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Labor market flows in the cross section and over time

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ABSTRACT

Many theoretical models of labor market search imply a tight link between worker flows (hires and separations) and job gains and losses at the employer level. We use rich establishment-level data to assess several theoretical models and to study the relationship between worker flows and jobs flows. Hires, quits, and layoffs exhibit strong, highly nonlinear relationships to employer growth rates in the cross section. Simple statistical models of these relationships greatly improve our ability to account for fluctuations in aggregate worker flows and enable us to construct synthetic measures of hires, separations, quits, and layoffs back to 1990.

1. Introduction

Many theoretical models of labor market search carry strong implications for the relationship of hires and separations to job gains and losses at the employer level. Partly motivated by these theories, we exploit establishment-level data from U.S. sources to study the empirical relationship between worker flows and job flows in the cross section and over time. The evidence supports a hybrid view that incorporates aspects of several distinct theories of labor market dynamics. Tracking the cross-sectional distribution of establishment growth rates and applying simple models of cross-sectional behavior greatly improve our ability to account for aggregate fluctuations in hires, separations, quits, and layoffs.

Previous work has not delivered a thorough and convincing explanation for the relationship between worker flows and job flows. One difficulty is that worker flow and job flow measures typically derive from different data sources, and are comparable only at high levels of aggregation. Even then, standard sources of data on these measures differ in scope, sampling frequency, and other respects that hinder direct comparison. We overcome these difficulties by exploiting micro data from the Job Openings and Labor Turnover Survey (JOLTS). JOLTS data yield internally consistent measures of hires, separations, quits, layoffs, job creation, and job destruction at the establishment and aggregate levels.

To deal with weaknesses in the JOLTS sample design, we rely on the comprehensive Business Employment Dynamics (BED) to track the cross-sectional distribution of establishment-level growth rates over time. Specifically, we combine BED data on the establishment growth rate distribution with JOLTS data for hires, separations, layoffs, and quits conditional on establishment growth rates to measure the aggregate worker flow rates. Combining JOLTS and BED data also enables us to construct synthetic data on worker flows back to 1990, nearly doubling the time-series length of JOLTS-type worker flow measures.

To guide our empirical work, we consider several theoretical models. Models in the spirit of seminal work by Mortensen and Pissarides (1994) (hereafter MP) imply a tight link between job flows and worker flows. Our empirical work assesses

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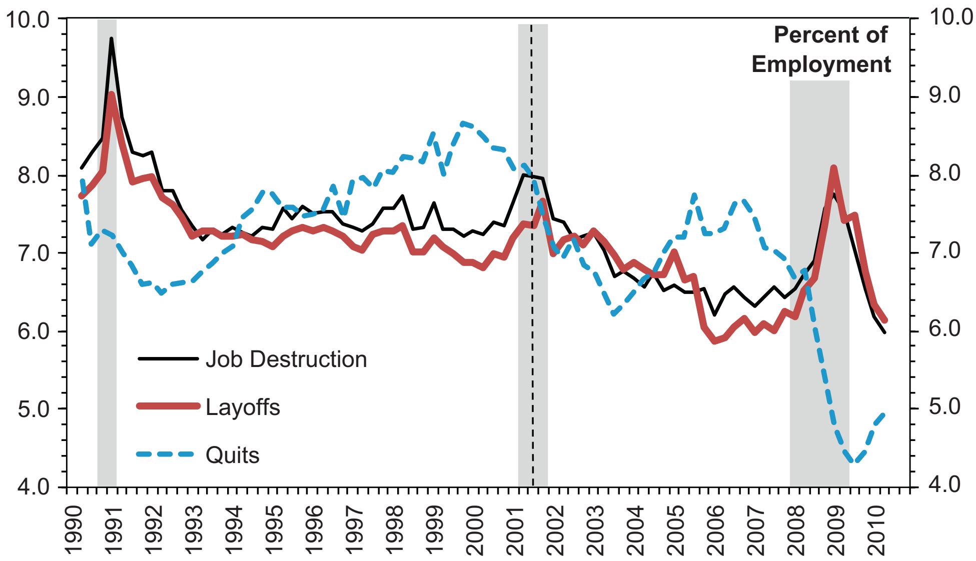

Fig. 1. Quits, layoffs, and job destruction.
Sources: Quit and layoff rates (2001Q3–2010Q2) are authors' calculations using JOLTS establishment microdata weighted to an aggregate value for each quarter using growth rate densities from the BED. Job destruction rates (1990Q2–2010Q2) are authors' tabulations directly from the BED data. All estimates are seasonally adjusted. All rates are percentages of employment. Backcasted estimates of the quit and layoff rates are included to the left of the dashed vertical line.

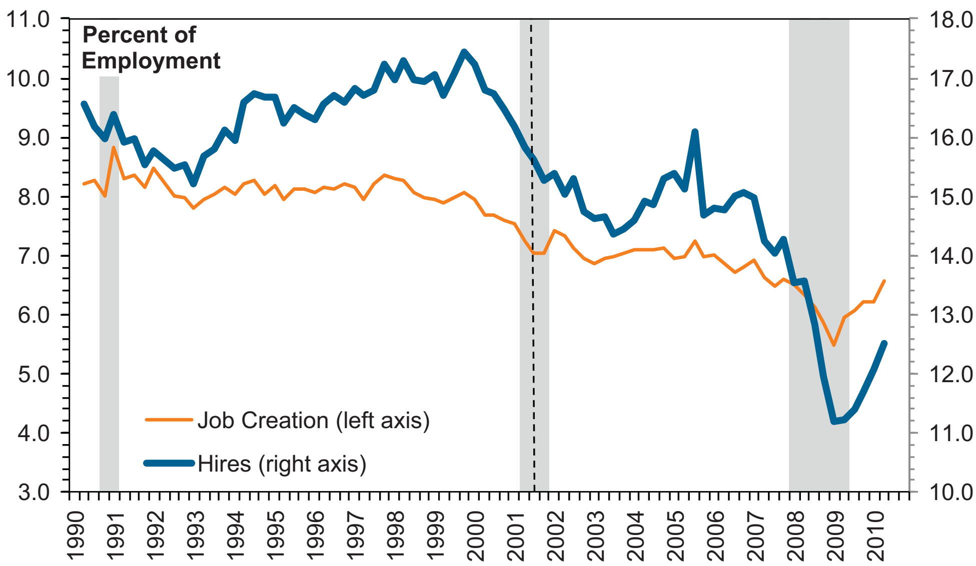

Fig. 2. Hiring and job creation.
Sources: Hiring rates (2001Q3–2010Q2) are authors' calculations using JOLTS establishment microdata weighted to an aggregate value for each quarter using growth rate densities from the BED. Job creation (1990Q2–2010Q2) rates are authors' tabulations directly from the BED data. All estimates are seasonally adjusted. All rates are percentages of employment. Backcasted estimates of the hiring rate are included to the left of the dashed vertical line.

how closely models with these tight links fit the data. We also consider empirical specifications motivated by models that stress the role of search on the job, learning about match quality, firm profitability, and the impact of aggregate conditions on the propensity to quit. We evaluate alternative specifications in terms of their fit to cross-sectional patterns in the establishment-level data, their ability to generate the observed movements in aggregate worker flows, and their marginal explanatory power for aggregate worker flows after conditioning on aggregate variables.

Figs. 1 and 2 plot our quarterly, seasonally adjusted time series for JOLTS-type worker flow measures, along with job creation and destruction rates from the BED.[1] All rates cover the nonfarm private sector and are expressed as a percent of employment. We define job creation as the sum of employment gains at new and expanding establishments as in

[1] To conform to the BED sampling frequency, we cumulate monthly establishment-level JOLTS observations to the quarterly frequency. We then construct our aggregate worker flow series by combining the cross-sectional relationships of worker flows to establishment-level growth rates in JOLTS micro data with employment growth rate distributions from the BED. This approach, described more fully in Section 3 below, follows Davis et al. (2010c).

Davis et al. (1996). We define job destruction analogously. Fig. 1 shows that job destruction and layoffs move together over time, while quits move counter to both. Job destruction and layoffs exhibit pronounced spikes in late 2008 and early 2009 and then decline in nearly parallel fashion. Fig. 2 shows that job creation and hires rates decline from 2006, bottom out in 2009Q1, and then partly recover. The hiring rate moves much more than the job creation rate over this period. Our study explores the micro level sources of these aggregate movements.

Looking across establishments, hiring and separation rates exhibit powerful elements of the ''iron-link'' behavior implied by MP-style search models. That is, hires are tightly linked to job creation, and separations are tightly linked to job destruction. When plotted as functions of establishment-level growth rates, hiring and separation rates exhibit nonlinear "hockey-stick" shapes. The hires relation is nearly flat to the left of zero growth (contracting employers) and rises more than one-for-one with employment growth to the right of zero (expanding employers), with a pronounced kink at zero. The separations relation is a mirror image of the hires relation. The hockey-stick shape for separations is starkly at odds with the simplifying assumption adopted in many search models of a uniform separation rate. Turning to the components of separations, both quits and layoffs rise with job destruction, but layoffs dominate the adjustment margin for rapidly contracting establishments. We also consider how the cross-sectional relations vary with aggregate conditions. As it turns out, the cross-sectional layoff relation is highly stable over time. In contrast, the cross-sectional quit relation varies markedly with aggregate conditions. Specifically, the quit relation shifts downward when aggregate conditions are weak, especially at contracting establishments.

Several theoretical models provide insight into the reasons for departures from an iron-link relationship between worker flows and job flows. Faberman and Nagypál (2008) consider a model of on-the-job search that delivers an ''abandon-ship'' effect at struggling employers. Firms vary in their idiosyncratic profitability and grow faster when more profitable. Because wages increase with firm profits in their model, workers at low-profitability firms are more likely to accept an outside offer. Consequently, quit rates decline with the idiosyncratic component of firm profitability. Barlevy (2002) considers a model with on-the-job search and a match-specific component of productivity. Because firms create fewer vacancies when aggregate conditions are weak, employed workers encounter better matches at a slower pace during recessions. As a result, workers tend to remain longer in poor matches, which Barlevy refers to as the ''sullying'' effect of recessions. In sum, Faberman and Nagypál highlight the role of cross-sectional variation in firm-level circumstances for quit rates, whereas Barlevy highlights the role of variation over time in aggregate conditions. Our evidence indicates that both effects are at work.

In Jovanovic (1979, 1985) and Moscarini (2005), gradual learning about match quality leads to a separation rate that declines with match tenure. Because more rapid growth involves a higher share of young matches, these models suggest that separations rise with the growth rate of expanding employers. Pries and Rogerson (2005) integrate elements of Jovanovic-style learning into an MP model. Separations occur because of job destruction, as in the MP model, and because of learning effects about match quality. Thus, the model of Pries and Rogerson generates elements of iron-link behavior in hires and separations while rationalizing a positive relationship between separations and growth at expanding employers. The data support this hybrid view of the cross-sectional relationship between hires, separations, and employer growth.

Motivated by these theoretical ideas, we develop parsimonious statistical models of how worker flows vary in the cross section, and how the cross-sectional relations move over time. The statistical models serve three objectives. First, they provide guidance in evaluating, developing and calibrating theoretical models of labor market flows. Second, they allow us to investigate whether tracking the cross-sectional growth distribution adds to our understanding of aggregate movements in labor market flows. Third, they yield a framework for constructing synthetic data on aggregate hires, separations, quits, and layoffs in the period before the advent of JOLTS.

When we consider specifications that impose time-invariant relations of worker flows to employer growth rates in the cross section, the statistical models perform reasonably well in tracking the aggregate movements of hiring and layoff rates. However, the same type of model fails miserably in tracking the aggregate behavior of quits. Consequently, it also fares poorly in accounting for the aggregate separations rate. When we allow the worker flow-employer growth relationships to vary with aggregate conditions, our ability to track aggregate quits and separations improves dramatically.

Our work in this paper has many antecedents. There is a large body of previous research on job flows and worker flows. We review research in this area in Davis and Haltiwanger (1999) and Davis et al. (2006). Labor market flows and job vacancies play central roles in modern theories of unemployment based on search and matching models. See, for example, Pissarides (2000), Rogerson et al. (2005), and Yashiv (2007) for reviews of work in this area. Models that treat hires as the outcome of a matching function carry implications for the relationship between hires and vacancies in the cross section and over time. We explore some of those implications in Davis et al. (2010a).

The paper proceeds as follows. Section 2 discusses the conceptual underpinnings that guide our empirical work. We start with the model of Cooper et al. (2007), which extends the basic MP model to multi-worker firms. We then consider models that endogenize the worker's quit decision, as in Faberman and Nagypál (2008) and Barlevy (2002), and conclude with models of learning about match quality, such as Jovanovic (1979). Section 3 describes our data and empirical

(*footnote continued*)
Worker flows prior to 2001Q3 in Figs. 1 and 2 are synthetic data, constructed as described in Section 5 below. The actual and synthetic series presented in Figs. 1 and 2 are available in supplemental electronic files for this paper.

measures. Section 4 presents our statistical models and investigates how well they account for worker flows in the cross section and over time. Section 5 constructs synthetic JOLTS-type data on worker flows, and Section 6 concludes.

2. Conceptual underpinnings and theoretical implications

In thinking about worker flows and job flows, it is useful to begin with an identity:

$$e_{it} = e_{it-1} + h_{it} - l_{it} - q_{it} \tag{1}$$

where e_{it} is employment at establishment i in period t and h, l, and q denote hires, layoffs, and quits, respectively. Separations are the sum of quits and layoffs. Theory provides guidance about how employers use hires, layoffs, and quits to adjust employment and about the factors that lead to worker turnover in excess of employment changes. In what follows in this section, we first consider search and matching models that involve an "iron link" between hires and job creation on the one hand and separations and job destruction on the other. We then consider theories that relax the iron link. Lastly, we discuss aggregate implications and motivate our empirical specifications.

2.1. Models with an iron link

Every hire reflects a newly created job in the canonical search and matching model of Mortensen and Pissarides (1994), and every separation reflects a job that vanishes. That is what we mean by an iron link between worker flows and job flows. One goal of our study is to assess how well this iron link characterizes the data. However, the basic MP model has no role for multi-worker employers, an essential aspect of our empirical work. So we borrow from Cooper et al. (2007, CHW) to illustrate the implications of the iron link in a multi-worker version of MP.[2]

Employers in the CHW model face common and idiosyncratic shocks and produce output according to a strictly concave function of the labor input. When hiring new workers, employers incur fixed and variable costs of posting vacancies. Workers separate for exogenous reasons, and some employers layoff additional workers subject to fixed and variable firing costs. Employers choose layoffs and vacancies – effectively, hires as well – to maximize the present discounted value of profits. Workers do not search on the job.

The following law of motion links employment changes and worker flows in CHW:

$$e_{it} = (1-\overline{q})e_{it-1} + \eta(U_t, V_t)v_{it} - l_{it} \tag{2}$$

where $\overline{q}$ is the quit rate, $\eta(U_t,V_t)$is the job-filling rate, and v_{it} is the number of vacancies posted at the beginning of the period.[3] The job-filling rate derives from a standard matching function with constant returns to scale in the aggregate numbers of unemployed workers and vacant jobs. Period-t hires for the employer are $h_{it} = \eta(U_t,V_t)v_{it}$.

An employer in the CHW model operates in one of three regions each period, depending on the aggregate and idiosyncratic shock values: (i) positive vacancies and zero layoffs, (ii) zero vacancies and positive layoffs, or (iii) an inaction region with zero vacancies, no layoffs, and no replacement hiring. Solving the model yields a stochastic equilibrium path for the cross-sectional distribution of employment changes, hires, quits, and layoffs. The realized path depends in complex ways on the interaction of the aggregate and idiosyncratic driving forces and the key parameters of the revenue, cost, and matching functions. Aggregate shocks shift the entire cross-sectional distribution of growth rates, while parameters governing adjustment costs and the variance of idiosyncratic shocks strongly influence its shape. Model-based outcomes exhibit an iron-link mapping of job flows to hiring, layoffs, and quits.

Fig. 3 depicts the iron link. It shows the relationship of the hiring, layoff, and quit rates to employer growth rates in the cross section. There is a mass point with no hiring or layoffs at growth rate $-\overline{q}$. To the right of $-\overline{q}$, employers post vacancies and hire new workers. Employers in this range have zero layoffs, and hiring rises one-for-one with increases in employment. To the left of $-\overline{q}$, employers engage in no hiring and the layoff rate rises one-for-one with the rate at which the employer contracts.

Given the iron link relations illustrated in Fig. 3, the cross-sectional distribution of employment growth rates fully determines aggregate hires and layoffs. This feature of the model has interesting implications. For example, modest recessions that shift the central tendency of the cross-sectional distribution from positive values to a value near zero produce large drops in aggregate hires with relatively little increase in aggregate layoffs. In contrast, a deep recession that shifts much of the mass in the cross-sectional distribution across the kink point in Fig. 3 produces a large jump in layoffs. Thus, the highly nonlinear micro relations in Fig. 3 imply differential responses of hires and layoffs to mild and deep recessions. Below, we treat the aggregate implications of cross-sectional worker flow relations in a more formal manner.

[2] Other recent search-theoretic analyses with multi-worker firms include Elsby and Michaels (2008), Veracierto (2009), Fujita and Nakajima (2009), Schaal (2010), and Trapeznikova (2010).

[3] We use uppercase letters for aggregate quantities and lowercase letters for establishment outcomes.

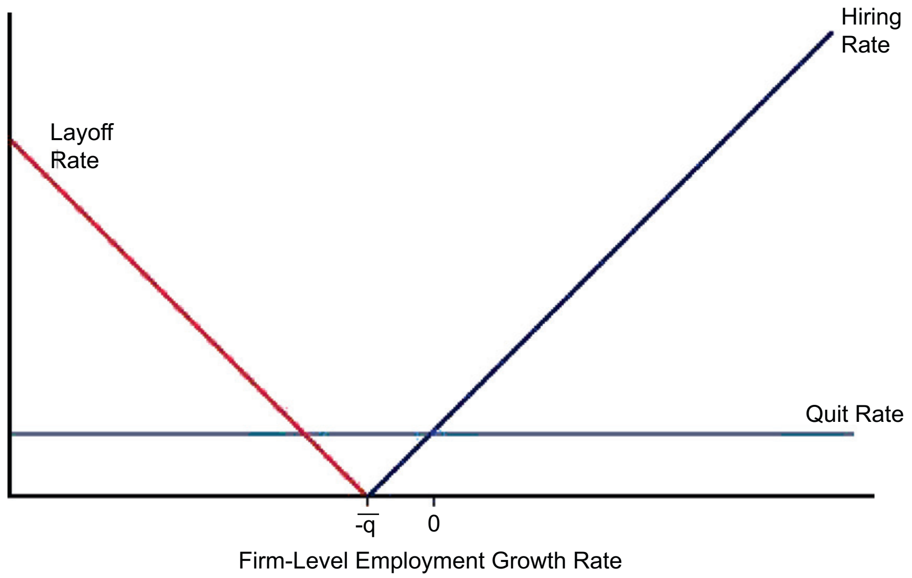

Fig. 3. Implied worker flows from a search model with multi-worker firms, constant exogenous quit rate. *Notes:* The figure depicts hiring, layoff, and quit rates as a function of the firm-level quit rate for a search model with multi-worker firms and a constant, exogenous quit rate, $\overline{q}$, faced by all firms. See text for model details.

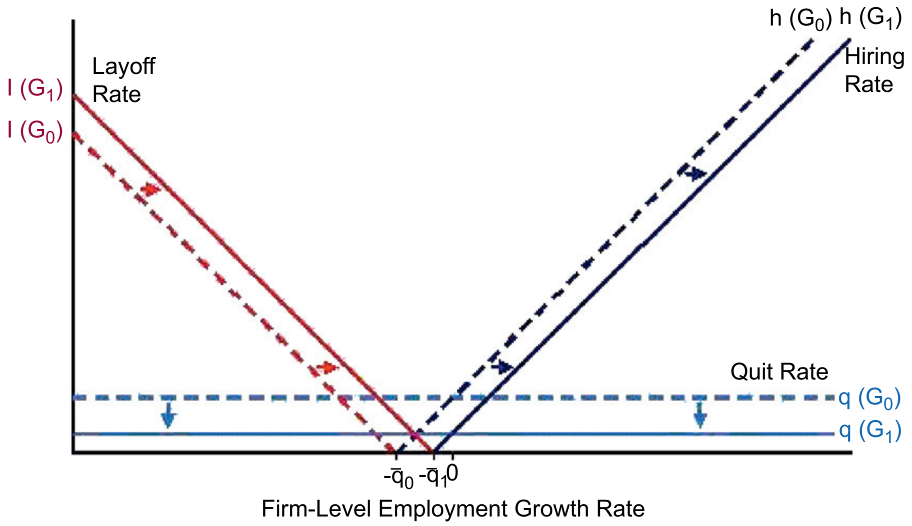

Fig. 4. Implied worker flows from a search model with multi-worker firms, time-varying exogenous quit rate. *Notes:* The figure depicts hiring, layoff, and quit rates as a function of the firm-level quit rate for a search model with multi-worker firms and a exogenous quit rate, $\overline{q}$, that varies with aggregate conditions, G, and is faced by all firms. See text for model details.

2.2. *Relaxing the iron link*

There are several ways to relax the iron link feature of MP-style models. If we exogenously vary the quit rate in the CHW model, we obtain the implications shown in Fig. 4. As the quit rate varies, the kink point moves and the layoff and hires relations shift accordingly. Specifically, a fall in the quit rate from $q(G_0)$ to $q(G_1)$ causes the cross-sectional hiring and layoff relations to shift rightward. That is, the fall in the quit rate creates an environment where employers require fewer hires when expanding and more layoffs when contracting to achieve a given growth rate. More generally, if the quit rate varies systematically with labor market slack, then so do the cross-sectional relations for hires and layoffs. This insight applies in more complex models as well.

Models with endogenous quit behavior deliver other interesting implications. As discussed in the introduction, the model of Faberman and Nagypál (2008) implies that quit rates decline with employer growth rates in the cross section. Workers are more likely to abandon struggling employers because they pay lower wages and cannot match outside offers from more profitable employers. Inspecting Figs. 3 and 4, it is apparent that a nonlinear quit relation implies nonlinear relations for one or both of hires and layoffs as well. Somewhat paradoxically, weaker employers face greater needs for replacement hiring to offset, at least partly, a greater attrition rate. Thus, the model of Faberman and Nagypál can deliver a negative slope in the hires relation over some range. In the model of Barlevy (2002), employers post fewer vacancies when aggregate conditions are weak. As a result, poorly matched employees encounter new job opportunities at a slower rate, and they quit less frequently. This implication of the Barlevy model provides an explanation for the downward shift in the quit rate in Fig. 4 and the resulting shifts in the layoff and hiring relations.

Models that feature learning about match quality as in Jovanovic (1979) yield additional insights. Under weak conditions, these models imply that employment relationships dissolve at a rate that declines with match duration. A newly hired worker is more likely to quit because he learns a job is not to his liking, or to be fired because his employer learns he cannot perform. Naturally, the proportion of new employees tends to rise with an employer's expansion rate. Thus, learning about match quality can cause quits and layoffs to rise with the growth rate of employment at expanding employers. Learning also leads to additional separations at shrinking employers when recent replacement hires do not work out. More generally, learning about match quality implies that worker flows beget further worker flows, as stressed by Hall (1995), Pries (2004), and Pries and Rogerson (2005).

The lesson of this discussion is that the stark relations depicted in Figs. 3 and 4 are too simple to fully capture the patterns in the data. Nevertheless, we think Figs. 3 and 4 are useful starting points for two reasons. First, they provide a straightforward exposition of the links between worker flows and establishment-level growth in a prominent class of search models. We will investigate how closely the data conform to the relations exhibited in Figs. 3 and 4. Second, our discussion provides guidance for formulating statistical models that relate worker flows to employer growth rates.

2.3. Implications for aggregate outcomes and the relationship to cross-sectional behavior

To draw out the aggregate implications of the iron link relation and the other theoretical effects discussed above, express the aggregate hiring rate as

$$H_t = \sum_g f_t(g) h_t(g) \tag{3}$$

where $h_t(g)$ is the mean hiring rate for establishments with growth rate g at time t, and $f_t(g)$ is the corresponding share of employment with growth rate g at t. This equation implies that movements in the aggregate hiring rate arise from changes over time in the cross-sectional relationship between hires and establishment growth rates, shifts in the growth rate distribution, and interactions between the two. Analogous remarks apply to separations, quits and layoffs. Of course, Eq. (3) is simply an accounting identity. Moving beyond the identity requires behavioral models of the micro relationships between worker flows and employer growth rates.

Consider, for example, the CHW model with its time-invariant iron link between worker flows and establishment growth. Substituting the behavioral relations shown in Fig. 3 into (3) yields the following expressions for aggregate rates of hires, layoffs, and quits:

$$\begin{aligned}
\overline{H}_t &= \sum_g f_t(g) \overline{h}(g),\\
\overline{L}_t &= \sum_g f_t(g) \overline{l}(g),\\
\overline{Q}_t &= \sum_g f_t(g) \overline{q} = \overline{q}, \ \forall t
\end{aligned} \tag{4}$$

In the empirical work below, we fit $\overline{h}(g)$, $\overline{l}(g)$, and $\overline{q}(g)$ relations using JOLTS micro data pooled over the 2001 to 2010 period. In doing so, we allow the quit rate to vary with employer growth, and we let the data freely determine the kink points, if any, in the cross-sectional relations. We also allow for hires in excess of job creation and separations in excess of job destruction. Even under these relaxed conditions, Eq. (4) preserves a key aggregate implication of the iron link: fluctuations in aggregate worker flows arise entirely from movements in the cross-sectional distribution of establishment growth rates. We will evaluate how well this implication describes the behavior of aggregate worker flows.

More generally, the cross-sectional behavioral relations vary over time, and we write $\tilde{h}_t(g)$, $\tilde{l}_t(g)$, and $\tilde{q}_t$, for the hiring, layoff, and quit relations, respectively, in period t. Proceeding as before and replacing the time-invariant relations in (4) with $\tilde{h}_t(g)$, $\tilde{l}_t(g)$, and $\tilde{q}_t$ yield the corresponding aggregate flow rates. When the cross-sectional behavioral relations vary over time, movements in the establishment-level growth rate distribution no longer suffice to fully account for fluctuations in aggregate worker flows. Nevertheless, we can still obtain informative characterizations of the aggregate flows in terms of statistical models for $\tilde{h}_t(g)$, $\tilde{l}_t(g)$, and $\tilde{q}_t$. Moreover, we can combine these models with data on $f_t(g)$ to construct synthetic measures of aggregate worker flows outside the period covered by JOLTS data.

Fig. 4 illustrates a case where the cross-sectional relations exhibit iron-link behavior in any given period, but they shift up and down over time with the aggregate quit rate. In this case, the behavioral relation for the hires rate takes the form $\tilde{h}_t(g) = \overline{h}(g) + X_t\beta$, where X is a vector of indicators for aggregate labor market conditions and β is a parameter vector that governs the size of the upward and downward shifts in the cross-sectional hires relations. Analogous remarks apply to the cross-sectional relations for separations, layoffs, and quits. We investigate statistical models of this form and evaluate their ability to account for the cross-sectional and aggregate behavior of worker flows. We also investigate more flexible models that allow the shape of the cross-sectional relations to vary systematically with aggregate conditions.

3. Data and measurement

We now turn to the description of the two data sources used and describe the key methodological concepts for the analysis.

3.1. Data sources

This study relies on two micro data sources, Business Employment Dynamics (BED) and the Job Openings and Labor Turnover Survey (JOLTS), both produced by the BLS. The BED contains longitudinally linked administrative records for all businesses covered by state unemployment insurance agencies—virtually a census of nonfarm private business establishments. The data are quarterly and include employment and payroll for each establishment plus information on industry, location, and whether the establishment belongs to a multi-unit firm. The BLS uses the BED to produce quarterly statistics on gross job creation and destruction from 1992, although micro data exist back to 1990.[4] Our BED micro data run from 1990Q2 through 2010Q2. Data access restrictions preclude our use of BED data for Connecticut, Florida, Massachusetts, Michigan, Mississippi, New Hampshire, New York, Pennsylvania, and Wyoming. Time-series data on job creation and destruction rates generated from our version of the BED closely mimic the published series that cover all states.

The JOLTS samples about 16,000 establishments each month and includes data on employment in the pay period covering the 12th of the month. Establishments report hires, quits, layoffs, and other separations (deaths, retirements, and intra-firm transfers) over the course of the month. For quits, the establishments identify employees who left voluntarily (excluding retirements and intra-firm transfers). For layoffs, the establishments identify involuntary separations initiated by the employer.[5] The survey begins in December 2000 and covers the nonfarm economy. Our JOLTS micro data run from January 2001 through June 2010.

To construct quarterly worker flows at the establishment level, we require observations in all three months of the quarter. Dropping observations that violate this requirement reduces the number of establishments in our JOLTS sample by about 12%. This sample restriction produces slightly lower aggregate worker flow rates, but it does not alter their cyclical patterns. We also address other measurement issues related to the JOLTS data: timing differences in the measurement of worker flows and employment, the construction of sample weights at a quarterly frequency, and imputed worker flow rates for opening and closing establishments. The latter are covered by the BED but are not captured in the JOLTS sample frame. The appendix (available in the supplemental electronic files for this paper) explains in detail how we address these matters. Our final sample contains over 277,000 establishment-quarter observations.

3.2. The cross-sectional distribution of establishment growth rates

We compute employment growth as the difference between employment in the third month of the current quarter and the third month of the previous quarter, and we divide by the simple mean of current and previous employment to obtain a rate. (We use the same average of current and previous employment to compute worker flow rates.) This approach yields consistent aggregation and ensures that all growth rates are bounded, with entry and exit corresponding to values of $+2$ and -2. Given the comprehensive nature of the BED, we compute the cross-sectional distribution of employment growth rates directly from the micro data without need to adjust for sample weights. We focus on employment-weighted outcomes throughout the paper, unless noted otherwise.

Fig. 5 displays kernel density estimates of the establishment-level growth rate distribution in 2006Q1–2006Q4, a period of expanding aggregate employment, and 2008–2009, a period of sharp contraction. There is a clear leftward shift of the growth rate distribution from 2006 to the 2008–2009 period. Table 1 reports summary statistics for the growth rate distribution in selected expansion and contraction periods. Establishments with steady employment levels over the quarter account for 13.9–16.1% of aggregate employment, depending on time period. Establishments that grow or shrink by more than 10% in the quarter account for 31% of employment in 1991, 29% in 1998–1999, and 26% in 2006 and 2008–2009. This evolution towards a more compressed growth rate distribution is also apparent in the behavior of aggregate worker flows.

3.3. Measuring aggregate worker flows

To measure aggregate worker flow rates, we combine JOLTS-based estimates of mean worker flow rates by growth rate bin with BED-based measures of the growth rate distribution. This method exploits identities of the sort described by

[4] For more details on the BED, see Spletzer et al. (2004). The BLS does not publish job flow statistics for 1990–1991 because of issues related to administrative changes during that period. We follow Faberman (2008b) to address those changes.

[5] The JOLTS survey instructions for layoffs and discharges include the following examples: layoffs with no intent to rehire, layoffs lasting more than 7 day, discharges resulting from mergers, downsizing, or closings, firings or other discharges for cause, terminations of permanent or short-term employees, and terminations of seasonal employees (whether or not they are expected to return next season). For more details on the JOLTS, see Clark and Hyson (2001), Faberman (2008a), and Davis et al. (2010c). Details on recent revisions to JOLTS methodology are available at http://www.bls.gov/jlt/methodologyimprovement.htm.

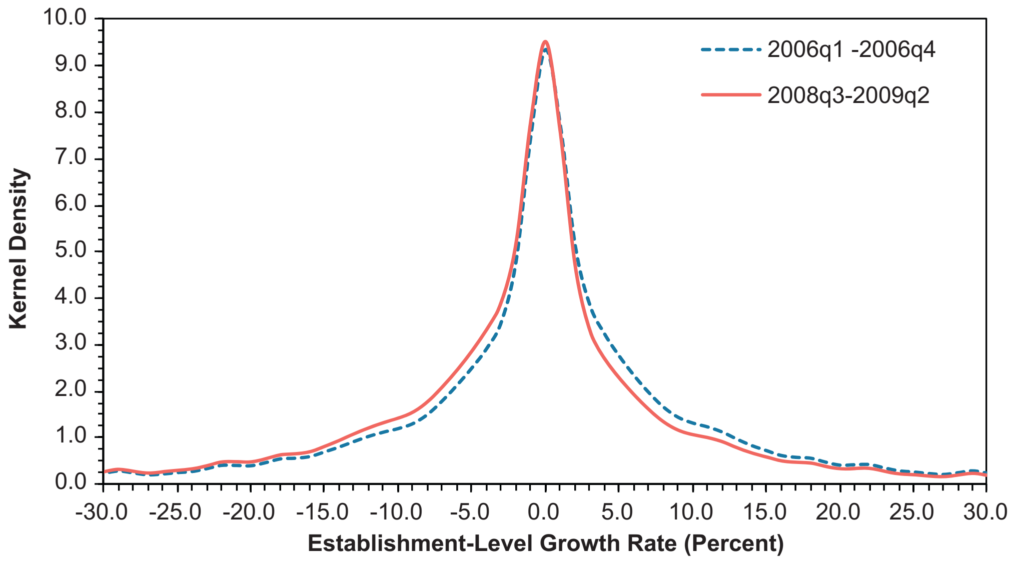

Fig. 5. The cross-sectional distribution of establishment-level growth rates.
Source: Authors' tabulations using BED establishment data. Estimates are employment-weighted kernel density functions of establishment-level growth rates.

Table 1
Cross-sectional distribution of establishment-level growth rates, selected periods.
Source: Authors' tabulations using BED establishment-level data for the indicated time periods. Table entries report employment shares in the indicated growth rate categories. The last row reports the average growth rate of aggregate employment in the indicated periods.

Fraction of employment at	1991	1998–1999	2001Q2–2003Q1	2006	2008Q3–2009Q2
Establishments with contractions $>10\%$, including closings	16.0	14.0	14.5	12.6	14.0
Establishments with contractions $\leq 10\%$	27.4	26.9	29.3	28.0	30.8
Establishments with no net change	14.3	13.9	14.8	15.5	16.1
Establishments with expansions $\leq 10\%$	27.4	30.0	28.0	30.7	27.4
Establishments with expansions $>10\%$, including openings	14.8	15.2	13.4	13.2	11.6
Average quarterly growth rate during period (%)	−0.35	0.64	−0.43	0.43	−1.59

Eq. (3). We use 195 bins that partition the full range of feasible growth rates, with narrower bins near the mode of zero growth. In defining bins, we allow for mass points at −200%, 0%, and 200% growth corresponding to exit, no change, and entry, respectively. Letting $w_t(g)$ denote the mean worker flow rate for bin g in quarter t, we measure aggregate worker flow rates as

$$W_t = \sum_g f_t(g) w_t(g) \tag{5}$$

Because our JOLTS sample covers continuing establishments only, we do not have JOLTS-based worker flow rates for exits and entrants. Thus, we impute worker flow rates for entrants and exits when implementing (5). See the appendix for details. We prefer the aggregate worker flows computed according to (5) by combining BED and JOLTS data to the published JOLTS data, because our approach encompasses worker flows at exits and entrants, and because the BED provides a more accurate measure of the cross-sectional growth rate density. See Davis et al. (2010c) for additional discussion and analysis on this point.

4. Worker flows in the cross section and over time

Guided by the theoretical discussion in Section 2, we specify statistical models of how worker flows vary with employer growth in the cross section and how the cross-sectional relations move over time. We fit the models to establishment-level data and asses them in terms of cross-sectional fit, ability to replicate the time-series behavior of aggregate worker flows, and the marginal explanatory power of model-implied values for aggregate worker flows after conditioning on business cycle indicators. We also use the estimated statistical models to evaluate certain implications of the theoretical models.

4.1. Empirical specifications

Our first specification treats hires, separations, layoffs, and quits as time-invariant functions of establishment-level growth rates. Specifically, for each worker flow rate we regress the establishment-level observations on a vector of dummy variables for the 195 growth rate bins:

$$w_{et}(g) = \alpha(g) + \varepsilon_{et}(g) \tag{6}$$

where e indexes establishments, g indexes growth rate bins, and t indexes quarters. Fitted values in (6) given by $\hat{w}^D(g) = \hat{\alpha}(g)$ describe the average cross-sectional worker flow relations in our JOLTS sample. This "fixed cross section" specification is consistent with the iron link feature of MP models, but it is flexible enough to accommodate learning about match quality as in Pries and Rogerson (2005) and the abandon-ship effect in Faberman and Nagypál (2008). Note that a strict MP-type iron link implies a perfect fit for (6). We examine R-squared values for fitted versions of (6) to quantify how closely the data conform to this implication. We also examine the shape of the fitted relationships to gauge whether and how closely they match the implications of various theoretical models.

Recall that quit rates, and therefore hiring and separation rates, rise and fall in a pro-cyclical manner in the model of Barlevy (2002). To accommodate such behavior, our "baseline" specification relaxes (6) to let the cross-sectional relations shift up and down as functions of business cycle indicators:

$$w_{et}(g) = \alpha(g) + \beta_1 G_t^+ + \beta_2 G_t^- + \beta_3 \Delta G_t + \beta_4 JF_t + \varepsilon_{et}(g) \tag{7}$$

where G_t is the growth rate of aggregate employment, $G_t^+ = \max\{0, G_t\}, G_t^- = \min\{0, G_t\}$, $\Delta G_t = G_t - G_{t-1}$ is an accelerator term and JF_t is the job-finding rate calculated from Current Population Survey data on unemployment by duration.[6]

To let the cross-sectional relations respond to business cycle conditions in more complicated ways, we extend the baseline specification by adding terms that involve interactions between the cycle indicators and the establishment-level growth rates. Specifically, we introduce a set of five indicator variables, $I(g)$, for establishment-level growth rates less than or equal to -10%, greater than -10% but less than zero, exactly zero, positive but less than 10%, and greater than or equal to 10%. Thus, our "flexible" specification is given by

$$w_{et}(g) = \alpha(g) + \beta_1 G_t^+ + \beta_2 G_t^- + \beta_3 \Delta G_t + I(g)\delta_1 G_t + I(g)\delta_2 JF_t + \varepsilon_{et}(g) \tag{8}$$

Specification (8), unlike (7), allows the worker flow response to aggregate conditions to differ among establishments based on how rapidly they grow or shrink.

4.2. Worker flows and employer growth in the cross section

Fig. 6 displays worker flow relations estimated from the fixed cross-section specification (6). The figure shows clear similarities to the theoretical relations in Fig. 3. For example, the hiring relation exhibits a hockey-stick shape similar to the one implied by MP models. There are also clear departures from the implications of MP models. First, hires rise more than one-for-one with job creation to the right of zero. As discussed in Section 2, this pattern suggests that a higher incidence of recently formed matches at more rapidly growing establishments leads to higher rates of learning about match quality, generating higher separation rates, and more need for replacement hires. Second, hires occur at all growth rates, another piece of evidence that points to replacement hiring. Third, while there is a pronounced kink in the hiring relation, it occurs at zero growth rather than the mean quit rate. Finally, the hires rate declines with establishment growth rates over much of the range to the left of zero. This pattern is consistent with an abandon-ship effect in which more rapidly declining employers face a greater need for replacement hiring.

Many of these same effects appear in the separations relation, which is nearly a mirror image of the hires relation. For example, separation rates rise with job creation rates to the right of zero, in line with the view that rapidly growing employers experience high turnover rates among recent hires. To the left of zero, separations rise more rapidly than job destruction, in line with the abandon-ship effect and a greater need for replacement hires at more rapidly shrinking employers.

Turning to the breakdown of separations into quits and layoffs, several other patterns emerge. Layoffs rise sharply with job destruction, and they dominate the employment adjustment margin among rapidly shrinking employers. In contrast, quits account for a larger share of separations at establishments that shrink by less than 20% in the quarter—and at growing establishments. In the appendix, we display a version of Fig. 6 that covers a wider range of growth rates. The zoomed-out version of Fig. 6 reveals even more clearly that quit rates top out at about 20% per quarter, and that layoffs are the primary margin of employment adjustment at rapidly contracting establishments. Quit and layoff rates, like the hiring rate, are smallest at employers with stable employment levels.[7]

The patterns in Fig. 6 differ from the cross-sectional relationships found by Abowd et al. (1999) using the establishment-level data for France. They find that hiring is the primary margin of employment adjustment at the establishment level, even for contracting establishments. This interesting point of contrast between their results and ours may reflect differences between France and the United States in the nature of labor adjustment. The topic warrants investigation in future work.

[6] We use standard methods to calculate the job-finding rate from data on unemployment by duration. For details, see Davis et al. (2010b). We use the published data from Current Employment Statistics to compute the growth rate of aggregate employment.

[7] For visual clarity, Fig. 6 omits the cross-sectional relation for other separations (deaths, retirements, and intra-firm transfers). They are very small on average, amounting to about a half percent of employment, and somewhat greater at rapidly contracting establishments.

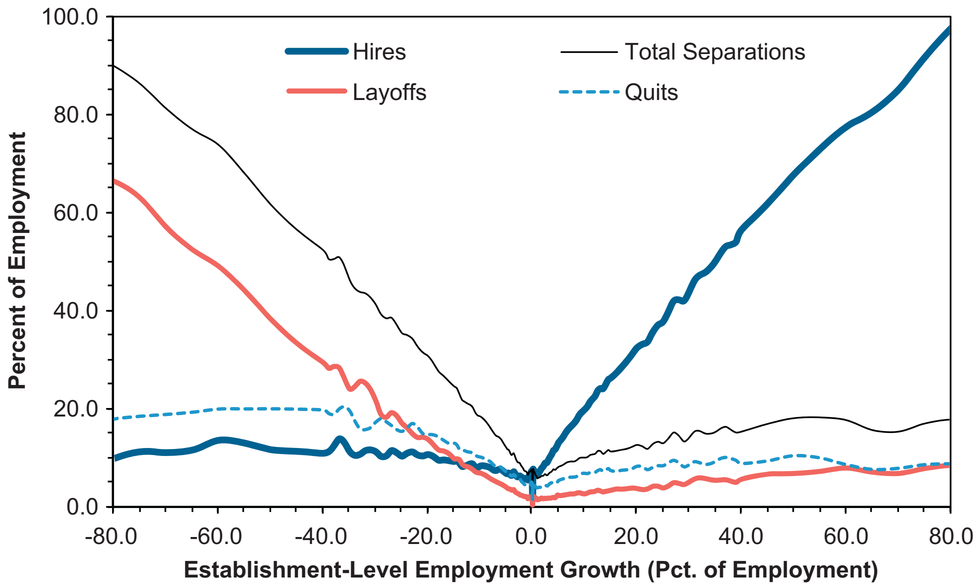

Fig. 6. Worker flow rates as a function of establishment-level growth.
Source: Authors' calculations using JOLTS establishment data pooled over 2001Q1–2010Q2. Estimates are employment-weighted averages of the establishment-level growth rates within intervals. Save for the endpoints and zero growth point; estimates are smoothed using a 5-bin moving average.

Table 2
R-squared values for regression models fit to establishment-level data, 2001Q1–2010Q2.

	Fixed cross-section specification	Augmented fixed cross-section	Augmented baseline specification	Augmented flexible specification
Hiring rate	0.542	0.543	0.545	0.588
Separation rate	0.507	0.509	0.511	0.556
Quit rate	0.159	0.162	0.170	0.239
Layoff rate	0.463	0.466	0.467	0.521

Notes: Table entries report R-squared values for worker flow rate regressions fit to establishment-level JOLTS data. The fixed cross-section specification contains dummy variables for 195 growth rate bins. The augmented version adds 192 slope terms, one for each growth rate bin excluding those for exit, exit and no employment change. The augmented baseline specification adds four time-varying business cycle indicators, and the augmented flexible specification also includes terms that allow for interactions between the cycle indicators and five dummy variables for broad establishment growth rate categories. See text for details. Regressions are fit by weighted least squares using sample weights and employment weights.

Table 2 presents regression R-squared values for several specifications fit to the establishment-level JOLTS data. A potential concern about our specifications is that the 195-bin partition is too coarse to adequately approximate the underlying relationships of worker flows to employer growth rates. To investigate this concern, we augment each specification by adding 192 bin-specific slope terms. (There is no reason to introduce slope terms for the zero-width bins at -2, 0, and $+2$.) Comparing the first two columns in Table 2 reveals, however, that the bin-specific slope terms yield very modest gains in the regression fit of the fixed cross-section specification. For the sake of simplicity and parsimony, we drop the bin-specific slope terms in the rest of the paper.

As discussed above, the strict iron-link feature of MP-type models implies a perfect fit for the fixed cross-section specification. We do not take this implication literally, because MP models deliberately abstract from many real-world features that play a role in worker flows. Still, it is interesting to ask how fully employer growth alone accounts for establishment-level variation in worker flows. According to Table 2, the fixed cross-section specification accounts for 54% of establishment-level variation in hiring rates and 51% for separation rates. It accounts for 47% of the variation in layoff rates and 16% of quit rate variation. These R-squared values fall well short of a perfect fit, but we are somewhat surprised by the extent to which the fixed cross-section model accounts for establishment-level variation in hires, separations, and layoffs. In this regard, it is worth mentioning some of the many factors omitted from the model. In particular, it contains no controls for industry, employer size or age, wages, job tenure, education, other worker characteristics, the longer-term growth trajectory of the employer, local labor market conditions, and aggregate labor market conditions. Despite these omissions, this simple specification accounts for more than half of the variation in hiring and separation rates across employers. Clearly, the employer growth rate is a major proximate determinant of worker flows.

The remaining columns of Table 2 show the gains in fit from introducing cycle indicators and allowing for interactions between the cycle indicators and establishment-level growth rates. The baseline specification, which adds cycle indicators only, yields very modest gains in fit. The flexible specification, which also includes the interaction terms, improves the fit by several percentage points for each type of worker flow. Evidently, the relationship of worker flow rates to employer growth rates varies with aggregate labor market conditions. Table 2 also shows that even the flexible specification accounts for only about a quarter of the cross-sectional variation in establishment-level quit rates.

The large role for establishment-level variation in quit rates conditional on own growth rate is an interesting finding, but it need not matter for movements in aggregate quit rates. To see this point, consider a multi-worker MP model with quit rates that vary exogenously among establishments. In particular, suppose the idiosyncratic component of the establishment-level quit rate is drawn from a common, time-invariant distribution. This assumption generates dispersion in worker flow rates among establishments with the same employment growth rate. Suppose, in addition, that the common component of quit rates varies with aggregate conditions as in our earlier discussion of Fig. 4. Under these assumptions, there is dispersion in worker flow rates among establishments with the same employment growth rate, but common factors drive the average shape and location of the cross-sectional worker flow relations.

For the analysis that follows, what matters is how well our statistical specifications capture variation in worker flow rates at the level of growth rates bins crossed with time periods. These bin-quarter outcomes provide building blocks for aggregation and the construction of our synthetic worker flow series. To obtain the bin-quarter outcomes, we compute the employment-weighted worker flow rates for all 195 bins by quarter. To evaluate how well our statistical models capture the bin-quarter variation in worker flow rates, we estimate analogs of (6)–(8) at the bin-quarter level of aggregation.

We summarize the main results of our regressions at the bin-quarter level here and report the full results in the appendix. The fixed cross-section specification accounts for 93% of the bin-quarter variation in the hiring rate and 92% for the separation rate. It accounts for 88% of the bin-quarter variation in layoff rates and 65% for the quit rate. The baseline and flexible specifications yield very modest improvements in fit for hires, separations, and layoffs. The gains in fit are larger for the quit rate, with an R-squared value of 69% for the flexible specification. The flexible specification yields modest gains in fit relative to the baseline specification for quits and tiny gains for hires, separations, and layoffs. That is, except perhaps for quit rates, the R-squared metric provides little evidence that the shapes of the cross-sectional relations vary systematically with the cycle indicators. The success of our statistical specifications in accounting for bin-quarter variation in worker flow rates bodes well for their ability to capture the behavior of aggregate worker flows.

4.3. *Aggregate behavior implied by the fixed cross-section specification*

We now investigate how well our cross-sectional statistical models account for the behavior of aggregate worker flows. To start, we compare the actual worker flows to the aggregate flows implied by the fixed cross-section specification. To generate the implied flows, we replace the $w_t(g)$ functions in (5) with $\hat{w}_t^D(g) = \hat{\alpha}(g)$ obtained by fitting the fixed cross-section model to JOLTS data from 2001Q1 to 2010Q2. Plugging in the BED data for $f_t(g)$ and the $\hat{w}_t^D(g)$ functions yields the model-implied worker flow rates.

Fig. 7 plots seasonally adjusted versions of the model-implied rates alongside the actual worker flow rates.[8] As seen in the figure, the layoff series implied by the fixed cross-section model captures much of the time-series variation in the actual layoff rate. The fixed cross-section model fares are less well in replicating the actual hires and separations rate, and it completely fails to replicate the actual quit rates. In fact, the quit rate series implied by the fixed cross-section model is essentially a flat line for most of the period. It also predicts a rise in the quit rate during the 2008–2009 downturn, which is nothing like the behavior of actual quit rates in this period.

Table 3 quantifies the extent to which the fixed cross-section model replicates movements in the actual worker flow rates. (Like Fig. 7, Table 3 includes results for other specifications that we discuss below.) The first column of Table 3 reports the standard deviation of the actual worker flow rates. The remaining columns in the top panel report the root mean squared value of the difference between the model-implied and actual rates. For hires, the rate implied by the fixed cross-section model accounts for 36% of the time-series variation in the actual hires rate, computed as 100 times [1–(0.872/1.366)]. The correlation between the model-implied and actual hiring rate is 0.94. For layoffs, the model-implied rate captures 41% of movements in the actual layoff rate, and the correlation between the two series is 0.82. The model performs less well in replicating the behavior of the separations rate, and it captures very little of the time-series variation in the quit rate. We turn next to the cyclical behavior of the cross-sectional worker flow relations.

4.4. *Shifts in the cross-sectional relations over time*

Before proceeding to the baseline and flexible specifications, we fit the fixed cross-section specification separately for three periods: 2001Q2–2003Q1 (a mild recession followed by a prolonged "jobless recovery"), 2006Q1–2006Q4 (an expansion period) and 2008Q3–2009Q2 (a deep recession). Each period covers four or eight consecutive quarters to ensure that seasonal effects do not drive the estimation results. For this exercise, we restrict attention to quarterly growth rates

[8] We seasonally adjust the model-implied and actual worker flow rates using the Census X-11 procedure. We also drop the time series observations for 2001Q1 and Q2, because the JOLTS sample is much smaller in these early quarters—about 2700 observations per quarter as compared to more than 6300 in other quarters.

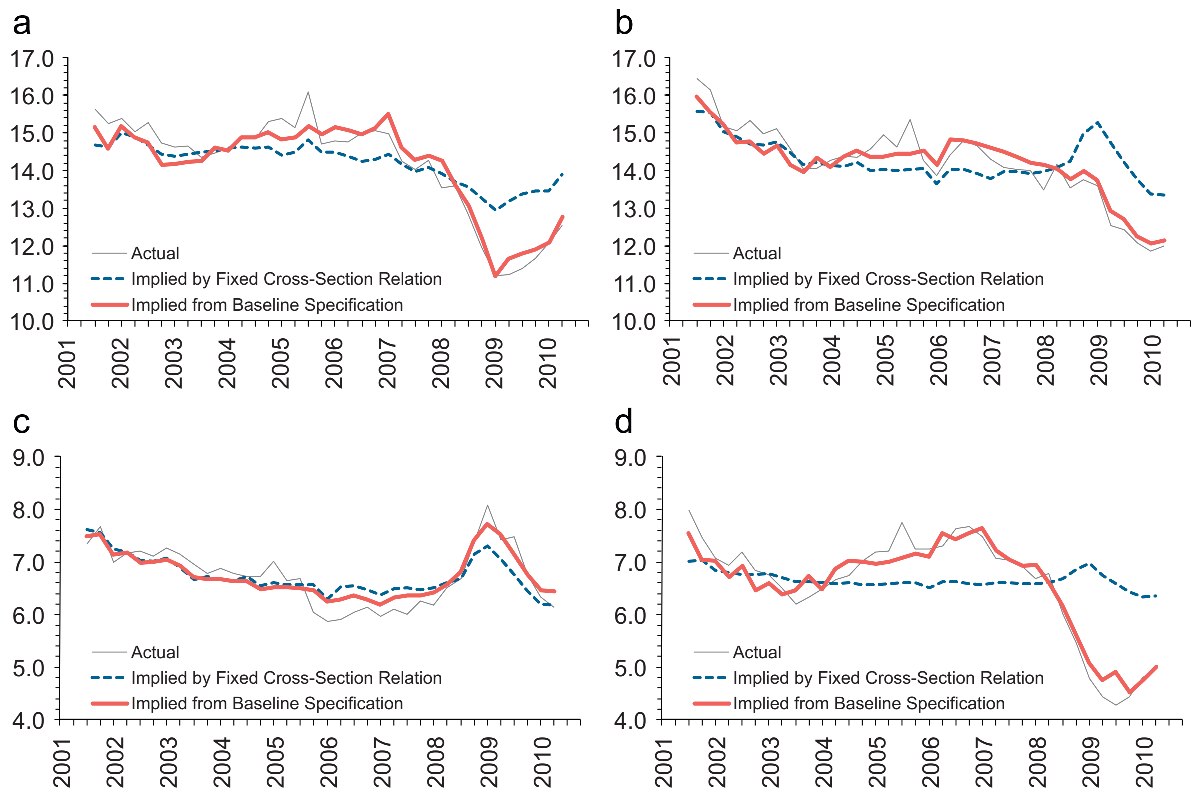

Fig. 7. Aggregate flows compared to flows generated by alternative statistical models. (a) Hiring Rate, (b) Separation Rate, (c) Layoff Rate and (d) Quit Rate. *Source:* Authors' calculations using estimates of worker flow-growth relationships derived from the JOLTS establishment data interacted with growth rate densities derived from BED data for 2001Q3–2010Q2. See text for details of the methodologies. Estimates are seasonally adjusted.

Table 3
Model-implied worker flow rates compared to actual worker flow rates, aggregate time series data from 2001Q3 to 2010Q2.

	Actual series	Implied by fixed cross-section	Implied by baseline specification	Implied by flexible specification
	Standard deviation	*Root mean squared value: actual series minus model-implied series*		
Hiring rate	1.366	0.872	0.375	0.373
Separation rate	1.052	0.862	0.355	0.352
Quit rate	1.018	0.986	0.264	0.242
Layoff rate	0.564	0.330	0.232	0.218
		Correlation of implied series with actual series		
Hiring rate		0.943	0.966	0.964
Separation rate		0.559	0.949	0.946
Quit rate		0.201	0.971	0.971
Layoff rate		0.824	0.924	0.928

Notes: All results in this table pertain to seasonally adjusted time series. Unadjusted data yield broadly similar results. See text for details of estimation and aggregation methods.

from −30% to 30% to focus on bins with ample observation counts. Establishments in this growth rate range account for about 90% of aggregate employment.

Fig. 8 displays the results. The layoff relation displays considerable stability over time. Rapidly shrinking establishments rely more heavily on layoffs (conditional on own growth) during the severe recession of 2008–2009, but the layoff relation is nearly time invariant throughout the rest of the growth rate range. In other words, there is a strong element of iron-link behavior in the cross-sectional layoff relation. In marked contrast, the quit relation shifts up and down as aggregate employment expands and contracts. Conditional on own-establishment growth, the quit rate is several percentage points lower in 2008–2009 than in the other two periods. This pattern holds for the entire growth rate range and is most pronounced at rapidly shrinking establishments. Moreover, for shrinking establishments there is a clear ordering of the cross-sectional quit relations over the cycle: quit rates are highest in the 2006 expansion period, somewhat lower in the weak labor market early in the decade, and much lower in the severe recession of 2008–2009. Extending our earlier metaphor, workers abandon ship at higher rates at more rapidly contracting employers, but they are much more likely to go down with the ship when stormy seas prevail.

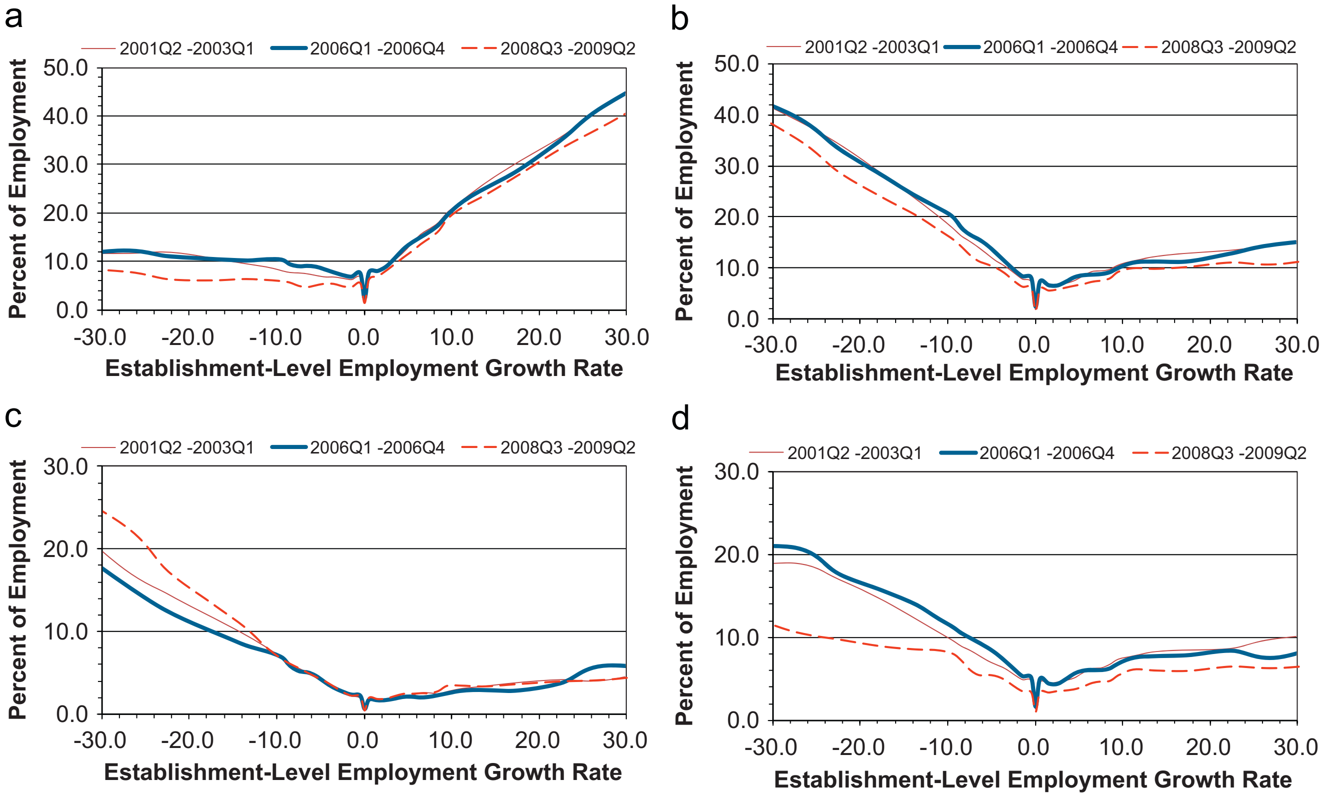

Fig. 8. Worker flows and vacancies as a function of establishment-level growth, selected periods. (a) Hiring Rate, (b) Separation Rate, (c) Layoff Rate and (d) Quit Rate.
Source: Authors' calculations using JOLTS establishment data pooled over the listed periods. Estimates are employment-weighted averages of the establishment-level growth rates within intervals that increase in width with the absolute value of the growth rate. Save for the zero growth point, reported estimates are smoothed using a 3-bin moving average.

The separation relation largely inherits the cyclical behavior of the quit relation, although there are partly offsetting shifts in the underlying quit and layoff relations at rapidly shrinking establishments. Otherwise, the shifts in the separation relation look smaller only because the vertical scale covers a larger range. The cross-sectional hiring relation exhibits more stability over time than the separation relation, but it is less stable than the layoff relation. In particular, employers face less need for replacement hires in weak labor market conditions, and this effect is stronger at shrinking employers.

Summing up, Fig. 8 shows that the cross-sectional relations shift over time in a systematic cyclical manner. The quit relation, in particular, is highly sensitive to aggregate labor market conditions.

4.5. *Results for the baseline and flexible specifications*

To evaluate the performance of the baseline and flexible specifications, we proceed in the same manner as before with the fixed cross-section specification. That is, we estimate the specifications (7) and (8) over the 2001Q1–2010Q2 period, generate model-implied worker flow rates by plugging the estimated functions into (5), and then compare to the actual worker flow rates. Fig. 7 and Table 3 contain the results. As it turns out, the estimation results for the baseline and flexible specification imply nearly identical worker flow rates. Thus, we omit the worker flow rates implied by the flexible specification in Fig. 7 and focus on rates implied by the simpler baseline specification. See the appendix for plots of the worker flow rates implied by the flexible specification.

Fig. 7 shows that the baseline specification greatly improves on the fixed cross-section model in terms of replicating the actual worker flow rates. The improvement is especially dramatic for the quit rate. The baseline specification captures the large drop in hiring and quit rates during 2008 and 2009 and the subsequent turnaround in the hiring rate. It also captures the broad swings in the quit rate in the first seven years of the decade. The baseline specification yields less improvement for the layoff rate, because shifts in the fixed cross-section specification already account for much of the movements in the layoff rate. However, the baseline specification captures more of the layoff spike in late 2008 and 2009, reflecting the shift away from quits and towards layoffs for contracting establishments seen in Fig. 8. By more accurately tracking quits and layoffs, the baseline model replicates a declining and weakly procyclical total separations rate.[9]

[9] Close inspection of Fig. 7 reveals that the worker flow rates implied by the baseline specification exhibit less high-frequency variation than the actual worker flow rates. In this regard, we remark that the "actual" rates are subject to greater sampling error than the model-implied rates, because estimation of the actual rates entails no pooling across time periods. Recall that the JOLTS sample size is fairly modest, and that a small number of

Table 4
Marginal explanatory power of worker flow rates implied by the fixed cross-section specification, 2001Q3–2010Q2.

	Actual rate regressed on four cycle indicators	**Actual rate regressed on cycle indicators and rate implied by fixed cross section specification**
	R-squared value	*R-squared value [p-value]*
Hiring rate	0.808	0.966 [0.000]
Separation rate	0.652	0.944 [0.000]
Quit rate	0.929	0.961 [0.000]
Layoff rate	0.525	0.880 [0.000]

Notes: The cycle indicators are positive and negative pieces of the aggregate employment growth rate, the change in the growth rate of aggregate employment, and the job-finding rate. The specification used in the rightmost column also includes the aggregate worker flow rate implied by the fixed cross section model. The *p*-value is for the null hypothesis of a zero coefficient on the model-implied worker flow rate. Each regression has 36 quarterly observations covering the period from 2001Q3 to 2010Q2. See text for additional details.

Turning to Table 3, the third and fourth columns show that the baseline and flexible specifications capture most of the time-series variation in the worker flow rates. The baseline specification accounts for 74% of the time-series variation in the hires rate, computed as 100 times $[1-(0.375/1.366)]$, 66% for the separations rate, 74% for the quit rate, and 59% for the layoff rate. The correlation between actual and model-implied flow rates is high in all cases, 0.92 for quit rate implied by the baseline specification and 0.95–0.97 for the other worker flows. The flexible specification yields modest improvements in fit according to the root mean squared value of the discrepancy between actual and model-implied rates but no improvements in correlation.

The results for the baseline specification support for the view that statistical models of the sort depicted in Fig. 4 yield a reasonably accurate accounting of movements in the aggregate worker flow rates. Put differently, by estimating the shape *and cyclical shifts* in the cross-sectional worker flow relations and combining them with the cross-sectional distribution of establishment growth rates, we can account for most of the movements over time in aggregate worker flow rates. We exploit this finding in Section 5 to construct synthetic measures of aggregate worker flow rates before the advent of JOLTS.

4.6. The marginal value of tracking the cross section

Thus far, our aggregate analysis focuses on the extent to which model-implied worker flow rates replicate actual worker flow rates. We now turn the question around and investigate whether tracking the cross section improves our understanding of the aggregate worker flow rates. We proceed as follows. First, we regress each aggregate flow rate on several cycle indicators. We use the same cycle indicators as before: the positive and negative pieces of the aggregate employment growth rate, an accelerator term, and the job-finding rate. The regression *R*-squared value serves as our metric of how successfully the cycle indicators account for time-series movements in the worker flow rates. Second, we expand the regression specification for each worker flow rate to include the rate implied by the fixed cross-section specification, i.e., the rate generated by plugging $\hat{w}_t^D(g) = \hat{\alpha}(g)$ into Eq. (5). Because this specification involves time-invariant cross-sectional relations, all movements in the model-implied rates arise from movements in the cross section of establishment growth rates. We use the incremental *R*-squared contribution to gauge the marginal value of tracking the cross section.

Table 4 reports the results. Column 1 shows that the cycle indicators account for most of the variation in aggregate worker flow rates. *R*-squared values range from 53% for the layoff rate to 93% for the quit rate. Column 2 shows the marginal value of tracking the cross section. The model-implied worker flow rate is highly statistically significant in all cases, and its inclusion yields dramatic improvements in fit. The *R*-squared value jumps from 53% to 88% for layoffs, from 65% to 94% for separations, and from 81% to 97% for hires. The incremental *R*-squared gain of 3% points for the quit rate corresponds to a reduction in the standard error of the residual by more than half. Clearly, the cross section contains a great deal of useful information in accounting for movements in aggregate worker flow rates. We see this result as an important finding, because it says that economic and statistical models of worker flows in the cross section offer the promise of large advances in our understanding of aggregate hires, separations, layoffs, and quits.

4.7. On the quit-layoff distinction

As we have stressed, MP-type models imply a tight, time-invariant link between separations and job destruction. Our results show that such a link exists between layoffs and job destruction but not between quits and job destruction.

(*footnote continued*)
establishments at the extremes of the growth rate distribution account for a disproportionate share of the estimated actual worker flows. Thus, we place little weight on high-frequency movements of the actual flow rates not captured by the model-implied rates.

Our evidence also shows that much of the variation in aggregate layoff rates reflects changes over time in the cross-sectional growth rate distribution interacted with a stable cross-sectional layoff relation. In contrast, movements in the growth rate distribution alone account for little of the variation in aggregate quit rates. Instead, the main story for quits appears to involve worker responses to outside labor market conditions.

These sharply different proximate determinants of quits and layoffs are noteworthy in light of other research on differences in worker outcomes between quits and layoffs. Using Current Population Survey data, Elsby et al. (2010) find that about 90% of laid-off workers flow into unemployment as compared to less than 20% of workers who quit. Earlier studies by Leighton and Mincer (1982), Mincer (1986), and McLaughlin (1990) find a similar pattern using other data sources. Much other research finds that laid-off workers have inferior earnings paths compared to workers who quit. Elsby et al. (2010) also show that higher layoffs account for most of the rise in unemployment inflows in recessions, confirming many previous studies. Theoretical models that abstract from the quit-layoff distinction cannot address these empirical regularities.

We also find that quit rates and separation rates are closely related to employer growth rates in the cross section, and that the behavior of quits and separations varies strongly with aggregate labor market conditions. These aspects of our results are at odds with standard simplifying assumptions in many search models. In particular, many models posit a uniform separation (or quit) rate in the cross section and abstract from forces that link separations and quits to aggregate conditions. In our view, relaxing these assumptions is likely to produce better economic models of worker flows and their connection to unemployment outcomes. Recent theoretical work that endogenizes quits, layoffs and hiring in search models with multi-worker firms includes Veracierto (2009), Schaal (2010), and Trapeznikova (2010). Another issue is whether the empirical findings on the quit-layoff distinction can be accommodated in models with privately efficient separation outcomes. See Hall and Lazear (1984) and McLaughlin (1990, 1991) on this issue.

5. Synthetic data on aggregate worker flows

Our empirical methods and results provide a framework for constructing synthetic data on worker flows before the advent of JOLTS. The key idea is to combine statistical models for the cross-sectional worker flow relations with data on the cross-sectional distribution of establishment growth rates. We employ exactly that approach. Specifically, we use the estimated baseline specification (7) and data on G_t, G_t^+, G_t^-, ΔG_t, and JF_t to construct the time series of estimated cross-sectional relations $\hat{w}_t^B(g)$. We plug these functions into (5) along with BED data on the cross-sectional distribution of establishment growth rates to construct data for the pre-JOLTS period. BED micro data are available from 1990Q2, so our synthetic worker flow series start then. Figs. 1 and 2 plot the resulting synthetic flows through 2001Q2 and actual flows thereafter. We use synthetic rates for the first two quarters of 2001, because the JOLTS sample sizes are much smaller in early 2001.

As seen in Fig. 1, layoff and job destruction rates move together closely. Both series spike sharply in the 1990–1991 recession, exhibit a moderate but prolonged rise in the 2001 recession, and rise very sharply in 2008–2009. The quit rate is strongly procyclical, declining around all three recessions. Fig. 2 shows that hiring and job creation rates also move together. Both series exhibit mild declines during the 1990–1991 recession, a moderate decline during the 2001–2003 period, and a precipitous drop during the 2008–2009 recession. The hiring rate exhibits larger swings over the cycle, reflecting a greater need for replacement hiring during booms when job creation is also high.

Figs. 1 and 2 also show a downward drift in worker and job flow rates in the period covered by our data. This result indicates that U.S. labor markets became less fluid and dynamic over period covered by our data, at least as measured by worker flows and job flows. For example, job creation, hiring, and quit rates are higher during the expansion in the second half of the 1990s than the expansion from 2004 to 2006. It can be difficult to disentangle cyclical and secular movements over a twenty-year period, but we have documented a downward drift in the pace of labor market flows using other data sources, some of which extend back in time to the 1970s and 1980s (see Davis et al., 2006, 2010b).

We carry out two validation exercises for our synthetic worker flow measures. First, we sort the micro data into two broad regions to conduct a cross-region validation exercise. Specifically, we fit the baseline specification to JOLTS data for the Northeast–Mideast region, an aggregate of the standard Census regions for the Northeast and Midwest. We evaluate the own-region performance of the baseline specification as before by quantifying how closely the model-implied rates replicate the actual own-region rates. To conduct the cross-region validation exercise, we combine estimated models based on data for the Northeast–Midwest region with growth rate distributions for the South-West region to generate model-implied rates for the South-West region. We then compare the resulting model-implied rates to the actual rates for the South-West region. In other words, we rely on data for the Northeast–Midwest region to estimate the statistical model used to generate synthetic data for the South-West region. We also reverse the roles of the two regions and repeat the same steps.[10]

[10] Regional versions of the aggregate variables used to estimate our baseline specification are not readily available, so we use national aggregates for this purpose. This substitution of national for regional aggregates is likely to degrade the quality of the resulting model-implied series and cause us to understate the performance of our method for constructing synthetic data. We also note that in generating the cross-validation series, we remove the mean difference between the own-region and cross-region model-implied worker flow rate based upon the fixed cross section distribution model.

Table 5 presents the results for the own-region comparison between actual and model-implied rates and for the cross-region validation exercise. The root mean squared values of the difference between actual and model-implied rates are typically larger when the baseline statistical model is fit using data for the other region. In some cases it is much larger. However, even when based on micro data for the other region, model-implied rates remain highly correlated with actual rates, ranging from 0.79 to 0.96. The appendix shows plots for the full set of region-specific worker flow rates—actual rates and model-implied rates based on own-region and other-region micro data. It is evident in both regions that both of the model-implied rates track the actual series reasonably well. This pattern holds especially for layoffs (which from Table 5 is also the series for which the differences in root mean squared error are the smallest).

In our second validation exercise, we compare the behavior of our layoff rate series to three measures that should, in theory, exhibit similar behavior: the job destruction rate, the inflow rate into unemployment as measured by Current Population Survey (CPS) data on unemployment by duration, and initial claims for unemployment insurance (UI) as a percent of covered employment. We focus on layoffs in this exercise, because conceptually similar series are available from

Table 5
Results of cross-region validation exercises for synthetic worker flows.

	Northeast–Midwest region		**South-West region**	
	Own region	***Cross-region validation***	***Own region***	***Cross-region validation***
	Root mean squared value of actual minus model-implied rate			
Hiring rate	0.558	0.674	0.404	0.600
Separation rate	0.579	0.668	0.356	0.549
Quit rate	0.404	0.481	0.283	0.525
Layoff rate	0.322	0.339	0.242	0.234
	Correlation of actual and model-implied rates			
Hiring rate	0.888	0.842	0.967	0.961
Separation rate	0.865	0.785	0.948	0.880
Quit rate	0.891	0.874	0.973	0.939
Layoff rate	0.863	0.845	0.916	0.918

Notes: "Own Region" results involve a comparison of regional worker flows to flows generated by fitting the baseline statistical model to micro data for the same region. "Cross-Region Validation" results involve a comparison of regional worker flows to flows generated by fitting the baseline statistical model to micro data for the other region. In conducting the Cross Region Validation exercise, we remove a region fixed effect for each worker flow rate. Each regional time series measure has 36 quarterly observations covering the period from 2001Q3 to 2010Q2. See text for additional details.

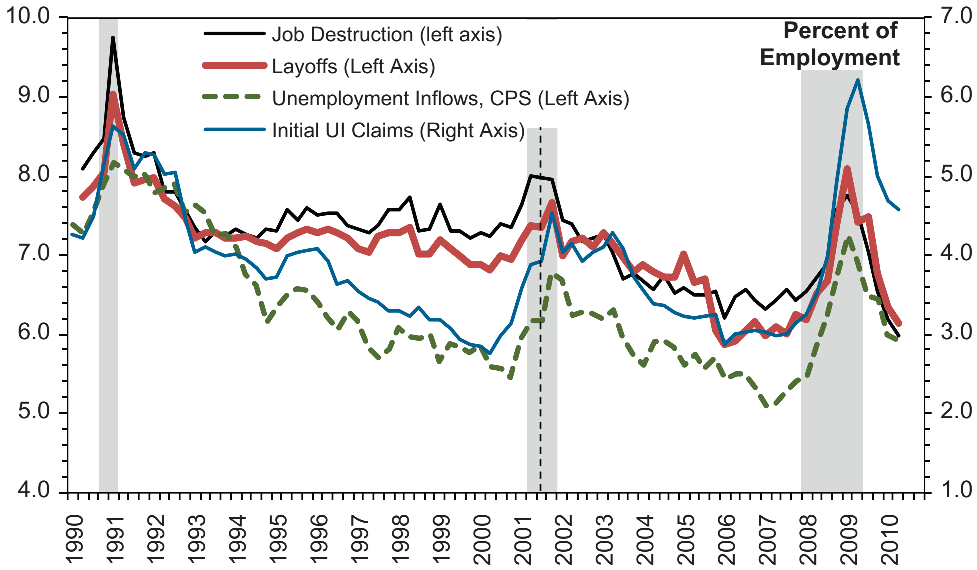

Fig. 9. Synthetic Layoff estimates compared to other job loss data.
Sources: Layoff rates (2001Q3–2010Q2) are authors' calculations using JOLTS establishment microdata weighted to an aggregate value for each quarter using growth rate densities from the BED. Prior to 2001Q3 (to the left of the dashed vertical line), layoff rates are a synthetic series based on our baseline statistical model of worker flows (see text for details). Job destruction rates are authors' tabulations directly from the BED data. Unemployment inflow rates are calculated from the CPS. Initial unemployment insurance claims rates are from published statistics. All estimates are seasonally adjusted. All rates are percentages of employment.

several distinct data sources. Both the layoff and UI claims series capture involuntary separations of workers from jobs. As we remarked above, Elsby et al. (2010) show that most laid-off workers flow into the CPS unemployment pool.

Fig. 9 plots our synthetic and actual layoff rate series alongside the other three measures. The four series exhibit a remarkable degree of co-movement, especially with respect to cyclical fluctuations.

All three series exhibit strong countercyclical behavior and sharp spikes in each of the three recessions covered by our sample period. The most notable departure is that the two unemployment series show greater declines during expansions. Nevertheless, Fig. 9 supports the view that our synthetic layoff estimates capture important features of actual layoff behavior outside the JOLTS sample period.

6. Concluding remarks

We exploit establishment-level data from the JOLTS and BED data to study the relationship between worker flows and job flows in the cross section and over time. To put structure on the empirical analysis, we begin with models that imply a tight link between job flows and worker flows in the spirit of the seminal work by Mortensen and Pissarides (1994). Consistent with these models, we find powerful, highly nonlinear relationships of worker flows to employer growth rates in the cross section. The layoff relation, in particular, exhibits considerable stability over time. We also find much evidence that other economic forces play important roles in the cross-sectional and time-series behavior of worker flows. These forces include learning about match quality and the need for replacement hires, on-the-job search, an abandon-ship effect that yields higher quit rates at struggling employers, and strongly pro-cyclical movements in quit rates even after conditioning on the employer's growth rate.

We develop statistical models for evaluating how well various models and views fit the patterns in the data. Aggregate fluctuations in layoffs are well captured by empirical specifications that impose a tight cross-sectional link between worker flows and job flows. Aggregate fluctuations in quits are not. Allowing the cross-sectional relations to vary with aggregate conditions leads to huge improvements in the ability of the statistical models to account for the aggregate behavior of quits and large improvements for the other worker flows as well. We also show that the cross section contains information that greatly improves our ability to account for movements in aggregate worker flow rates. These findings indicate that economic and statistical models of worker flow behavior in the cross section can significantly enhance our understanding of aggregate hires, separations, layoffs, and quits.

Aggregate hires are much more volatile than aggregate job creation over time. In a cyclical downturn, hires fall because of a decline in job creation rates and because quit rates fall sharply. That is, the strong procyclicality of quits drives a wedge in the aggregate relationship between hires and job creation. The strong procyclicality of quits also helps reconcile the differences in cyclicality between job destruction and separations.

We exploit our statistical models of worker flow behavior in the cross section and historical BED data to construct synthetic JOLTS-like measures of hires, separations, layoffs, and quits back to 1990. In this way, we nearly double the length of the time series on hires, separations, layoffs, and quits available for analysis in future research. While not the focus of the current analysis, these extended series show a downward drift over time in the pace of worker flows. Other sources of data also point to secular declines in the pace of worker flows and job churning activity in the U.S. economy over the past 30 years or more. Investigating the reasons for the secular declines in the pace of job and worker reallocation activity is an important topic for research.

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Appendix A. Supplementary materials

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.jmoneco.2011.10.001.

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