the labor force) and are not limited to the nonfarm private sector. As Figure 6 shows, 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 1980s to about 2 percent by the mid-1990s and through the end of our sample period. Escape rates, while strongly cyclical, exhibit little or no secular change.

## IV. The Impact of Job Destruction and Business Variability on Unemployment Flows

We turn now to the relationship of unemployment flows and escape rates to our measures of business variability and job destruction. We first discuss issues that arise in choosing our empirical specifications and interpreting the results. For reasons we shall explain, we rely on within-industry time variation to drive our preferred regression estimates. The Web Appendix reports how unemployment inflows co-vary with job destruction across industries. The cross-industry pattern is very similar to the low-frequency within-industry pattern documented in the main text.

### A. *Issues Related to Specification and Interpretation*

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.[11] By allowing for heterogeneity in

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[11] 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

Panel A. US manufacturing, 1947–2005
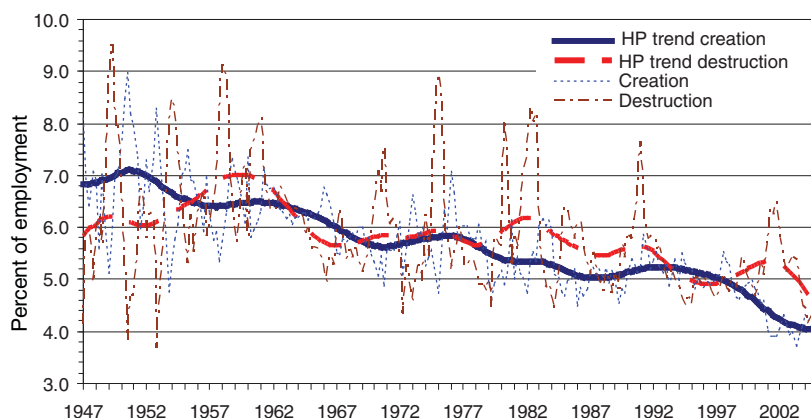


Panel B. Nonfarm private sector, 1990–2005



FIGURE 5. QUARTERLY JOB CREATION AND DESTRUCTION RATES
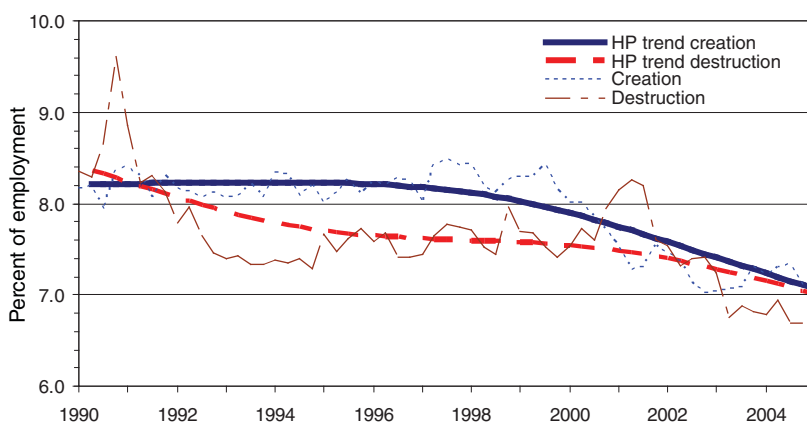
*Notes:* The upper panel for manufacturing job flows is spliced from multiple sources. The lower panel is constructed entirely from the BED. See Faberman (2008) and Davis, Faberman, and Haltiwanger (2006) for details of how we construct these series. The HP trends reflect a smoothing parameter of $\lambda = 1,600$.

the impact of common shocks, it is easy to generate a trend decline in business-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

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capital-producing sector in real business cycle models. Exchange rate movements differentially affect importing and exporting firms (e.g., Ana L. 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 (Jason G. Cummins, Kevin A. Hassett, and R. Glenn 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 (Alan J. Auerbach and Hassett 2005). Anil K. Kashyap, Jeremy C. Stein, and David W. Wilcox (1993) and Mark Gertler and Simon Gilchrist (1994) find greater sensitivity to monetary shocks among smaller firms. Davis and Haltiwanger (2001) find that the magnitude of job destruction 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., Todd E. Clark 1998).
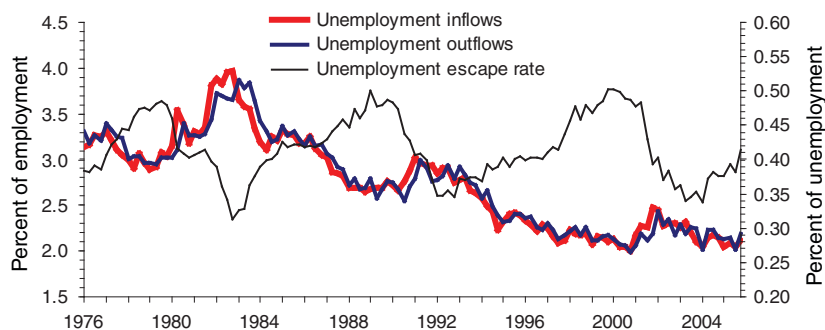
FIGURE 6. QUARTERLY AVERAGES OF MONTHLY UNEMPLOYMENT INFLOW, OUTFLOW AND ESCAPE RATES, 1976–2005

*Notes:* Inflow and outflow rates plotted on the left axis, and the escape rate plotted on the right axis. The figure plots quarterly averages of seasonally adjusted monthly values.

shocks could reflect changes in the size and frequency of common shocks. To control for the average effects of common shocks, we include time effects in the regression specifications described below. The differential effects of common shocks across employers are, for our purposes, the same as idiosyncratic shocks.

Turning to a different issue, 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 such differences are correlated with our indicators for the intensity of idiosyncratic shocks, they could produce biased estimates for the effects on unemployment inflows and escape rates. To address this potential source of bias, we rely on industry and time effects as controls.

Unemployed persons in the MP model are also 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. Thus, changes over time in the composition of unemployed workers can 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, we do not think cyclical changes in the composition of newly unemployed persons are an important concern for our study.[12] Changes in the composition of the working-age population, which by their 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

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[12] Cyclical spikes in job destruction rates seldom last more than two quarters in US 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 (2007) provides evidence that cyclical movements in the composition of unemployed workers produce only modest changes in the average job-finding rate of unemployed persons.

this issue, we rely on time effects to control for changes in the overall composition of the working-age population and unemployment pool.

Another simplification in the basic MP model is the omission of many costs associated with gross and net changes in the number of workers. These adjustment costs are the subject of a large and varied literature.[13] For our purposes, it is important to recognize that the size and importance of adjustment costs differ across industries and perhaps over time. Industry and time effects in our regression specifications serve to control for these differences. However, our specifications do not control for differential industry-level changes over time in the importance of adjustment costs. Thus, we cannot rule out the possibility that differential industry trends in adjustment costs underlie the pattern of secular declines in business variability, job destruction, and unemployment flows that we find in the data.

Similar remarks apply with respect to wage determination. That is, wage-setting behavior can differ across industries or change over time in ways that affect business volatility and dispersion measures, job destruction, and unemployment flows.[14] Industry and time effects in our regression specifications serve to control for these differences as well. However, we cannot preclude the possibility that differential industry-level changes in wage-setting behavior partly drive the basic patterns that we document.

Finally, improvements in data quality over time could induce a spurious correlation between unemployment flows and our empirical indicators. Reduced measurement error in the employer-level observations or improved longitudinal links could produce trend declines in job destruction and business volatility—even when no such decline is truly present—and a spurious low frequency correlation with unemployment flows. A similar point applies to changes over time in the methods used to measure unemployment flows. We address this concern by controlling for time effects in our regression specifications and by relying on independent sources of data for our empirical measures. Time effects control for broad improvements (or deteriorations) across industries in the extent of measurement error. What might remain are industry-specific changes in the extent of measurement error. However, there is no apparent reason for industry-specific trends in any measurement error in the LBD-based and BED-based measures of business variability and job destruction to be correlated with industry-specific movements in CPS-based measures of unemployment flows.

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

Figures 7 and 8 show the joint evolution of job destruction rates and unemployment inflow rates in each 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

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[13] Cooper, Haltiwanger, and Willis (2007), for example, estimate a search model that allows for fixed and variable costs of posting vacancies and fixed and variable costs of firing workers. Nicholas Bloom (2009) considers a model that allows for a variety of labor and capital adjustment costs.

[14] Thomas Lemieux, W. Bentley MacLeod, and Daniel Parent (2009) provide evidence that the share of US workers with flexible pay rose during our sample period.

FIGURE 7. QUARTERLY JOB DESTRUCTION AND UNEMPLOYMENT INFLOWS BY MAJOR INDUSTRY

*Notes:* Each panel plots raw data and HP trends for the quarterly BED job destruction rate (bold) and the quarterly average of monthly CPS unemployment inflows, both expressed as a percent of employment, for the indicated industry. HP trends reflect a smoothing parameter of $\lambda = 1{,}600$.

among industries. As examples, consider two polar cases in Figure 7. The trend component of monthly unemployment inflows fell by nearly one-third (150 basis points) from 1990 to 2000 in construction, but it dropped only slightly in FIRE. Second, all industries in Figure 7, and most in Figure 8, show job destruction rates and unemployment inflow rates that move together over the longer term.
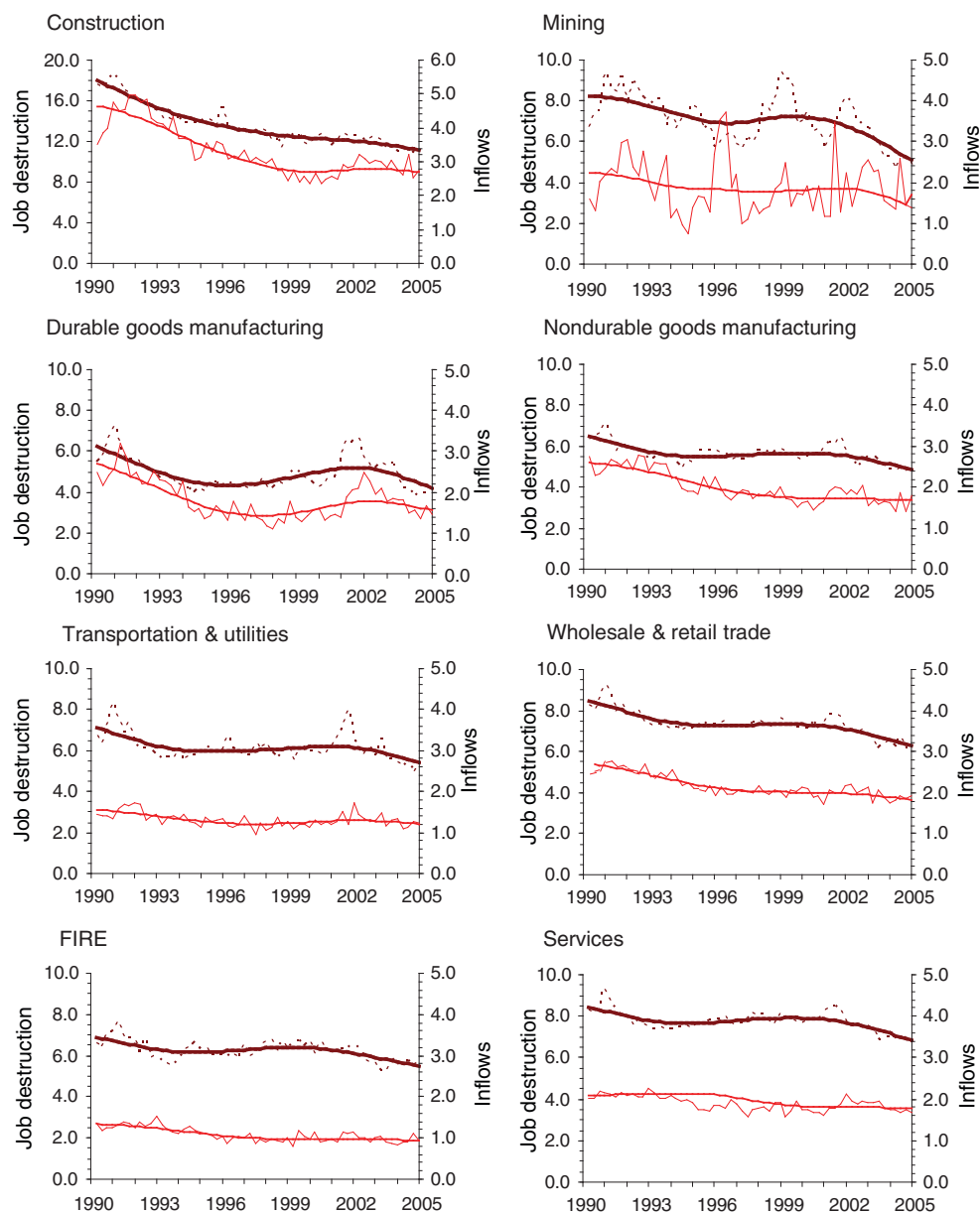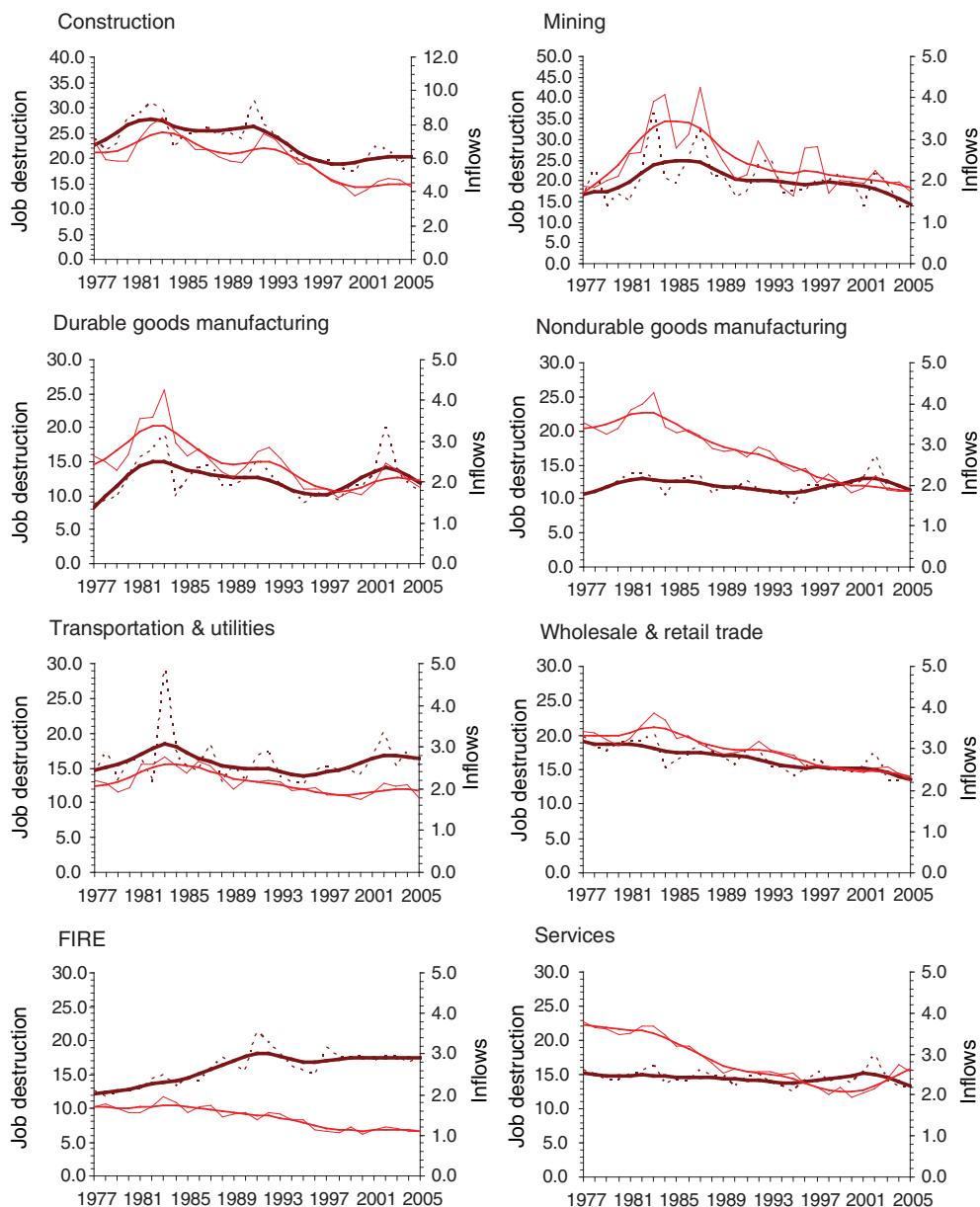
FIGURE 8. ANNUAL JOB DESTRUCTION AND UNEMPLOYMENT INFLOWS BY MAJOR INDUSTRY

*Notes:* Each panel plots raw data and HP trends for the annual LBD job destruction rate (bold) and the annual average of monthly CPS unemployment inflows, both expressed as a percent of employment for the indicated industry. HP trends reflect a smoothing parameter of $\lambda = 6.25$.

## C. *The Effect of Job Destruction and Other Indicators on Unemployment Incidence*

We now estimate the effect of job destruction and the other indicators on unemployment inflows. In keeping with our focus on longer term movements, we use

nonoverlapping three-year averages of industry-level outcomes. This averaging procedure yields 40 industry-level observations from 1990 to 2005 (5 per industry) for the BED-CPS matched data, and 80 industry-level observations from 1977 to 2005 (10 per industry) for the LBD-CPS data.[15] Using these data, we regress the unemployment inflow rate on each indicator. To isolate within-industry time variation, we include industry and time fixed effects in all specifications.

Table 3 reports our main results.[16] The top panel considers BED-CPS data from 1990 to 2005, and the bottom panel considers LBD-CPS data from 1977 to 2005. The chief result in Table 3 is the large, statistically significant effects of the job destruction, job reallocation, business volatility, and business dispersion measures on the rate of unemployment inflows. This result holds for both datasets and time periods. As discussed in Section I, this pattern is consistent with the view that changes in the intensity of idiosyncratic labor demand shocks have powerful effects on the incidence of unemployment, as measured by the unemployment inflow rate.

To appreciate the strength of the estimated effects, consider column 1 in the top panel. The estimated slope coefficient implies that a 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 observed drop in the private sector job destruction rate of 174 basis points from 1990 to 2005 yields a decline in the unemployment inflow rate of 48 basis points. This implied decline in the inflow rate amounts to 55 percent of the observed decline and 22 percent of the average inflow rate from 1990 to 2005. Analogous calculations using the quarterly job reallocation rate as the empirical indicator for idiosyncratic shock intensity yield very similar results.

The LBD-CPS results in panel B of Table 3 also imply powerful effects on the incidence of unemployment. The estimated slope coefficient in column 1 says that a drop of 100 basis points in the annual job destruction rate lowers the monthly unemployment inflow rate by 10.1 basis points. Applying this estimate to the job destruction drop of 540 basis points from 1983 to 2005 yields a decline in the monthly unemployment inflow rate of 55 basis points. This implied decline amounts to 28 percent of the actual decline in the unemployment inflow rate between 1982:Q2–1983:Q1 and 2005:Q2–2005:Q1.[17] The other indicators yield smaller, but still sizable, effects. Multiplying the 1983–2005 drop of 626 basis points in $\sigma(\text{Disp})$ by 0.051 yields an implied drop in the monthly unemployment inflow rate of 32 basis points. Analogous calculations for $\sigma(\text{Vol})$ yield an implied drop in the inflow rate of 35 basis points.

Figure 9 shows a scatter plot corresponding to column 1 in the top panel of Table 3. That is, we first sweep out industry and time effects, then plot the residual variation in the unemployment inflow rate against the residual variation in the job destruction rate. Similarly, Figure 10 presents the scatter plot corresponding to column 1 in panel B of Table 3. These plots provide strong visual confirmation that

[15] We average over 2004 and 2005 in the last two years of the LBD.

[16] The standard errors reported in Table 3 are robust to arbitrary forms of heteroscedasticity and to serial correlation within industries. See equation (10.59) and Section 10.5.4 in Jeffrey M. Wooldridge (2002). As Wooldridge remarks, conventional OLS standard errors have better small-sample properties under certain conditions. Using conventional OLS standard errors does not alter any of our inferences based on Table 3.

[17] Recall that we measure the annual job destruction rate for, say, 1983, using establishment-level employment changes between March 1982 and March 1983.

TABLE 3—UNEMPLOYMENT INFLOWS REGRESSED ON JOB DESTRUCTION AND BUSINESS
VARIABILITY MEASURES
(*Dependent variable: unemployment inflows, average of monthly rates*)

| Regressors | (1) | (2) | (3) | | |
|---|---|---|---|---|---|
| *Panel A. BED and CPS three-year averages, 1990–2005* | | | | | |
| $JD_{it}$ | 0.278 | | | | |
| | (0.041) | | | | |
| $JD_{it}\,|Cont$ | | 0.264 | | | |
| | | (0.148) | | | |
| $JD_{it}\,|Exit$ | | 0.327 | | | |
| | | (0.484) | | | |
| $JR_{it}$ | | | 0.174 | | |
| | | | (0.027) | | |
| $R^2$ | 0.956 | 0.956 | 0.959 | | |
| Within $R^2$ | 0.500 | 0.500 | 0.540 | | |

| Regressors | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| *Panel B. LBD and CPS three-year averages, 1977–2005* | | | | | |
| $JD_{it}$ | 0.101 | | | | |
| | (0.019) | | | | |
| $JD_{it}\,|Cont$ | | 0.098 | | | |
| | | (0.033) | | | |
| $JD_{it}\,|Exit$ | | 0.105 | | | |
| | | (0.063) | | | |
| $JR_{it}$ | | | 0.067 | | |
| | | | (0.016) | | |
| $\sigma_{it}(Vol)$ | | | | 0.048 | |
| | | | | (0.013) | |
| $\sigma_{it}(Disp)$ | | | | | 0.051 |
| | | | | | (0.013) |
| $R^2$ | 0.956 | 0.956 | 0.954 | 0.950 | 0.953 |
| Within $R^2$ | 0.306 | 0.306 | 0.285 | 0.222 | 0.264 |

*Notes:* The table reports estimated slope coefficients in regressions of the unemployment inflow rate on the indicated measures. All regressions include industry and time fixed effects. Robust standard errors reported in parentheses. $N = 40$ in panel A, and $N = 80$ in panel B.

low-frequency industry-specific movements in the job destruction rate drive large movements in the unemployment inflow rate.

Table 3 also considers whether job destruction has a more powerful impact on unemployment inflows when the job-destroying establishment exits completely. The point estimates mildly favor this hypothesis, but the data are not sufficiently informative to draw strong inferences in this regard. While there are good reasons to think that a given amount of job destruction yields more unemployment when the lost jobs are concentrated at employers with relatively sharp contractions, as we discussed in Section I, a definitive assessment of this hypothesis waits on future research.

We consider a number of robustness checks. First, we repeat the analysis in Table 3 using nonoverlapping five-year time averages of the industry-level outcomes. For the BED-CPS data, the analog to column 1 of Table 3(A) yields an estimated coefficient of 0.284 (0.047). For the LBD–CPS data, the analog to column 1 of Table 3(B) yields an estimated coefficient of 0.117 (0.032). These results are very similar to the ones
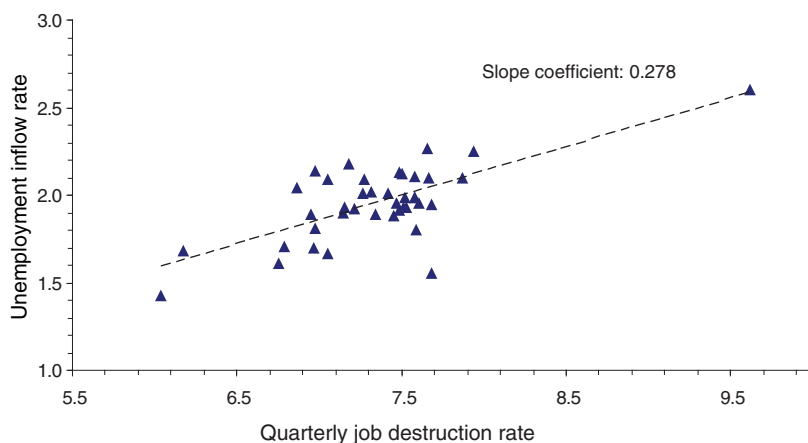
FIGURE 9. JOB DESTRUCTION AND UNEMPLOYMENT INFLOWS BY INDUSTRY, QUARTERLY DATA, CONTROLLING FOR PERIOD AND INDUSTRY EFFECTS

*Notes:* Data points are residuals of three-year means of monthly unemployment inflow rates and quarterly job destruction rates from regressions on time and industry effects (corresponding to Table 3(A), column 1). The overall means have been added back to the residuals. The dashed line is the fitted OLS relationship.
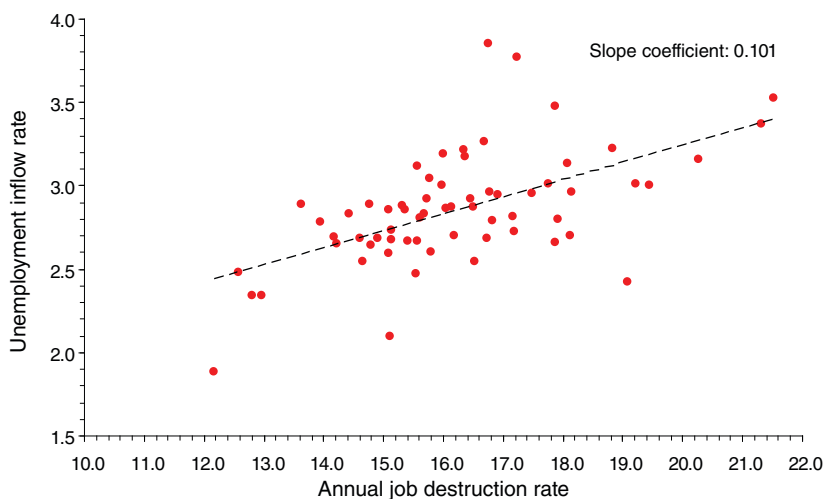


FIGURE 10. JOB DESTRUCTION AND UNEMPLOYMENT INFLOWS BY INDUSTRY, ANNUAL DATA, CONTROLLING FOR PERIOD AND INDUSTRY EFFECTS

*Notes:* Data points are residuals of 3-year means of monthly unemployment inflow rates and annual job destruction rates from regressions on time and industry effects (corresponding to Table 3(B), column 1). The overall means have been added back to the residuals. The dashed line is the fitted OLS relationship.

reported in Table 3 using three-year averages. Second, regressions using HP trend components in place of time-averaged data also yield very similar results. Third, the upper right corner of Figure 9 shows a large outlier that corresponds to the construction industry in the early 1990s. When we re-estimate the column 1 specification

in panel A of Table 3 excluding this observation, we obtain a slope coefficient estimate of 0.263 (0.096), which is nearly identical to the full-sample estimate.[18] Fourth, when we omit controls for time effects, we obtain essentially the same results in the top panel of Table 3 and substantially larger effects in the bottom panel.

Summing up, the evidence strongly supports the view that low-frequency movements in job destruction and business variability have powerful effects on the incidence of unemployment. The evidence also implies that secular declines in these measures account for much of the longer term decline in industry and aggregate unemployment inflow rates. Our evidence does not imply, nor do we believe, that a reduced intensity of idiosyncratic shocks is the only important driving force behind the secular decline in unemployment inflows. Shimer (1998) and Nir Jaimovich and Henry E. Siu (2009) provide evidence that an aging US labor force after 1980 is also important in this regard. Less experienced workers are relatively likely to become unemployed for reasons other than job destruction. The share of less-experienced workers declined over the period covered by our data, thereby contributing to a secular decline in the unemployment inflow rate.

### D. *Unemployment Escape Rates*

We now estimate the effects of our indicators for idiosyncratic shock intensity on the unemployment escape rate. As discussed in Section I, the MP model predicts that the steady-state job-finding rate rises with the intensity of idiosyncratic shocks. Aside from the MP model, we are interested in the low-frequency relationship of the job destruction and business variability measures to the unemployment escape rate. As before, we use nonoverlapping three-year averages of industry-level outcomes in each dataset and consider regression specifications that control for industry and time fixed effects.

Table 4 reports the results. The job destruction rate shows a negative and statistically significant estimated relationship to the escape rate, contrary to the steady-state implication of the basic MP model. Column 1 of panel A says that a decline in the job destruction rate of 100 basis points is associated with an increase in the monthly unemployment escape rate of 136 basis points. This is a fairly small effect, amounting to less than 4 percent of the average monthly unemployment escape rate during the 1990 to 2005 sample period. Analogous calculations based on column 1 of panel B yield an implied response that amounts to only 1 percent of the average unemployment escape rate during the 1977 to 2005 period. In short, we find no 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.

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[18] We also re-estimated Table 3 on samples that exclude all observations for the construction industry. Excluding construction in the BED-CPS sample yields large standard errors, and we no longer obtain statistically significant results unless we also omit controls for time effects. We are not especially troubled by this result, because we see no good reason to exclude construction industry observations. Moreover, when we exclude construction from the longer LBD-CPS sample, we continue to obtain large, statistically significant effects. See the Web Appendix for details of these and other results that explore the robustness of the Table 3 estimates.

TABLE 4—UNEMPLOYMENT ESCAPE RATES REGRESSED ON JOB DESTRUCTION AND BUSINESS
VARIABILITY MEASURES
(*Dependent variable: unemployment escape rate, average of monthly values*)

| Regressors | (1) | (2) | (3) | | |
|---|---|---|---|---|---|
| *Panel A. BED and CPS three-year averages, 1990–2005* | | | | | |
| $JD_{it}$ | −1.355 | | | | |
| | (0.367) | | | | |
| $JD_{it}\,|Cont$ | | −1.133 | | | |
| | | (1.122) | | | |
| $JD_{it}\,|Exit$ | | −2.132 | | | |
| | | (3.656) | | | |
| $JR_{it}$ | | | −0.753 | | |
| | | | (0.164) | | |
| $R^2$ | 0.946 | 0.947 | 0.943 | | |
| Within $R^2$ | 0.314 | 0.315 | 0.267 | | |

| Regressors | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| *Panel B. LBD and CPS three-year averages, 1977–2005* | | | | | |
| $JD_{it}$ | −0.813 | | | | |
| | (0.165) | | | | |
| $JD_{it}\,|Cont$ | | −0.925 | | | |
| | | (0.358) | | | |
| $JD_{it}\,|Exit$ | | −0.664 | | | |
| | | (0.458) | | | |
| $JR_{it}$ | | | −0.487 | | |
| | | | (0.084) | | |
| $\sigma_{it}(Vol)$ | | | | −0.395 | |
| | | | | (0.071) | |
| $\sigma_{it}(Disp)$ | | | | | −0.336 |
| | | | | | (0.063) |
| $R^2$ | 0.858 | 0.859 | 0.836 | 0.838 | 0.820 |
| Within $R^2$ | 0.382 | 0.385 | 0.285 | 0.292 | 0.216 |

*Notes:* The table reports estimated slope coefficients in regressions of the unemployment escape rate on the indicated measures. All regressions include industry and time fixed effects. Robust standard errors reported in parentheses. $N = 40$ in panel A, and $N = 80$ in panel B.

What might explain our results for the escape rate? One possibility is that time 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 industry-specific escape rates reflect the industry of most recent employment, not the industry to which the unemployed person "escapes." Our inability to correctly identify the relevant labor market for unemployed persons probably accounts for our weak empirical results with respect to the escape rate.

## V. Implications for the Rate of Unemployment

The results in Section IV show that declines in job destruction and business variability measures account for much of the decline in the unemployment inflow rate

since the early 1980s or early 1990s. To appreciate the implications for the rate of unemployment, consider a simple representation of unemployment dynamics:

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

where $u_t = U_t/E_t$ is the ratio of unemployed to employed persons in month $t$, $l_t$ is the unemployment inflow rate in $t$, and $f_t$ is the unemployment escape rate. As before, $l_t$ and $f_t$ are expressed relative to period-$t$ employment and unemployment, respectively.

Shimer (2007) presents evidence that US unemployment rate dynamics are well approximated by the steady-state values implied by current-month inflow and escape rates. Imposing $u_t = u_{t-1}$ and $E_t = E_{t-1}$ in (5) yields the implied steady-state unemployment rate,[19]

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

Figure 11 confirms that the steady-state approximation in (6) closely mimics the actual time path of the unemployment rate. We exploit this result in the remaining analysis.

Following Elsby, Michaels, and Solon (2009) and Fujita and Ramey (2009), equation (6) yields a useful decomposition for log changes in the unemployment rate:

$$(7) \qquad \Delta \log u_t = \Delta \log (l_t) - \Delta \log (f_t).$$

Using the average steady-state unemployment rate from the first ten years (1976–1985) and last ten years (1996–2005) of our sample period, we find that $\Delta \log u_t = -0.43$ with $\Delta \log l_t = -0.41$ and $\Delta \log f_t = 0.02$. That is, the long-term decline of 43 log points in the (steady-state) unemployment rate is overwhelmingly accounted for by the decline in the inflow rate. Recall from Table 3 that declining rates of job destruction account for 55 percent of the drop in unemployment inflow rates from 1990 to 2005 and 28 percent from 1982. Thus, the Table 3 results combined with the decomposition (7) imply that declines in the job destruction rate account for roughly one-quarter to one-half of the secular declines in the (log of) the unemployment rate.

To further develop this point, we again rely on the steady-state approximation (6), this time to compare the unemployment series implied by the 1976–1980 and 2001–2005 average unemployment inflow rates to each other and to the series implied by the contemporaneous inflow rate. In each case, we consider the actual time path of unemployment escape rates in calculating (6). The resulting series, plotted in Figure 12, highlight two related points. First, the drop in the inflow rate between the first and last five years of the sample implies a large drop in the unemployment

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[19] Alternatively, one can consider a stationary path with a constant employment growth rate, which yields $u = l/(f + g)$, where $g$ is the growth rate of employment. At a monthly frequency, however, the employment growth rate is tiny compared to the unemployment escape rate, and this approximation yields results virtually identical to (6). As a separate point, our expression for the steady-state unemployment rate differs in appearance from the one in Shimer (2007) because we define the unemployment rate relative to employment (rather than the labor force). See Section IIIB for an explanation of why we define the unemployment rate this way. At the economy-wide level, the ratio of unemployment to employment behaves similarly to the conventional unemployment rate except for a level shift.
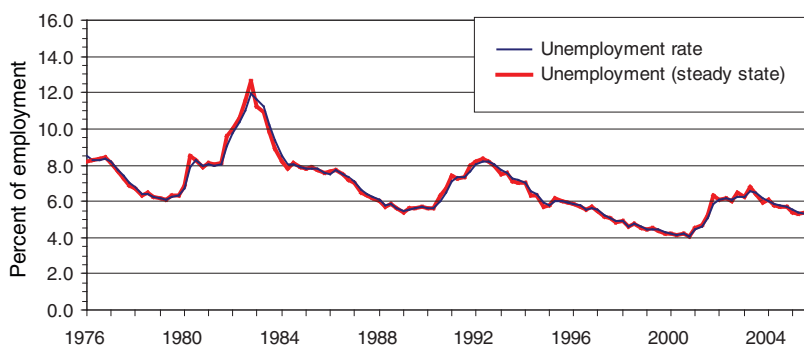
FIGURE 11. COMPARISON OF ACTUAL AND STEADY-STATE UNEMPLOYMENT RATES

*Notes:* Unemployment rate defined as ratio of unemployment to employment. The steady-state unemployment rate is computed according to equation (6) using current-period inflow and escape rates. The figure plots quarterly averages of monthly values.

rate for all realized values of the escape rate. The average difference between the unemployment rate based on the average 1976–1980 and 2001–2005 inflow rates is 2.2 percentage points, and the minimum difference is 1.8 percentage points. Second, the escape rate cannot account, by itself, for most of the decline in the unemployment rate since the early 1980s. The steady-state unemployment rate fell from 12.6 percent in the fourth quarter of 1982 to 5.1 percent in the fourth quarter of 2005, a decline of 7.5 percentage points. Over the same time period, the unemployment rate implied by the average 1976–1980 (2001–2005) inflow rate fell by only 2.4 (1.7) percentage points. That is, holding the inflow rate fixed, the escape rate accounts for less than one-third of the fall in the unemployment rate from 1982 to 2005.

These results suggest that a satisfactory theory of unemployment rate dynamics involves major roles for movements in both unemployment inflow and escape rates. In this respect, our message is similar to that of Elsby, Michaels, and Solon (2009) and Fujita and Ramey (2009). Our analysis differs from theirs in its focus on longer term movements in the unemployment inflow rate and in developing evidence that empirical indicators for the intensity of idiosyncratic shocks account for much of the secular decline in the inflow rate.

The secular decline in the inflow rate also has important implications for the cyclical behavior of the unemployment rate. To see this point, differentiate (6) to calculate the marginal effect of the job-finding rate on the unemployment rate:

$$(8) \qquad\qquad\qquad du/df = -l/(f^2).$$

That is, a secular decline in the job-loss rate lowers the unemployment rate response to cyclical movements in the job-finding rate. How big is this effect? Let $f = 0.41$ 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 weak labor markets in the early 1990s and early 2000s involved modest unemployment spikes compared to recessions in the 1970s and 1980s. This calculation also
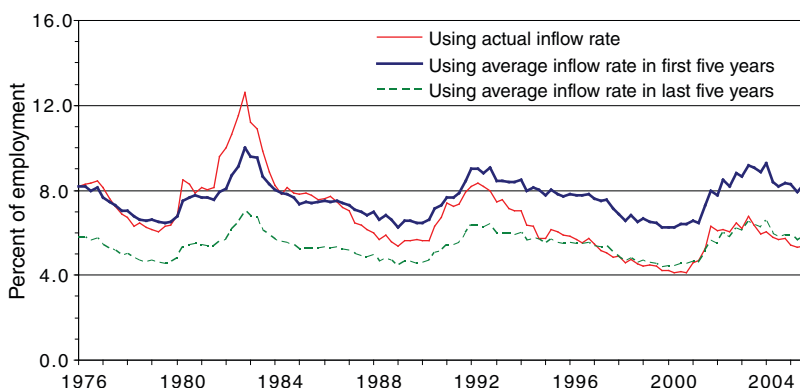
FIGURE 12. UNEMPLOYMENT RATE IMPLIED BY VARIOUS INFLOW RATES

*Notes:* Each curve shows the steady-state unemployment rate implied by equation (6) for the indicated inflow rate series. The figure plots quarterly averages of monthly values.

underscores a related point. Even when the focus is on cyclical unemployment fluctuations and one takes the view that cyclical movements in the job-loss rate are unimportant, the secular decline in the job-loss rate remains important because it affects the unemployment response to movements in the job-finding rate.

## VI. Concluding Remarks

The unemployment inflow rate fell by half from the early 1980s to the mid-1990s and remained at low levels through 2005. We show that this development roughly coincided with secular declines in job destruction, job reallocation, the volatility of establishment-level employment growth, and the cross-sectional dispersion in establishment-level growth rates. Motivated by these patterns in the aggregate data and by modern theories of unemployment, we use industry-level time series to estimate the relationship of unemployment inflows to the job destruction and business variability measures. The industry-level data allow us to control for unobserved time and industry fixed effects and to rely on lower frequency variation to estimate the relationship.

The industry-level data show a strong empirical relationship of unemployment inflows to the job destruction and business variability measures. The quantitative results are informative in three key respects. First, Table 3 provides reasonably precise estimates for the connection between job destruction and unemployment inflows. To the best of our knowledge, ours is the only study to estimate this relationship in a way that is suitable for calibrating to the steady-state properties of theoretical models. Second, our study is also the first to show that long-term declines in job destruction and business variability played a major role in the large secular declines in both unemployment flows and the rate of unemployment. Specifically, our results imply that declining job destruction accounts for about a quarter of the fall in unemployment since the early 1980s and about half since the early 1990s. Third, as we showed in Section V, the large secular decline in the unemployment inflow rate implies a fall by half in the sensitivity of the unemployment rate to cyclical movements in the job-finding rate.

We drew on JOLTS micro data to provide additional insight into the behavior of worker separations, job destruction, and layoffs. Figure 1 shows that worker separations are the main margin of adjustment for shrinking employers, and that separations are tightly linked to job destruction in the cross section. Figure 2 shows both quits and layoffs are important margins of employment adjustment for employers that shrink by moderate movements. However, the layoff-quit ratio becomes bigger as an employer shrinks more rapidly.

In closing, we return to the question of what our findings say about changes in the underlying structural characteristics of the economy. Secular declines in unemployment flows, job destruction rates, and business volatility and dispersion measures are consistent with the predictions of standard search and matching models when perturbed by a persistent fall in the intensity of idiosyncratic labor demand shocks. We think this interpretation is a natural one. However, our empirical evidence does not preclude a major role for other long-term structural developments with important effects on business variability, job destruction, and unemployment flows. For example, one might interpret our findings in terms of greater compensation flexibility over time or increased adjustment costs. Changes of either sort lead to smaller employment responses to labor demand shocks of given size. A careful assessment of these alternative interpretations is an important topic for future research.

### Appendix: The Mortensen-Pissarides Model and Its Steady-state Properties

The model is set in continuous time, and workers and firms discount the future at rate $r$. Workers are fixed in number, and each one is either employed and producing or unemployed and searching for a job. There is no on-the-job search. When employed, a worker receives wages that provide a fixed share $\beta$ of surplus in the job-worker match. When unemployed, a worker receives income (or imputed leisure value) $b$ per unit time.

Each firm has one job that can be either filled and producing or unfilled and searching for a worker. An unfilled job (vacancy) incurs recruiting costs $c$ per unit time. There are no other costs of creating or destroying jobs. The number of firms adjusts endogenously to satisfy a free-entry condition that ensures zero equilibrium asset value for unfilled jobs.

A filled job produces an output flow valued at $p + \sigma\varepsilon$, where $p$ is a common component of productivity, $\varepsilon$ is an idiosyncratic shock value, and $\sigma$ indexes the average magnitude of idiosyncratic shocks. The value of output in new jobs (i.e., newly filled by a worker) is $p + \sigma\varepsilon_u$, the upper support of the productivity distribution. Once a job is filled, productivity evolves exogenously according to Poisson arrival processes for common and idiosyncratic shocks. An idiosyncratic shock brings a new value of $\varepsilon$ drawn from distribution $F(x)$ with finite upper support $\varepsilon_u$ and no mass points. $F(x)$ has zero mean and unit variance so that $\sigma$ is the standard deviation of the job-specific productivity component $\sigma\varepsilon$.

Because it is costly and time consuming to find a new worker, a filled job is destroyed only when the idiosyncratic component falls below $\varepsilon_d < \varepsilon_u$, where the job destruction threshold $\varepsilon_d$ is an endogenous variable that depends on parameters of the model. The job destruction rate is $\lambda F(\varepsilon_d)$.

Unfilled jobs and unemployed workers meet according to a matching function $m(v, u)$, where $v$ and $u$ are the number of vacancies and unemployed workers, respectively, normalized by the fixed labor force. The matching function is homogeneous of degree one in $v$ and $u$, so we can write the job-finding rate for unemployed workers (i.e., the unemployment escape rate) as $m(v/u, 1)$.

We interpret $\sigma$ as the parameter that governs the intensity of idiosyncratic shocks in the MP model. In their appendix, Mortensen and Pissarides (1994) show that $p > b$ is sufficient to obtain $d\varepsilon_d/d\sigma > 0$ in steady-state equilibrium. That is, a lower value of $\sigma$ leads to a lower job destruction rate and a lower unemployment inflow rate. Under a stronger requirement that MP regard as reasonable and impose in their analysis, they also show that $(\partial \varepsilon_d/\partial \sigma)|_{v/u \text{ fixed}} > 0$.[20] That is, a lower value of $\sigma$ leads to a lower job destruction rate and a lower unemployment inflow rate for given labor market tightness. This result also implies that a lower value of $\sigma$ leads to a lower rate of unemployment in light of the steady-state condition for unemployment inflows and outflows:

$$u = \frac{\lambda F(x)}{\lambda F(x) + m(v/u, 1)}.$$

Finally, Mortensen and Pissarides (1994) also show that a lower value of $\sigma$ yields a lower steady-state unemployment escape rate.

Alternatively, one might be inclined to associate $\lambda$ with the intensity of idiosyncratic shocks, because a higher value of $\lambda$ means more frequent arrival of such shocks. However, the steady-state job destruction rate falls when $\lambda$ rises in the MP model. In part, this property of the model arises because the job-specific component of match output is less persistent at a higher value of $\lambda$, which increases the option value of a filled job for given values of $\varepsilon$ and $v/u$.

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[20] See page 402 and the discussion of equation (11) in Mortensen and Pissarides (1994).

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