Labor Market Institutions and the Macroeconomy

A Conference Organized by the IAB, Friedrich-Alexander University Erlangen-Nuremberg, and the Kiel Institute for the World Economy

New Evidence on Labor Market Flows and the Hiring Process

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Overview, Part I

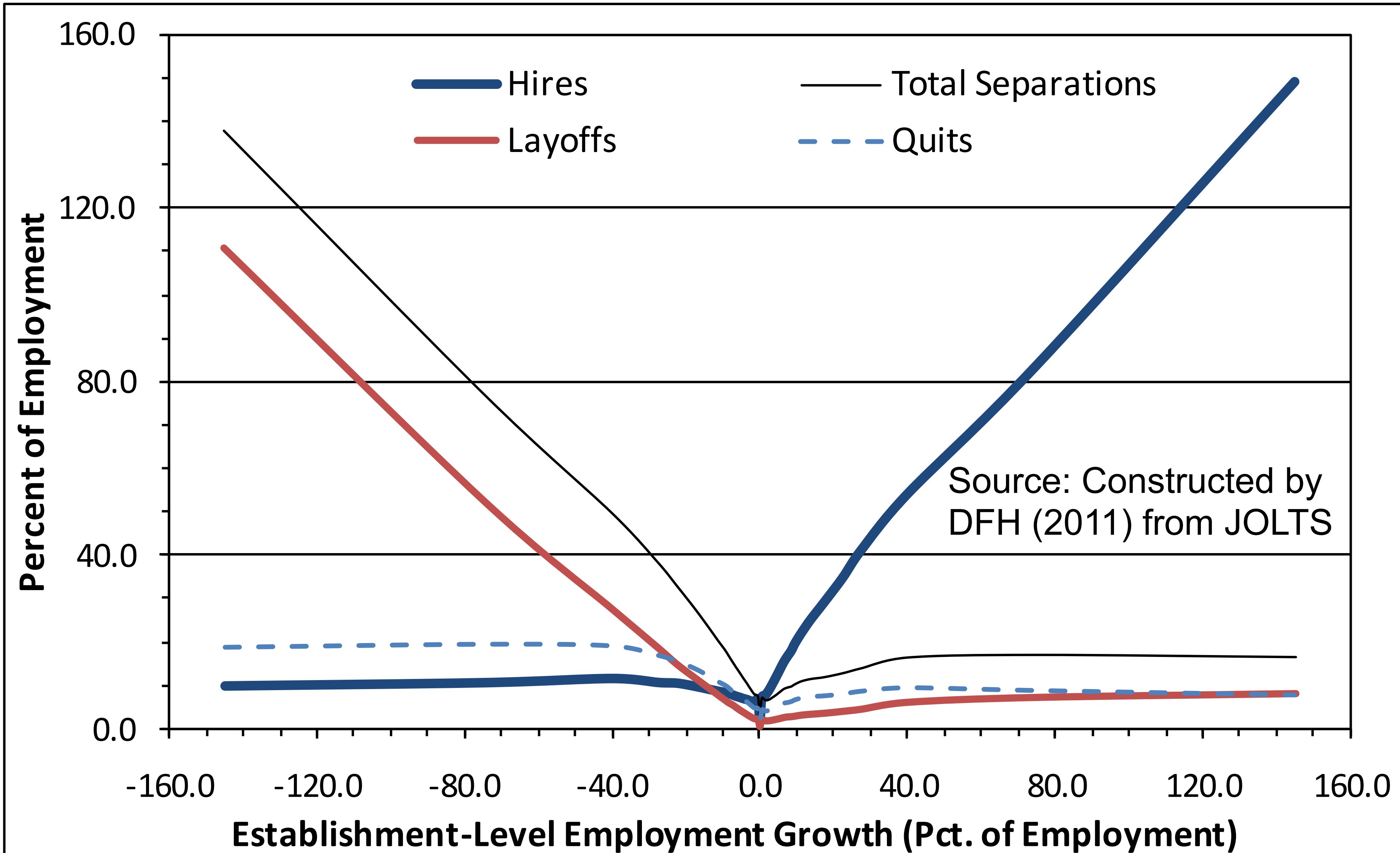
1. Examine joint behavior of worker flows and job flows in the CS of employer growth rates.
2. Interpret joint behavior in light of search and matching theories.
3. Use statistical models of worker flows in the CS to explain aggregate flows. How much gain?
4. Combine statistical models with administrative data on distribution of establishment growth rates to construct synthetic measures of hires, separations, quits and layoffs

Two U.S. Data Sets

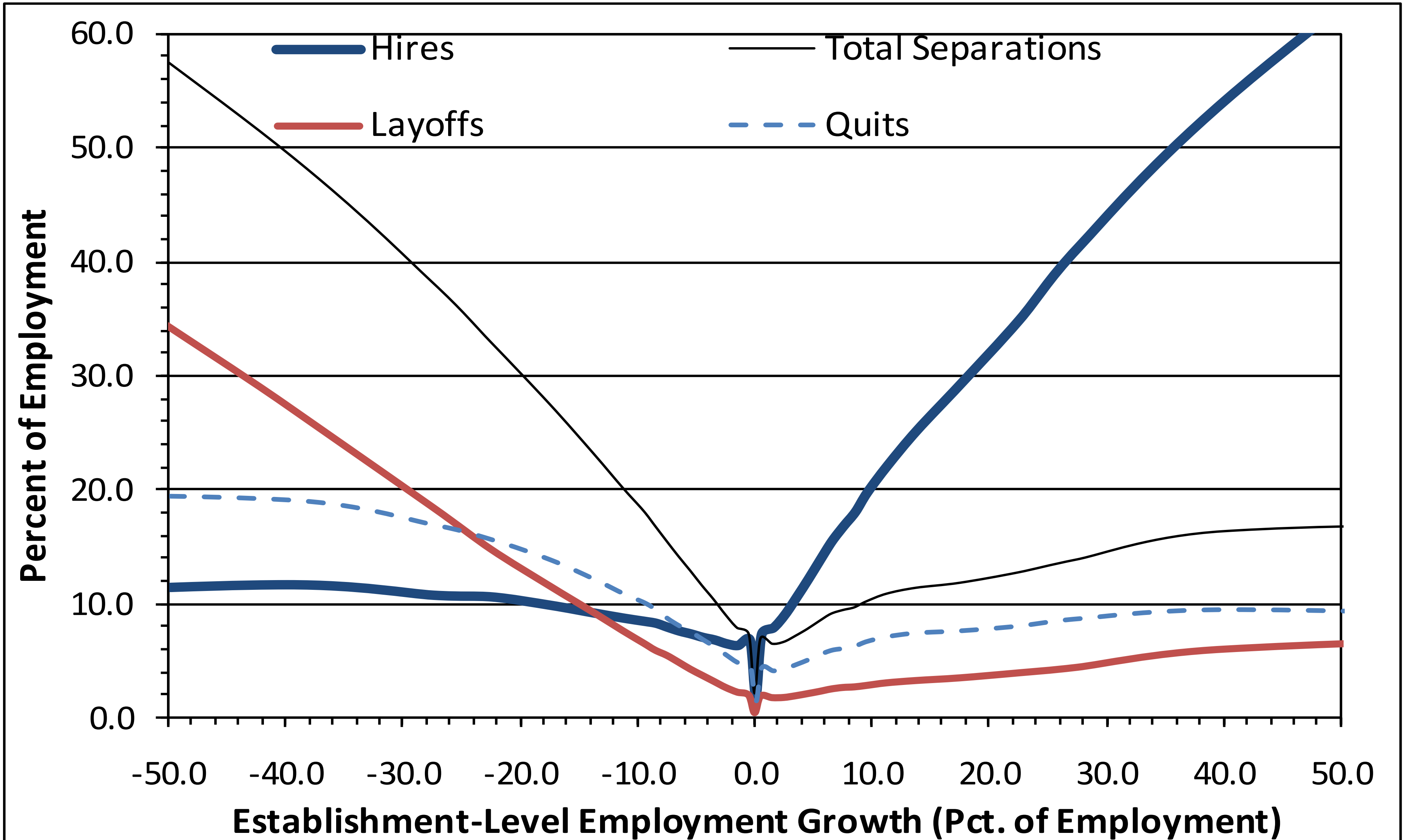
- Job Openings and Labor Turnover Survey (JOLTS)
  - Monthly sample of 16,000 establishments covering nonfarm economy. Rotating panel design.
  - Each establishment reports employment, hires, quits, layoffs, other separations, and (end-of-month) vacancies
  - Our micro sample covers Jan-2001 to June-2010 and includes all establishments with data for all three months in a quarter.

- Business Employment Dynamics Data (BED)
  - Quarterly administrative data on nearly all US establishments in the private sector
  - Micro Data cover 1990Q1 to 2010Q2
  - Micro data are longitudinally linked – allows calculation of establishment-level growth (i.e., job flows)

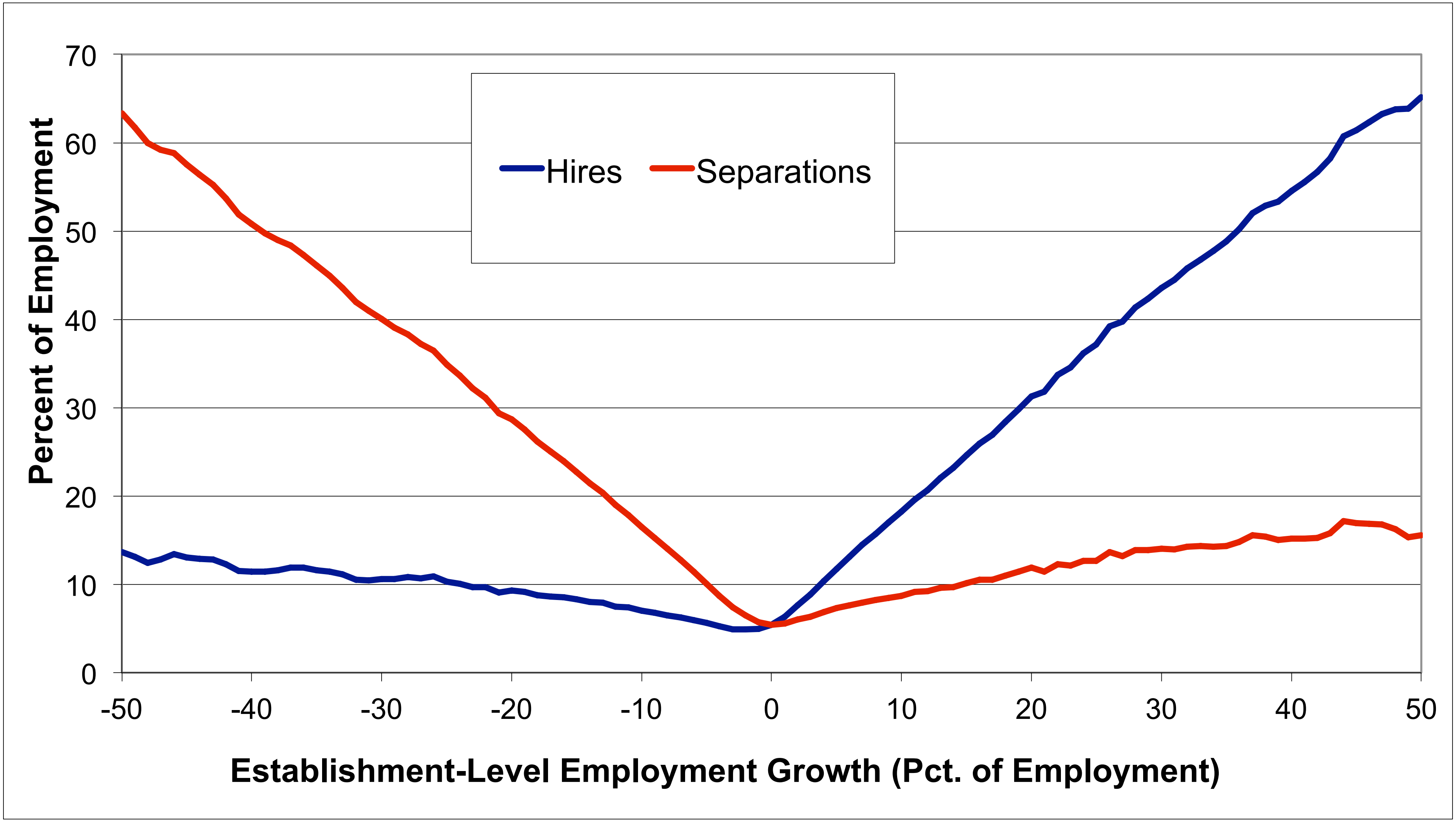
Quarterly Worker Flows in the Cross Section, United States, Pooled JOLTS Sample, 2001-2010



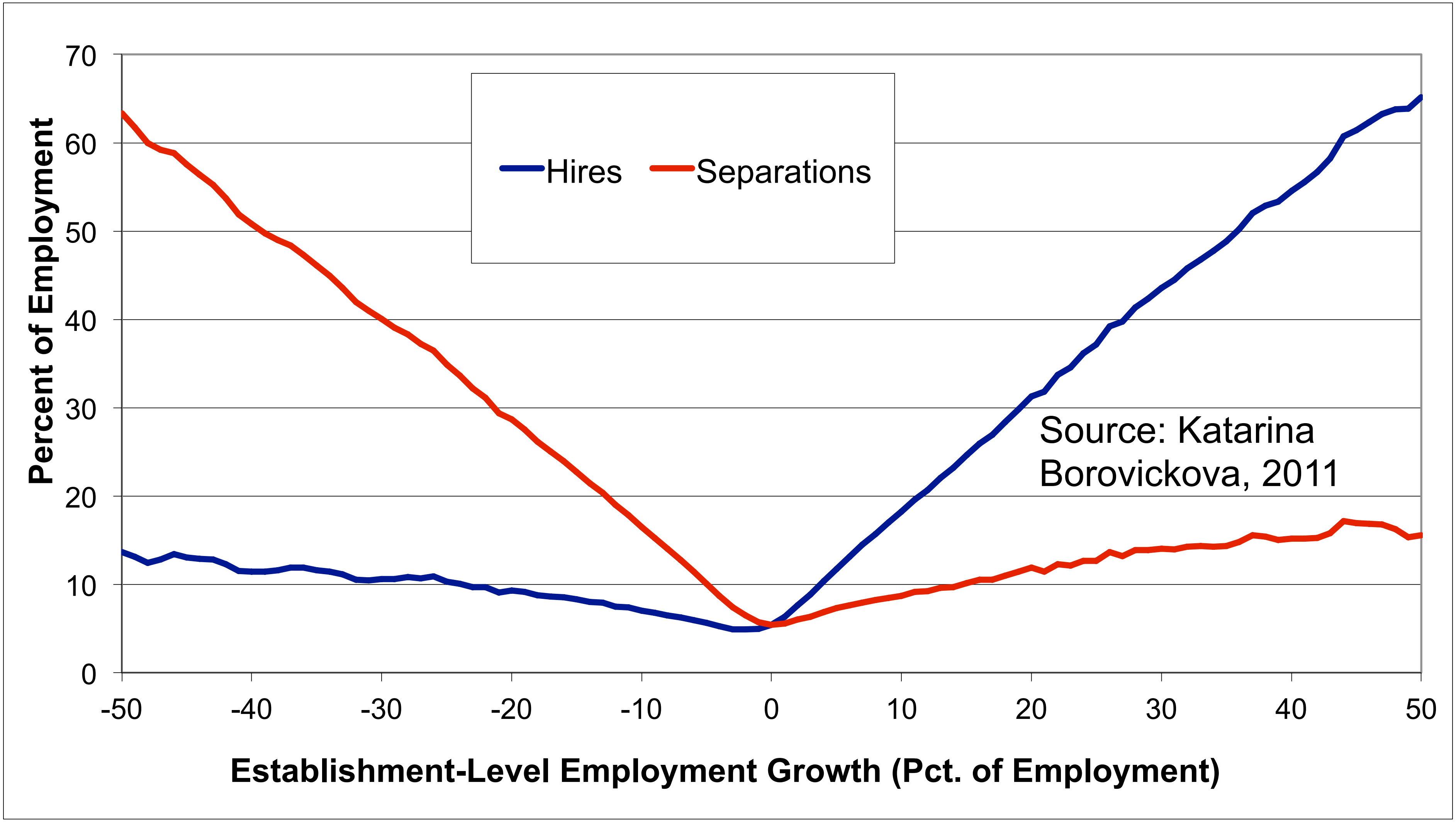
U.S. Worker Flows in the Cross Section of Employer Growth Rates (Zoomed In)



Quarterly Worker Flows in the Cross Section of Employer Growth Rates, Mystery Country



Quarterly Worker Flows in the Cross Section of Employer Growth Rates, Austria



Theory Sketch

- Search models in the spirit of Mortensen and Pissarides (1994) but with multi-worker firms
  - E.g., Cooper-Haltiwaner-Willis (2007), Elsby-Michaels (2008)
  - "Iron link" of hires to job creation & separations to destruction
- Learning about match quality as in Jovanovic (1979, 1985) and Moscarini (2005)
  - Pries & Rogerson (2005) is a hybrid of MP and learning
- On-the-job search with match-specific productivity and aggregate fluctuations (Barlevy, 2002)
  - Workers are more likely to quit bad matches when aggregate conditions are strong
- Employer search with persistent idiosyncratic firm profitability (Faberman & Nagypal, 2009)
  - Workers are more likely to quit employers with low productivity and slow growth (an "abandon-ship" effect)

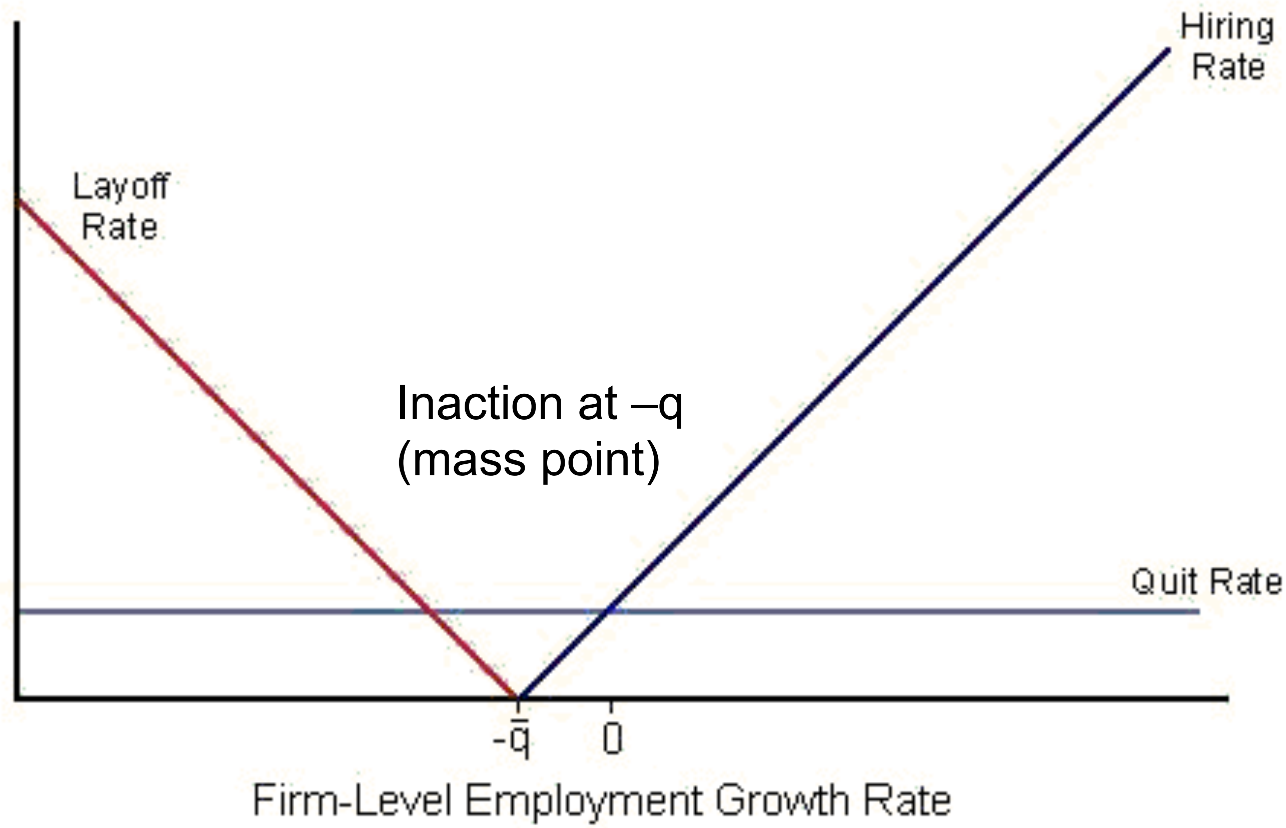
Standard Model with "Iron Link" Implications

- Consider an MP model with multi-worker firms
  - Cooper-Haltiwanger-Willis (2007, CHW)
  - Hires, vacancies and layoffs are endogenously determined subject to fixed and variable costs of posting vacancies and layoffs
  - Firms face aggregate and idiosyncratic profit shocks
  - Quit rate is exogenous and uniform
  - Workers are ex ante homogenous
  - Frictional search as in other MP models
- Write employer-level growth (hires – separations) as

$$
\begin{aligned}
e_{it} - e_{i,t-1} &= h_{it} - l_{it} - \bar{q} e_{i,t-1} \\
&= \eta(U_t, V_t) v_{it} - l_{it} - \bar{q} e_{i,t-1}
\end{aligned}
$$

where $\eta(\cdot)$ is the job-filling rate, which depends on aggregate unemployment (U_t) and vacancies (V_t)

CHW Model Properties



- **Movements in aggregate hires and layoffs arise entirely from shifts over time in CS distribution of employer growth rates.**
- **Adjustment costs and shock properties affect the shape and location of growth rate distribution, but not the iron link.**

Relaxing the Iron Link

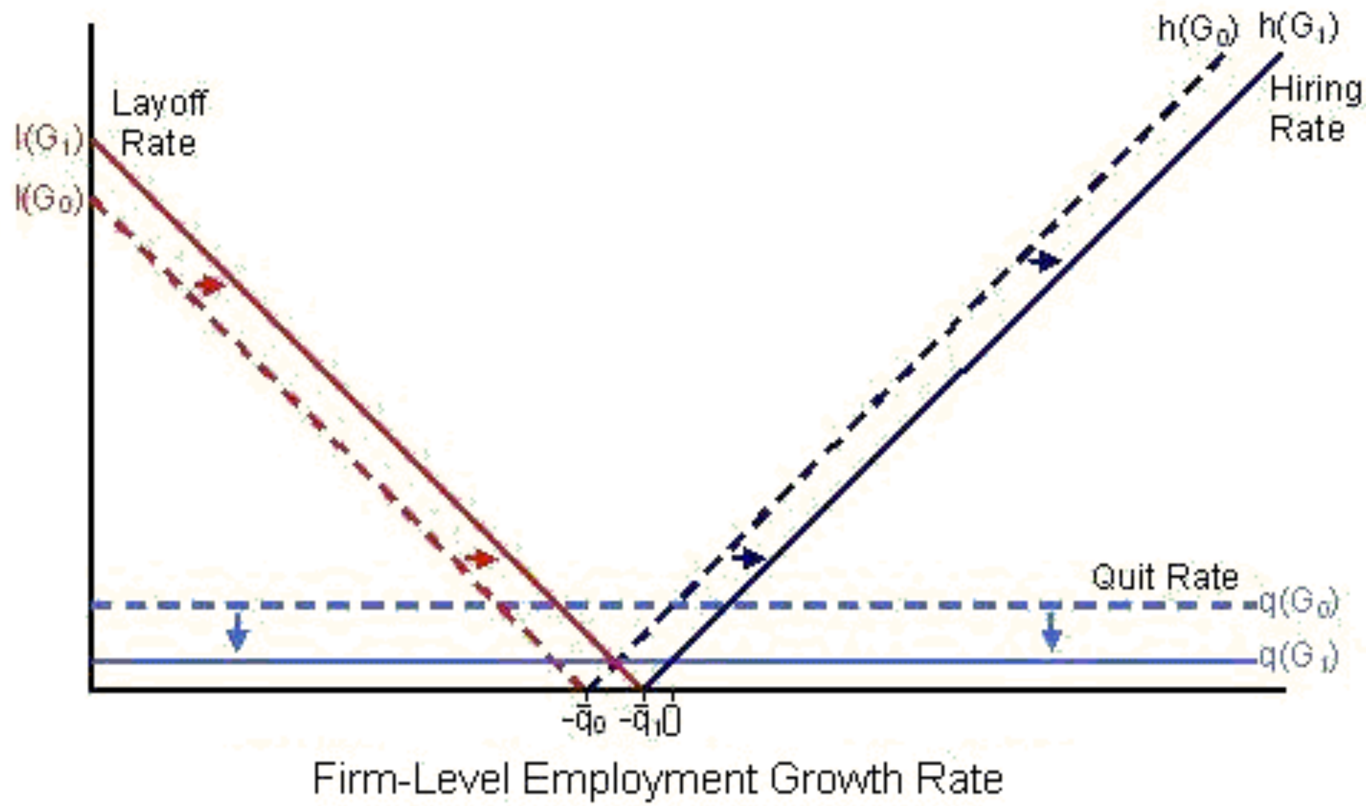
- **Simplest extension of CHW model:**
  - Quit rate remains exogenous but varies procyclically

$$q_t = \overline{q}(G_t)$$

where G_t = aggregate employment growth

- **Iron link continues to hold in a given cross section, but time variation in q_t shifts the micro hiring and and layoff relations**
- **Fluctuations in aggregate worker flows now arise from shifts in the growth rate distribution and shifts in the micro-level CS relations**

Exogenously Pro-Cyclical Quit Rates



- Quit rate drops when aggregate growth rate falls.
- Inducing rightward shifts in the hiring and layoff relations, including the kink point.

Endogenous Quits, 1
Higher Quit Rate at Weaker Employers

- Faberman-Nagypál (2008) model
  - Employers vary in idiosyncratic component of productivity
  - More productive firms grow faster
  - Employers engage in costly search, contact workers, and make offers
  - Bargained wage rises with employer productivity
  - Because they earn lower wages, workers at less productive employers are more likely to accept outside offers
  - Thus, quit rate declines with employer growth rates in CS
  - Rationalizes positive value and a negative slope in the CS hires relation to the left of zero.
- See, also, Trapeznikova (2010)

Endogenous Quits, 2
Higher Quit Rates in Stronger Labor Market

- Barlevy (2002) model with OTJ search
  - Employed workers quit when better offers arrive
  - Vacancies are scarcer and workers have fewer outside options in recessions → lower quit rate
  - Leads to shift and dilation of match quality distribution over business cycle
    - Shift: negative aggregate shock causes dissolution of bad matches (cleansing effect)
    - Dilation: lower outside options cause workers in bad matches to remain in those matches (sullying effect)
  - This model implies that CS quit-growth relation varies with business cycle, shifting up in booms

Endogenous Quits, 3
Separation Rates Decline with Job Tenure

- **Learning about match quality as in Jovanovic (1979, 1985), Moscarini (2005), Pries and Rogerson (2005) and many others**
  - Stochastic match quality
  - Employer and worker learn about match quality over time
  - Good matches survive, bad ones don't
  - Separation rate declines with match tenure
  - If growing employers have a larger proportion of young matches, then separation rate rises with employer growth rates in the cross section.

Relating Micro and Macro Behavior

- Express aggregate worker flow rates, W_t (rate of hires, quits, layoffs or separations), as

$$W_t = \sum_g f_t(g) w_t(g)$$

  - Group establishments by employment growth rates, g, and calculate the employment-weighted mean rate for each g in period t, $w_t(g)$
  - To recover the aggregate flow rate at t, weight each growth rate bin by its employment mass in period t, $f_t(g)$
  - Obtain $w_t(g)$ from JOLTS and $f_t(g)$ from BED

- Changes over time in aggregate flow rates arise from:
  1. Changes in average worker flow rates for a given g, or
  2. Shifts in the distribution of establishment-level employment growth
  3. Interaction between 1 and 2.

Statistical Specifications for CS Relations

1. **Fixed Cross-Section**

- Motivated by time-invariant "iron link" relations in basic multi-worker MP model, but we do not constrain the location of kinks:

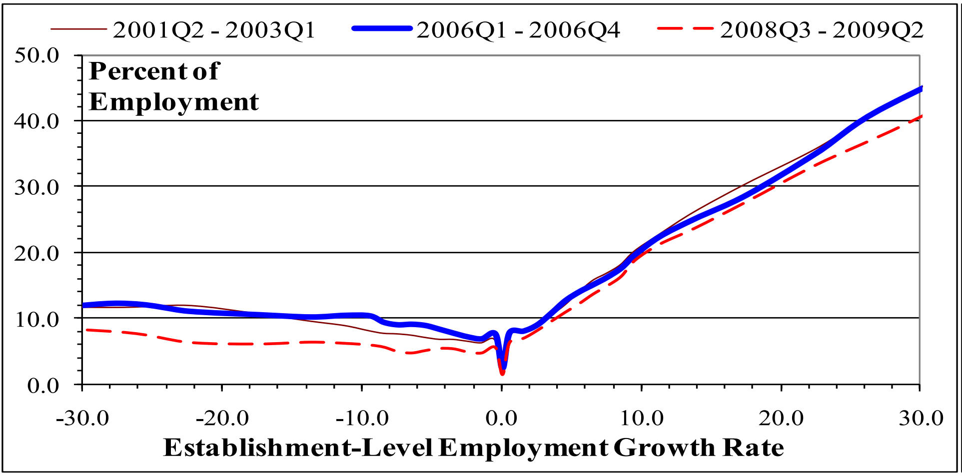
$$w_t(g) = \alpha(g) + \varepsilon_t^D(g)$$

where $w_t(g)$ is worker flow rate at establishment with growth rate g

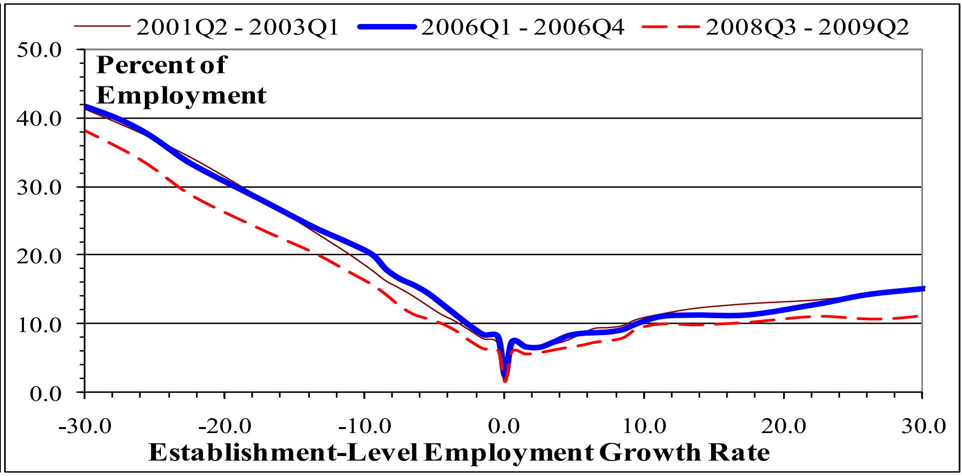
- Estimate this relation on the pooled sample of establishment-level observations from 2001 to 2010Q2.

C-S Relations in Three Periods

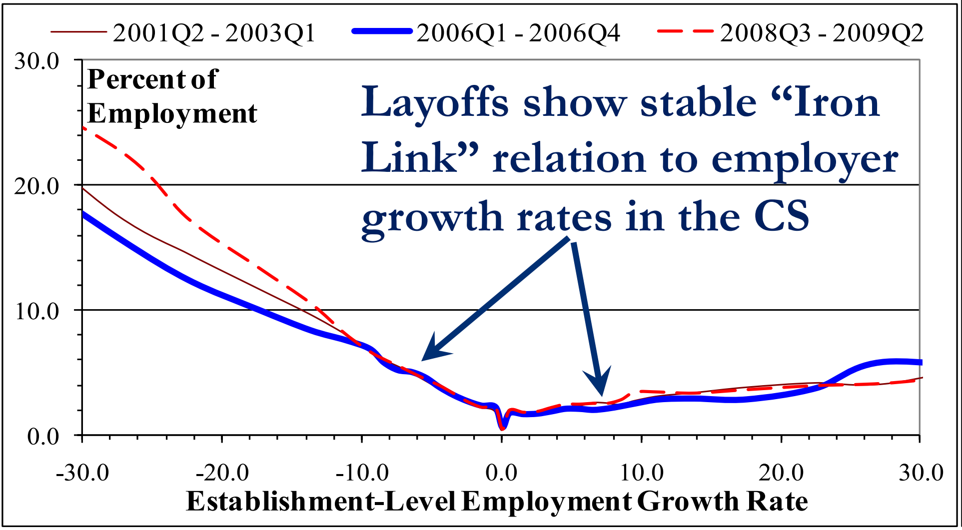
Hires



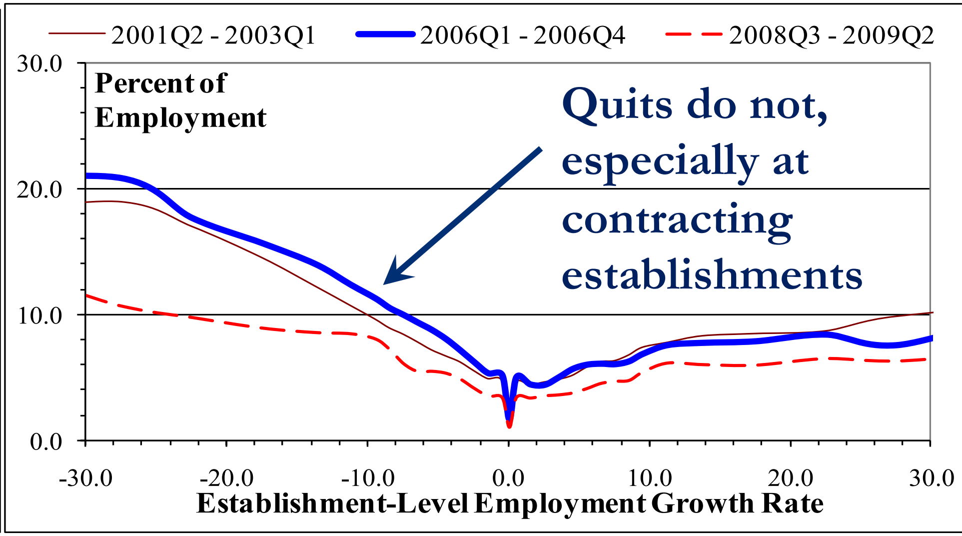
Total Separations



Layoffs



Quits



Statistical Specifications, cont'd

2. **Baseline**
   - Allow vertical shifts in CS relation as functions of cycle indicators :

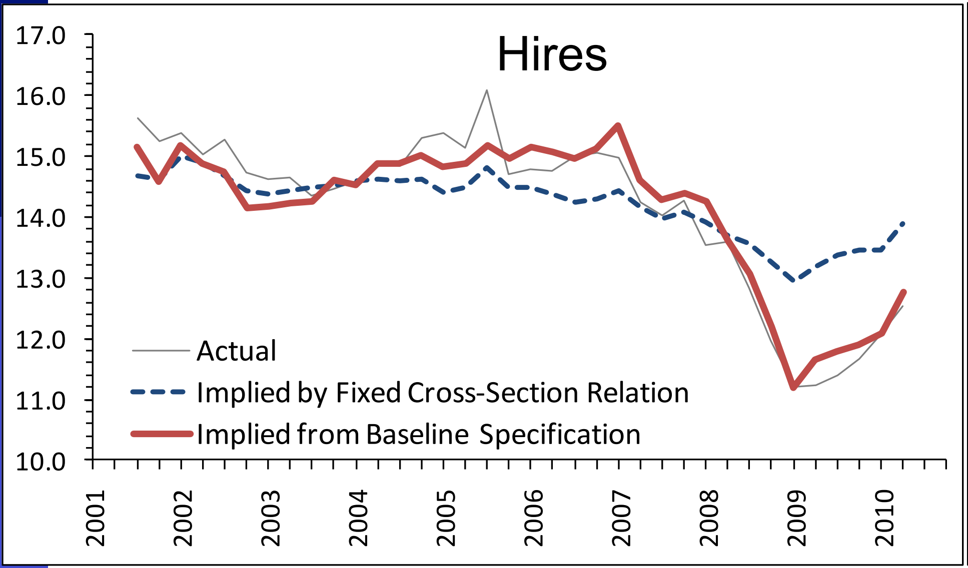
$$w_t(g) = \alpha(g) + \beta_1 G_t^+ + \beta_2 G_t^- + \beta_3 \Delta G_t + \beta_4 JF_t + \varepsilon_t^B(g)$$

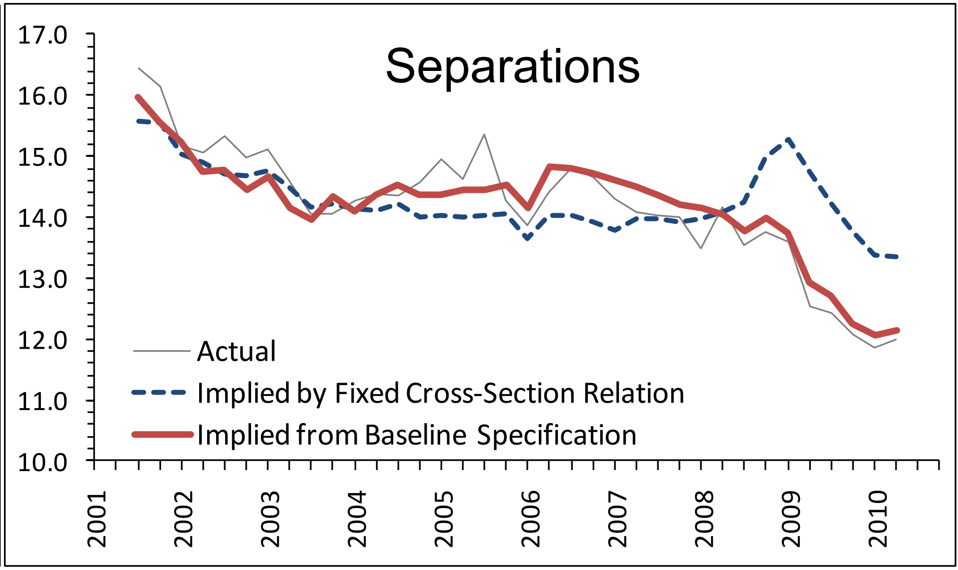
   - G_t = aggregate employment growth rate (+, -, change)
   - JF_t = job-finding rate of unemployed workers

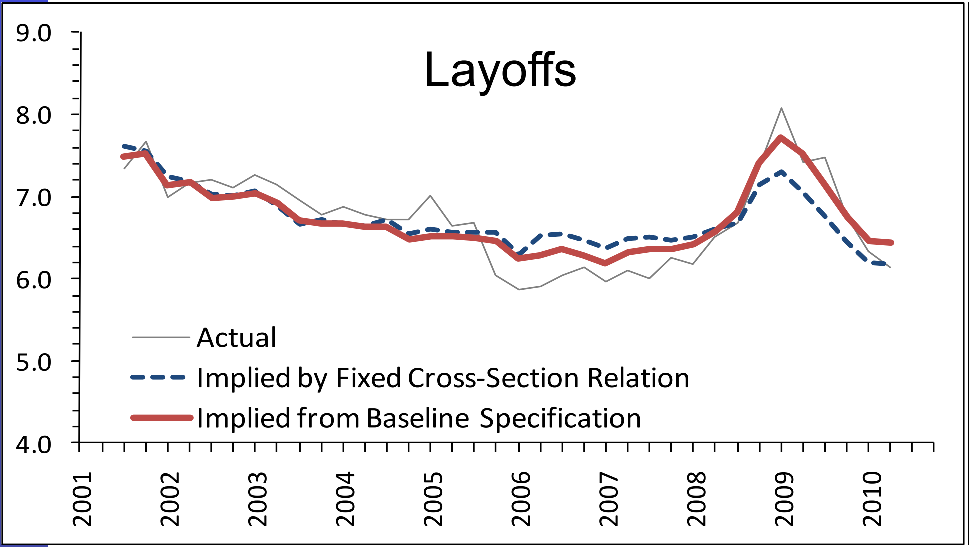
3. **Flexible**
   - Allow for more complex cyclical behavior
   - Interact cycle indicators with 5 dummy variables for broad growth rate intervals → Allows shape and location of CS relations to vary with cycle.

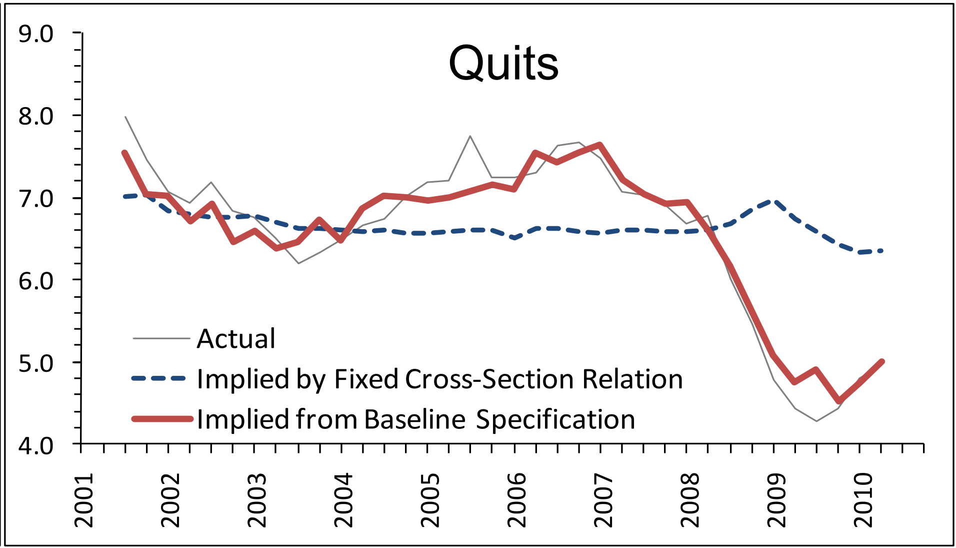
Worker Flows Implied by Statistical Specifications

$$\hat{W}_t = \sum_g f_t(g)\hat{w}_t(g)$$

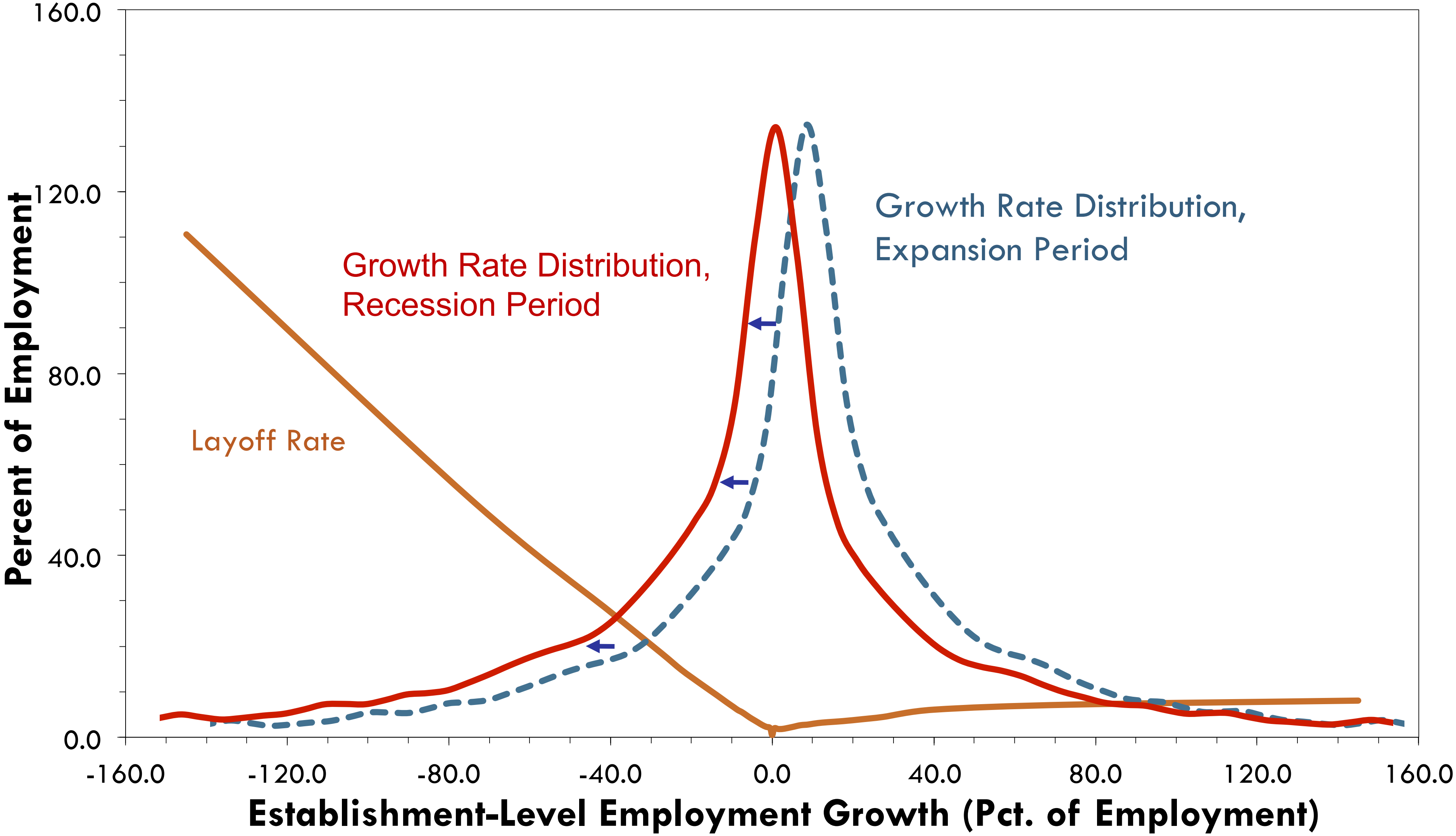








Leftward Shift in Growth Rate Distribution
And Interaction with the CS Layoff Relation



How Much Does Fixed CS Model Improve Fit for Aggregate Flows?

	R-Squared Values in Time-Series Regressions of the Indicated Rate on:	
	Aggregate Variables (4 Cycle Indicators)	**Adding One Variable: Worker Flow Rate Predicted by Fixed CS Model**
Hiring Rate	0.808	.966 [.000]
Separation Rate	0.652	.944 [.000]
Quit Rate	0.929	.961 [.011]
Layoff Rate	0.525	.880 [.000]

The entry in brackets reports the *p*-value of the coefficient on the prediction of the model that imposes a time-invariant cross-sectional relation.

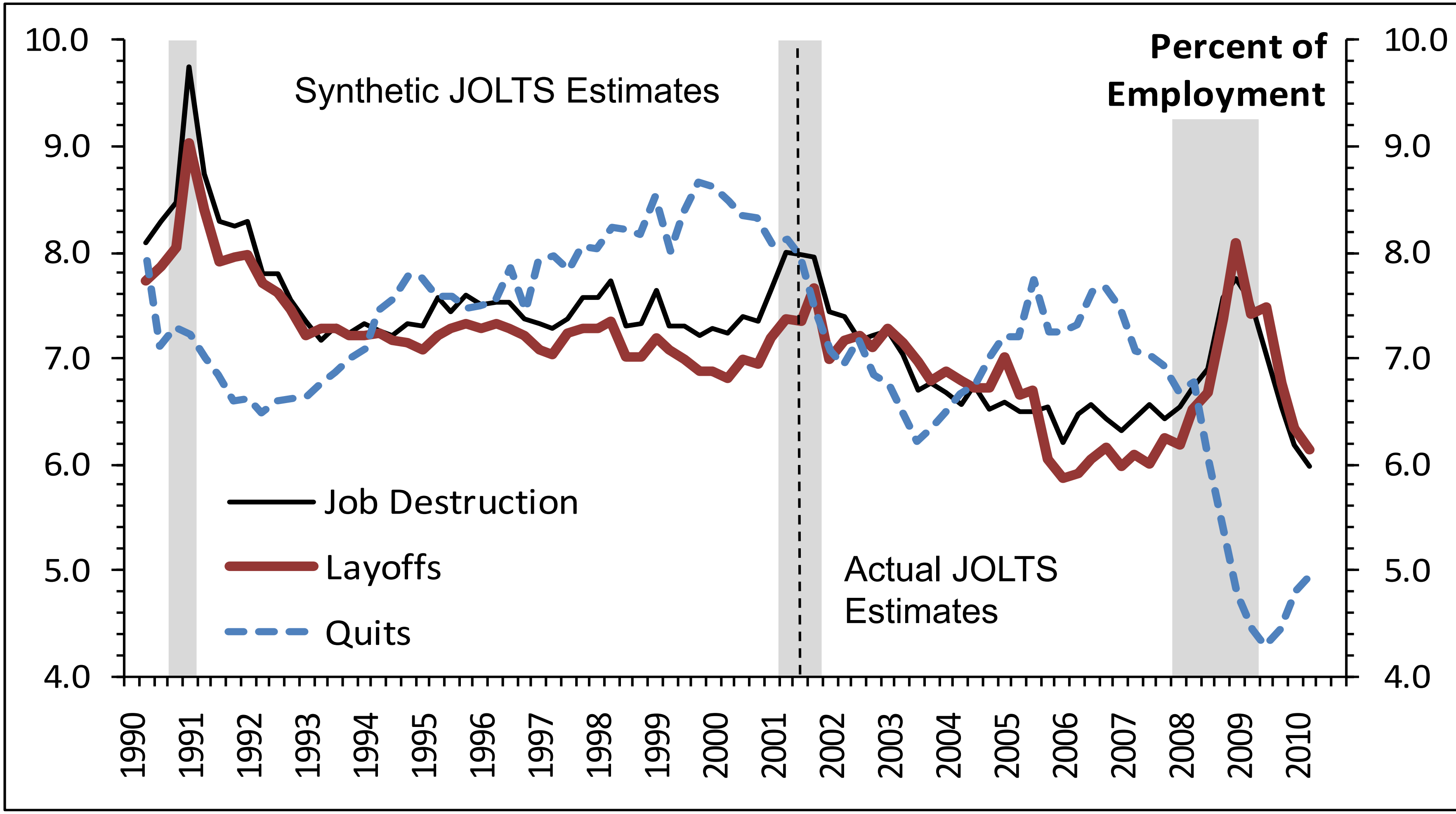
Constructing Synthetic JOLTS Data

- Baseline statistical model + quarterly data on the cross-sectional distribution of establishment-level growth rates → synthetic data for aggregate worker flows

$$\hat{W}_t = \sum_g f_t(g)\hat{w}_t(g)$$

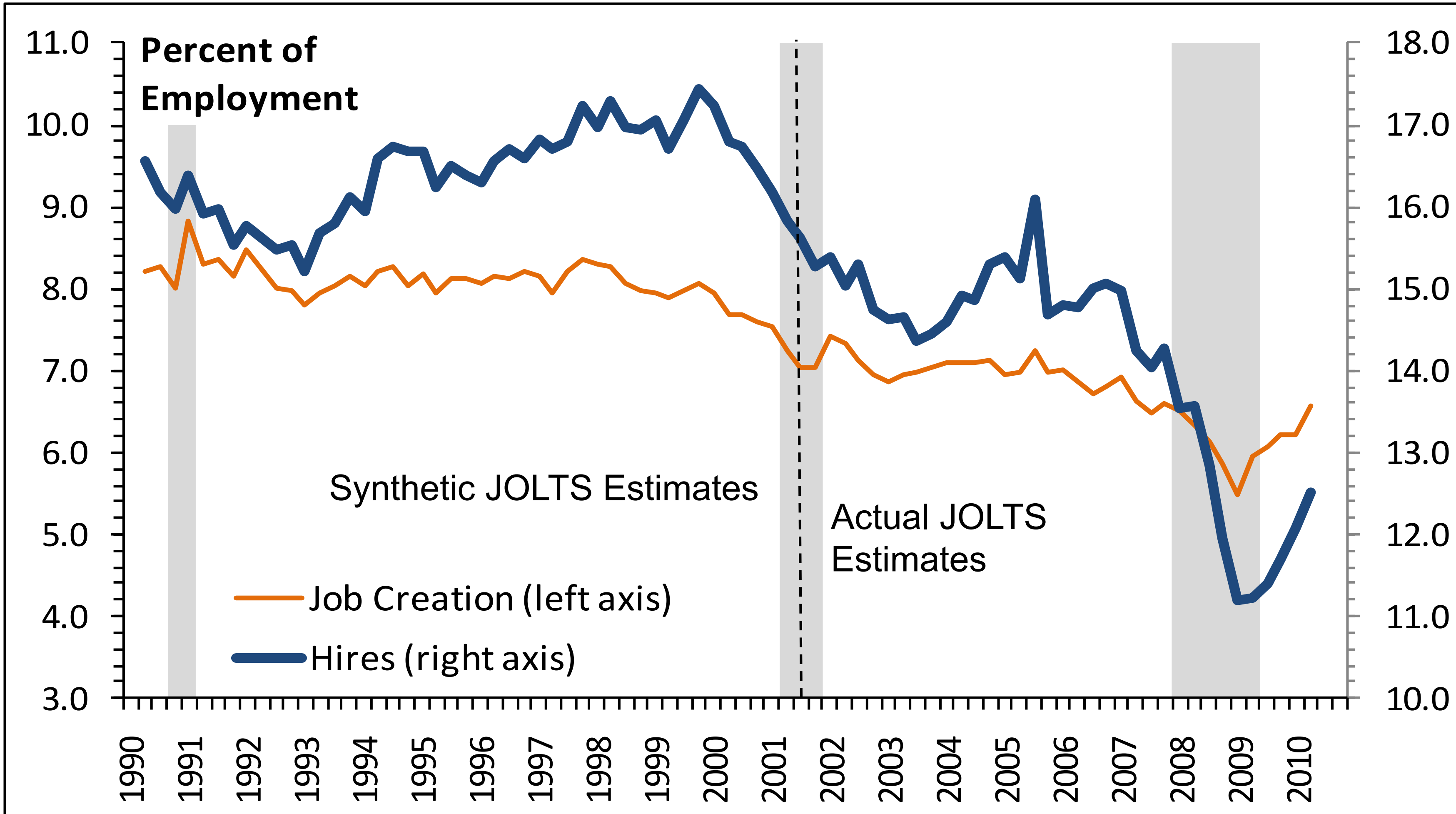
  - BED data on f + model-based $\hat{\mathbf{w}}$ from 1990 to 2001
  - BED data on f + JOLTS-based $\mathbf{w}$ from 2001 to 2010.

Quit, Layoff, and Job Destruction Rates



- Layoffs move with job destruction.
- Quits moves opposite to both.

Hiring and Job Creation Rates



- Hires tend to move with job creation but are more volatile.
- On the secular declines in worker flow rates, see DHJM (2006), Davis (2008) and DFHJM (2010).

Overview, Part II

5. **Use a simple model of daily hiring dynamics to identify the job-filling rate for vacancies**
6. **Big CS variation in job-filling rates. Why?**
   - Heterogeneity in the efficiency of search and matching
   - Scale economies (or diseconomies) in the hiring technology at the establishment or sectoral level
   - Employers use other instruments, in addition to vacancy numbers, to influence the pace of hiring.

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Overview, Part II

7. **Generalized matching function (GMF) defined over unemployment, vacancies, and other recruiting instruments.**
   - Estimate scale economies in the employer hiring technology
   - Estimate how recruiting intensity varies with hires rate
   - Construct a time-series index of recruiting intensity per vacancy
   - GMF outperforms standard MF in explaining fluctuations in the job-finding rate and the job-filling rate. GMF also yields a more stable Beveridge Curve.
   - GMF accounts for CS behavior of job-filling rates. Standard matching function does not.

A Model of Daily Hiring Dynamics

Daily laws of motion for flow of hires and vacancy stock:

$$h_{s,t} = f_t v_{s-1,t}$$

$$v_{s,t} = \left[(1 - f_t)(1 - \delta_t)\right] v_{s-1,t} + \theta_t$$

- **Where *s* indexes days, f_t is the daily job-filling rate in month *t*, δ_t is the rate at which unfilled vacancies lapse, and θ_t is the daily flow of new vacancies.**

Solving for the job-filling rate and vacancy flows

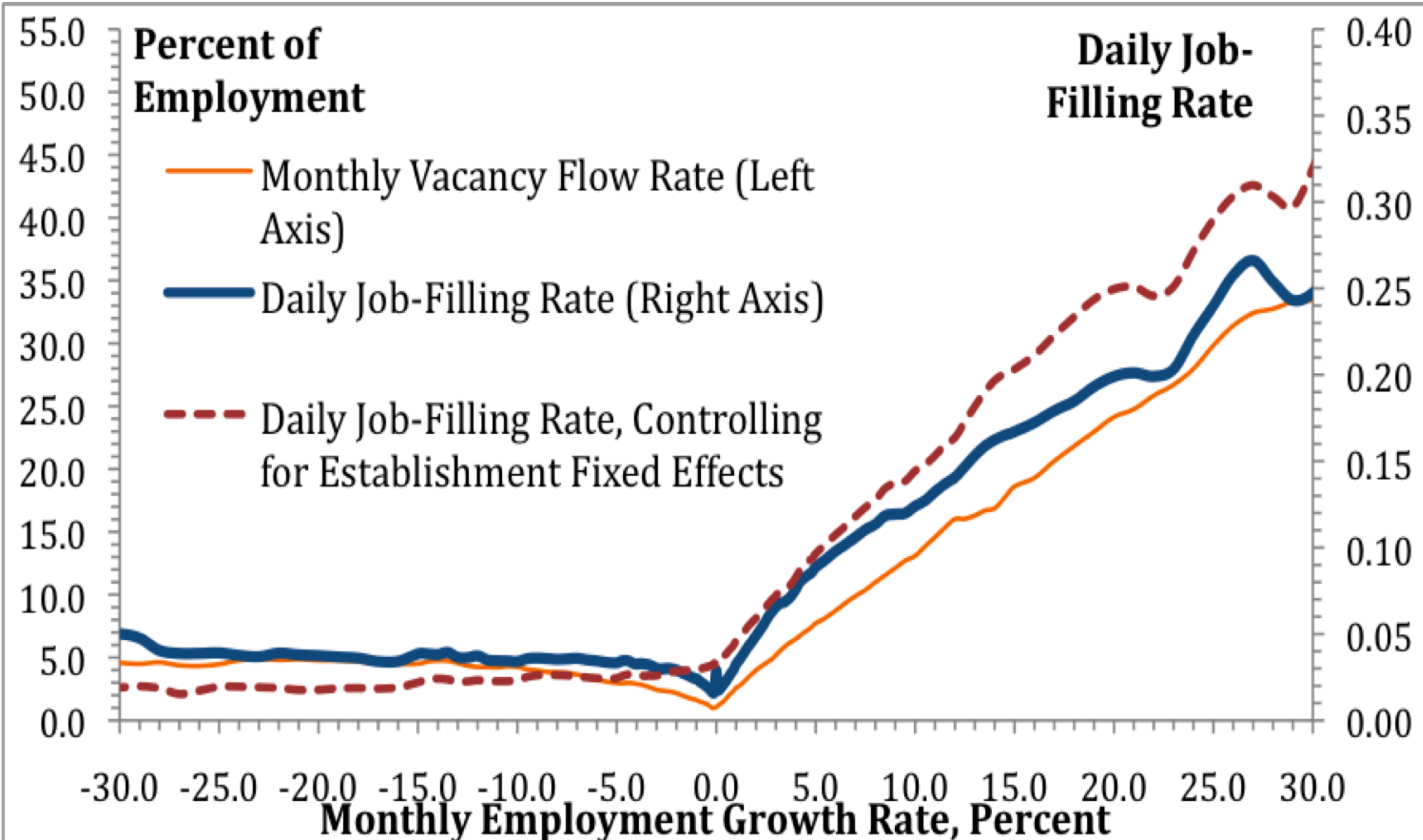
Use laws of motion to derive two equations relating end-of-month vacancy stock and hires flow during month, both observed, to two unknowns, $\{f_t, \theta_t\}$.

$$v_t = (1 - f_t - \delta_t + \delta_t f_t)^{\tau} v_{t-1} + \theta_t \sum_{s=1}^{\tau} (1 - f_t - \delta_t + \delta_t f_t)^{s-1}$$

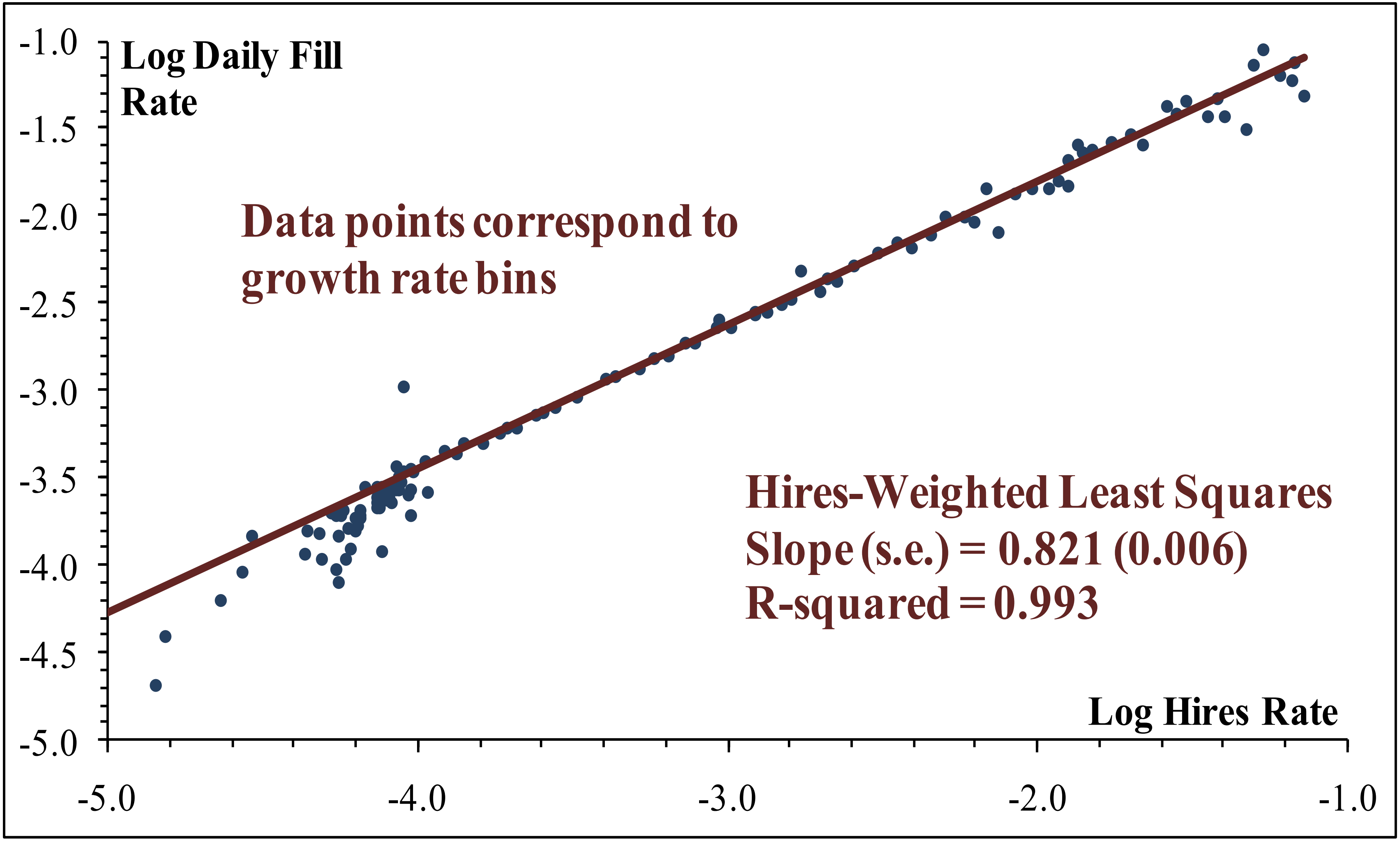
$$H_t = f_t v_{t-1} \sum_{s=1}^{\tau} (1 - f_t - \delta_t + \delta_t f_t)^{s-1} + f_t \theta_t \sum_{s=1}^{\tau} (\tau - s)(1 - f_t - \delta_t + \delta_t f_t)^{s-1}$$

Given data on δ_t, v_t, v_{t-1}, H_t, and a value for tau, solve numerically for f_t (daily job-filling rate) and θ_t (daily flow of new vacancies).

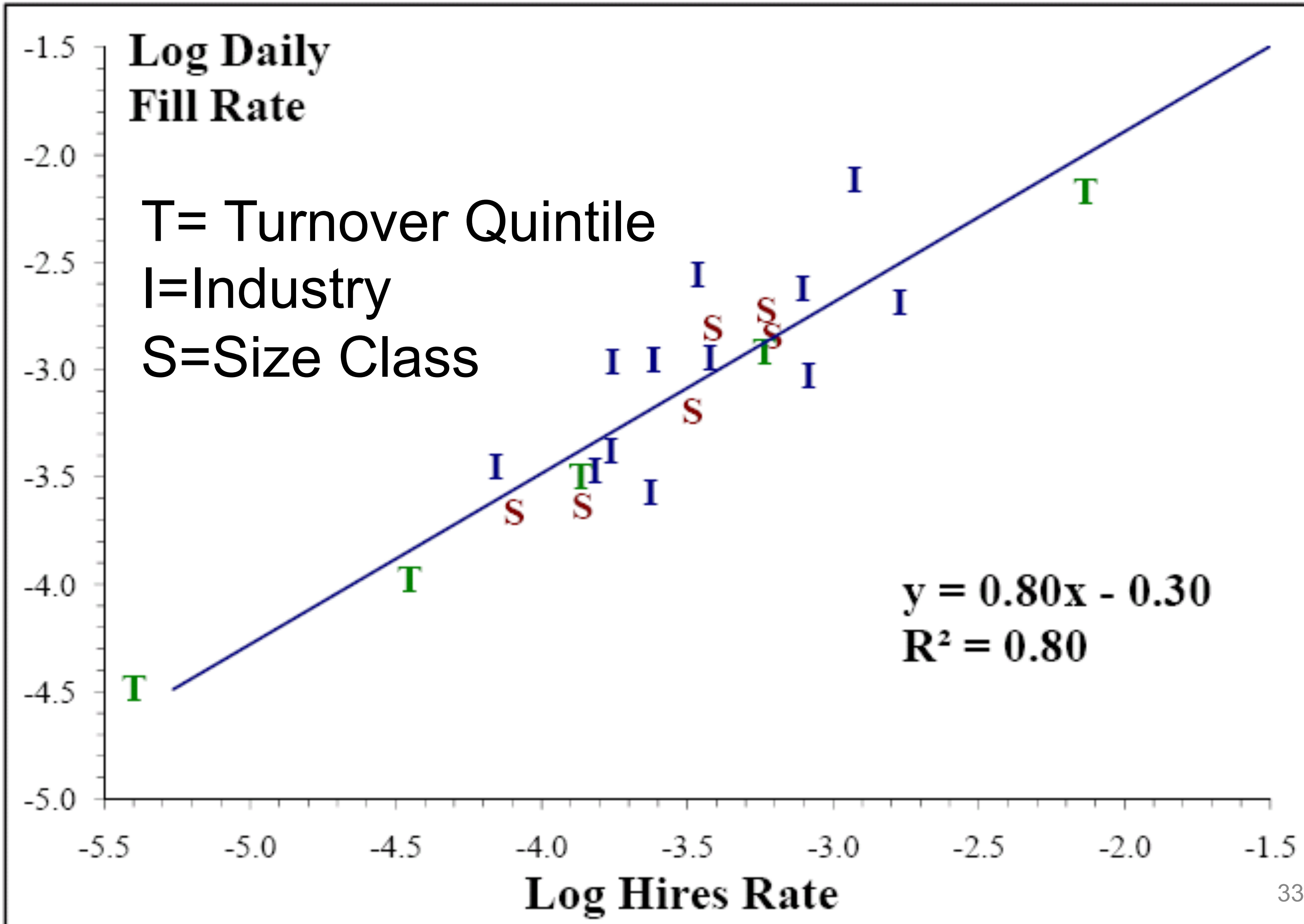
Vacancy Flows and Job-Filling Rate Relationships to Employer Growth Rates



Job-Filling Rate and Gross Hires Rate



Job-Filling Rate and Gross Hires Rate



Generalized Matching Function

$$H_{et} = \mu \left(\frac{v_t'}{u_t} \right)^{-\alpha} q(v_{et}, x_{et}), \text{ where } \sum_e q(v_{et}, x_{et}) = v_t'$$

- Job-filling rate is now $f_{et} = \tilde{f}_t q(v_{et}, x_{et}) / v_{et}$
- For $q(v_{et}, x_{et}) \equiv v_{et}$, aggregation delivers standard Cobb-Douglas matching function
- For $q(v_{et}, x_{et}) \equiv v_{et} \tilde{q}(x_{et})$, the hiring function satisfies CRS in vacancies at the micro level, and differences in f_{et} identify the effects of employer actions on other margins.

Quantifying the Roles of Other Instruments and Scale Economies

Let $q(v_{et}, x_{et}) \equiv v_{et}^{\gamma} \tilde{q}(x_{et})$ so that

job-filling rate becomes $f_{et} = \tilde{f}_t v_{et}^{\gamma-1} \tilde{q}(x_{et})$

$$\frac{d\log(f_{et})}{d\log(H_{et})} = \frac{d\log(\tilde{f}_t)}{d\log(H_{et})} + (\gamma - 1)\frac{d\log(v_{et})}{d\log(H_{et})} + \frac{d\log\left(\tilde{q}(x_{et})\right)}{d\log(H_{et})}$$

$$0.821 \quad = \quad 0 \quad + (\gamma - 1)(0.336) \quad + \frac{d\log\left(\tilde{q}(x_{et})\right)}{d\log(H_{et})}$$

- To preclude a role for employer actions on other margins requires a scale economy parameter value of $\gamma \approx 3.44$.

Estimating Scale Economies in the Establishment-Level Hiring Technology

- Basic idea: Exploit differences in scale of vacancies and hiring across industry-size cells to estimate returns to scale in employer hiring technology.
- Do **NOT** use time variation, because it is contaminated by the intensity, *x*. Control for cell-level growth rate for same reason.
- Control for differences in matching efficiency across industries and across employer size classes.
- Instrument using level of employment to deal with potential division bias.

Scale-Economy Regressions
Dependent Variable: Log(Job-Filling Rate)

Explanatory Variable →	**Log Beginning-of-Month Vacancies (Level)**		**Log Monthly Vacancy Flow (Level)**	
Estimation Method→	.OLS	IV	OLS	IV
Coefficient	-.059	.001	.065	.001
(std. error)	(.049)	(.051)	(.049)	(.051)
R^2	.779	.772	.780	.772
First-stage R^2	---	.985	---	.986
Implied γ	0.941	1.001	1.069	1.001

1. N=70 in all regressions. 5 or 6 size classes per industry (12).
2. All regressions include industry and size class fixed effects and the employment growth rate in the industry-size cell.
3. IV is two-stage LS regression using log(Employment Level) as the instrument. N=70 in all regressions.

Aggregate Implications

GMF with CRS at the employer-level implies:

$$H_t = \sum_e H_{et} = \mu \left(\frac{v'_t}{u_t} \right)^{-\alpha} \sum_e v_{et} \tilde{q}(x_{et}) = \mu \left(\frac{v'_t}{u_t} \right)^{-\alpha} v'_t = \mu v_t^{1-\alpha} u_t^{\alpha} \bar{q}_t^{1-\alpha},$$

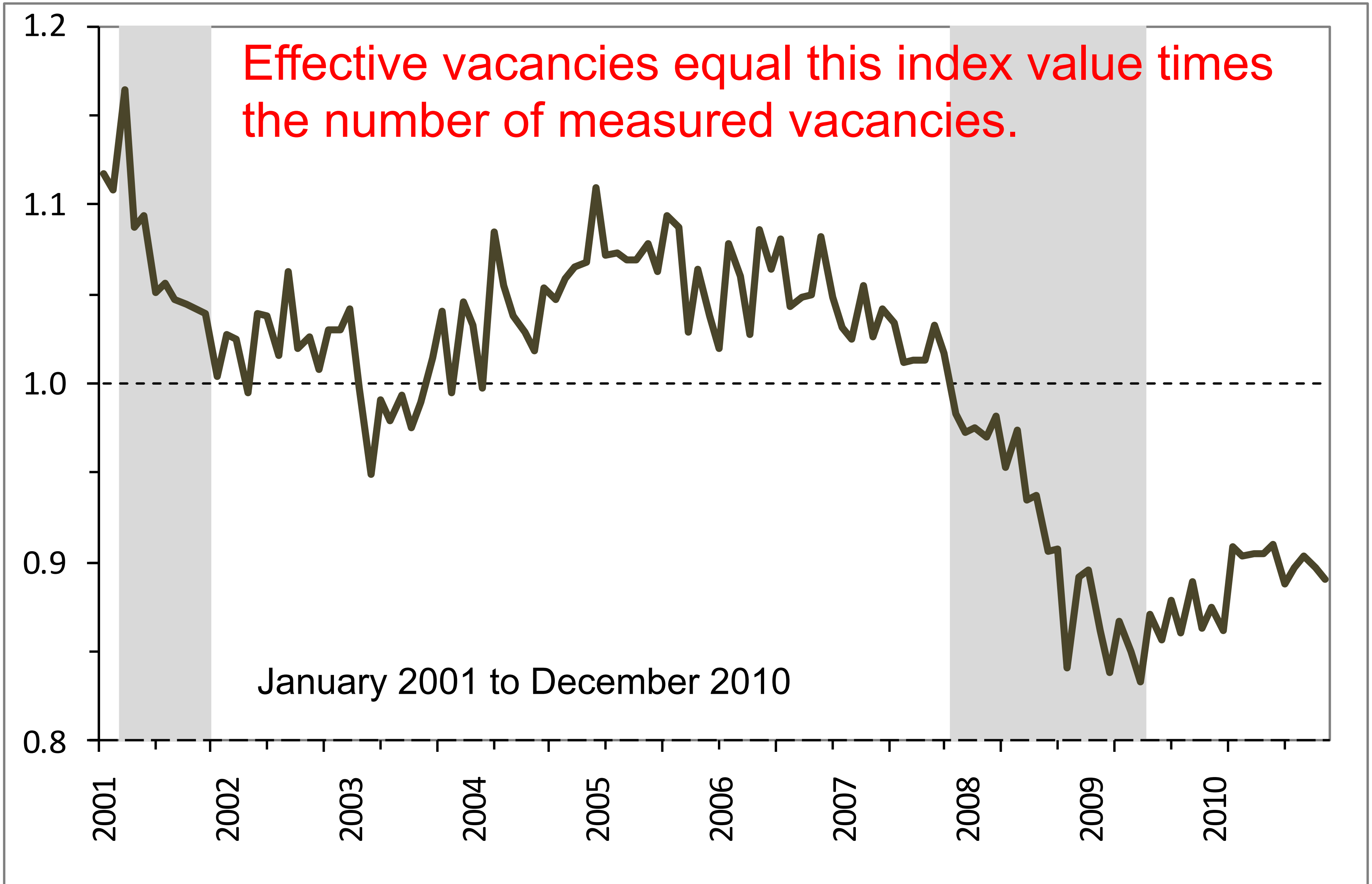
$$\text{where } \bar{q}_t = \sum_e (v_{et} / v_t) \tilde{q}(x_{et}) \text{ and } v'_t = v_t \bar{q}_t .$$

$$\Delta \log H = \alpha \Delta \log u + (1-\alpha) \Delta \log v + (1-\alpha) \Delta \log \bar{q}$$

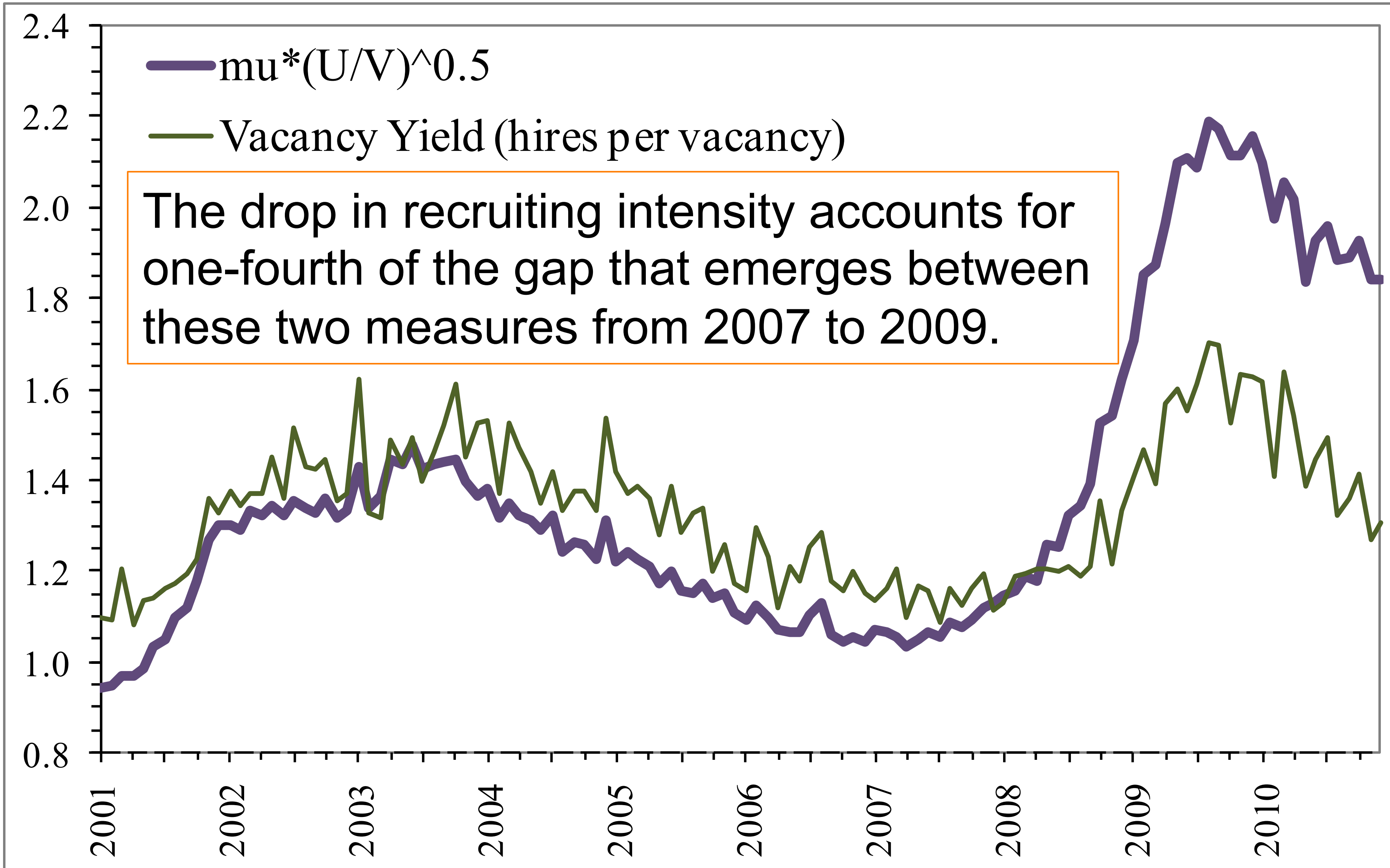
Working Hypothesis:

$$\frac{\Delta \log \bar{q}}{\Delta \log H} = \frac{\Delta \log q_{et}}{\Delta \log H_{et}} = 0.821$$

Recruiting Intensity Per Vacancy Series Implied by Working Hypothesis



Market Tightness and the Role of Recruiting Intensity Per Vacancy



Testing Performance of Standard vs. GMF

Specification	Std. Deviation, Dependent Variable	RMSE Using Standard Matching Function	Percent Drop in RMSE, Generalized MF	Non-Nested Test of Added Predictive Ability: p-value, H_0 = Standard Model	Non-Nested Test of Added Predictive Ability: p-value, H_0 = Generalized Model
Job-finding rate (Unemployment Escape Rate) Regressed on Tightness Ratio (v'/u)					
National Data	0.19	0.05	-2.4	0.02	0.98
Job-finding rate (Hires Per Unemployed) Regressed on Tightness Ratio (v'/u)					
National Data	0.38	0.07	-19.8	0.00	0.00
Northeast	0.34	0.13	-46.1	0.00	0.00
Midwest	0.39	0.08	-31.2	0.00	0.00
South	0.41	0.12	-19.2	0.00	0.00
West	0.45	0.12	-31.9	0.00	0.00
Unemployment Rate Regressed on Effective Vacancy Rate (v')					
National Data	0.28	0.11	-17.6	0.00	0.00
Northeast	0.25	0.16	-10.4	0.00	0.94
Midwest	0.27	0.10	-8.0	0.00	0.79
South	0.28	0.15	-17.3	0.00	0.09
West	0.32	0.16	-24.3	0.00	0.00

A Summary: Tools and Methods

1. **A useful descriptive tool: Relate worker flows and job-filling rates to growth rates in the CS.**
   - Yields empirical objects for assessing, calibrating and developing theory
   - Highlights the importance of nonlinear aggregation in labor market fluctuations
2. **How to combine CS statistical models with administrative data on employer growth rates to construct synthetic data.**
3. **A simple model + moment-fitting method that identifies job-filling rates from periodic data on the stock of vacancies and the flow of hires**

A Summary: Tools and Methods

4. **A generalized matching function (GMF):**
   - How to estimate the degree of scale economies (or diseconomies) in the employer hiring technology
   - How to identify the elasticity of recruiting intensity per vacancy with respect to the hires rate
   - A time-series index for recruiting intensity per vacancy
   - An aggregate time series for effective vacancies that outperforms the standard measure of vacancies in accounting for fluctuations in job-finding rates and job-filling rates, and that yields a more stable Beveridge Curve.

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ADDITIONAL SLIDES

U.S. Employment Growth Rate Distribution, Selected Periods, BED Data

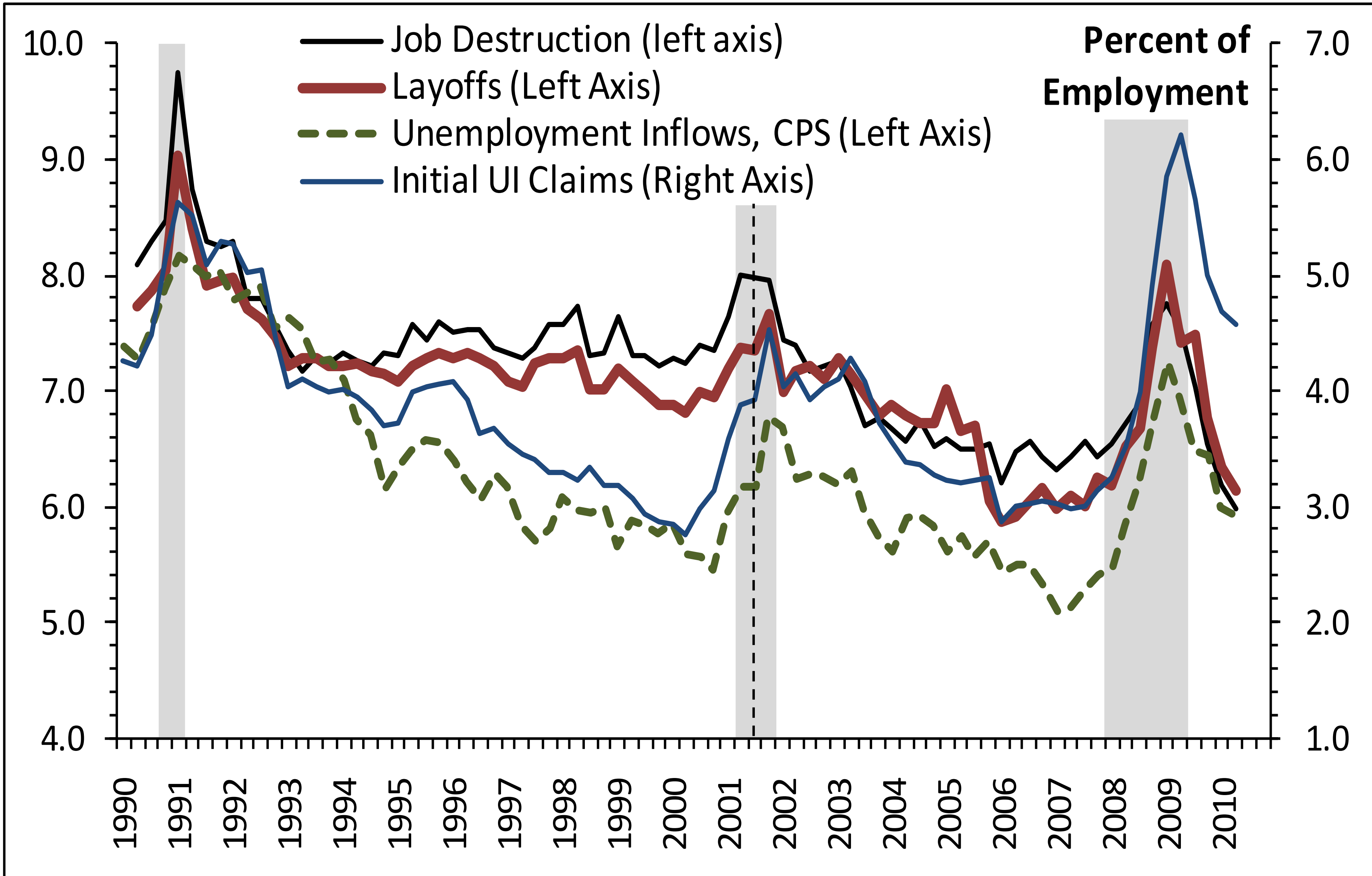
Fraction of Employment at…	1991	1998-99	2001q2-2003q1	2006	2008q3-2009q2
Establishments with Contractions > 10%, including Closings	16.0	14.0	14.5	12.6	14.0
Establishments with Contractions >= 10%	27.4	26.9	29.3	28.0	30.8
Establishments with No Net Change in Employment	14.3	13.9	14.8	15.5	16.1
Establishments with Expansions < 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

Fit of the Establishment-Level Regressions Used to Estimate the CS Worker Flow Relations

- Table entries show R-squared values for employment-weighted regressions on the indicated statistical models.
  - "Fixed Cross-Section" corresponds to the regression model used to fit the time-invariant CS relations displayed on the previous slides
  - "Augmented Fixed Cross-Section" relaxes the model slightly to allow for within-bin differences in the worker flow relations.

	Model Specification			
Dependent variable in descriptive CS regression	Fixed Cross-Section	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

Layoff Rates Compared to Other Job Loss Data



Closely Related Work in Progress

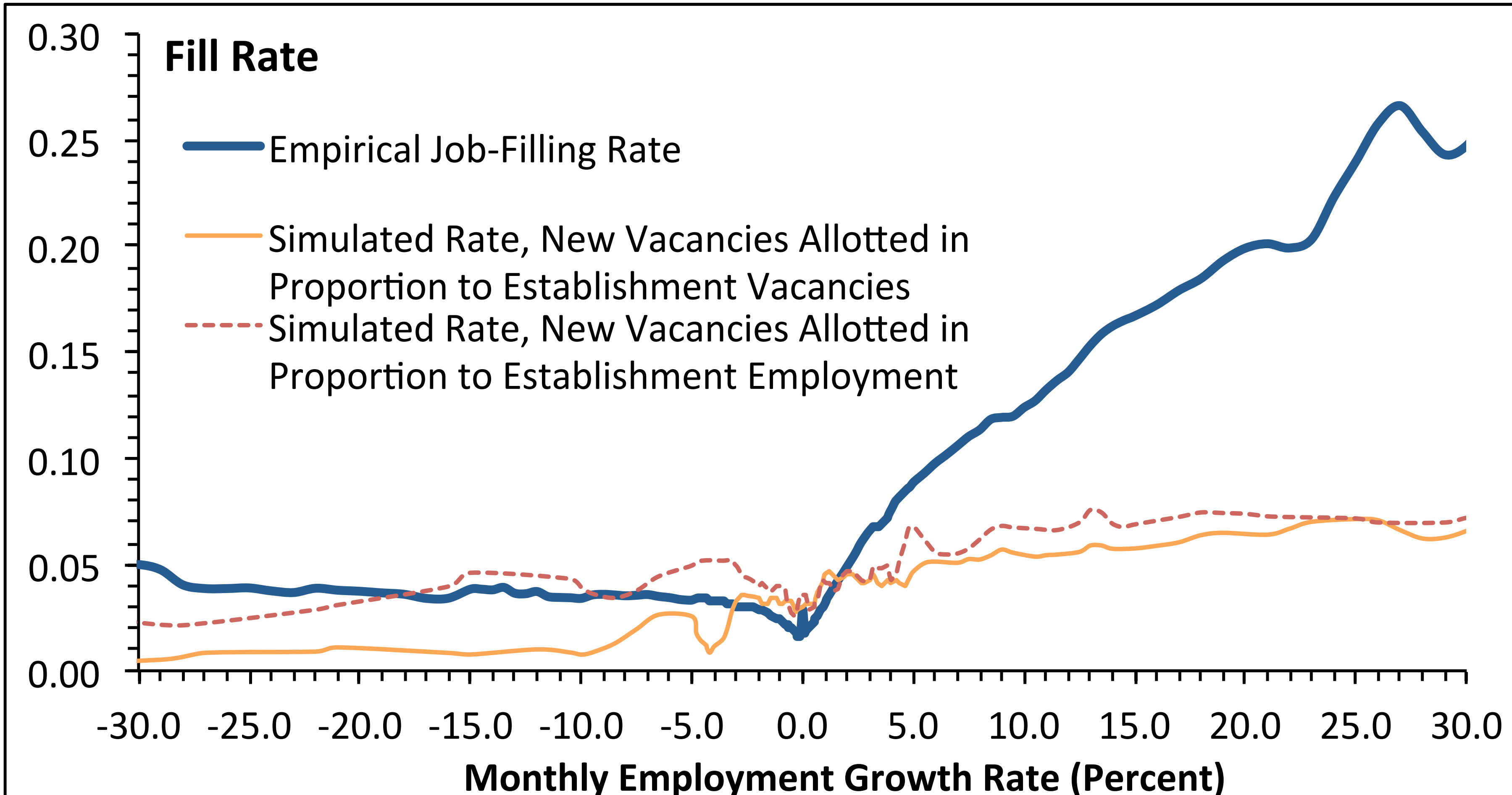
- **Apply the same statistical approach to the analysis of vacancies:**
  - Assess theoretical models
  - Construct synthetic JOLTS-like vacancy measures back to 1990
  - Construct highly disaggregated vacancy measures by region, industry, employer size, etc. (with the intention to overcome small-sample problems in disaggregated vacancy measures calculated directly from JOLTS).

Is It Just "Lucky" Employers Growing Faster?

Stochastic nature of job filling induces a positive relationship between realized employment growth and job-filling rates at the establishment level.

- "Lucky" employers fill jobs faster and, as a result, grow faster.
- To quantify this effect, we simulate hires and employment growth at the establishment level for fitted values of f, θ, δ, and the distribution of vacancies, allowing parameters and vacancy distributions to vary freely by employer size class.
- <u>Result:</u> Luck effect is much too small to explain the observed C-S relationship between job-filling rate and growth rate:
  - Luck alone → job-filling rate rises by 2 percentage points in moving from 0% to 10% monthly growth rate.
  - It rises by another 1 point in moving from 10 to 30%.

Simulated and Empirical Job-Filling Rates Compared



Textbook Equilibrium Search Model

- No role for "recruiting intensity" per vacancy
- Pissarides (2000, chapter 5) extends standard model to incorporate variable recruiting intensity per vacancy
  - Costs per vacancy are increasing and convex in intensity
  - His hiring technology and matching function are consistent with our generalized matching function (micro CRS case)
- *Optimal recruiting intensity is insensitive to aggregate conditions and same for all employers in the cross-section.* Why? Employers use vacancies to vary hires, and choose intensity to minimize cost per vacancy.
- Rejected by our CS evidence, specifically positive relationship of job-filling rates to employer growth and hires rate.
- Cannot explain role of other instruments for aggregate hires.

Additional Theoretical Implications

- A major role for recruiting intensity per vacancy is not fatal to standard equilibrium search models with random matching, but it calls for re-evaluation of widely used building blocks in the standard model
  - Dropping the standard free-entry condition for new jobs (and dispensing with the convenient result that equilibrium vacancy value is 0) leads to a meaningful role for recruiting intensity per vacancy. See Davis (2001), "Quality Distribution of Jobs …"
- The CS evidence on slides is hard to square with the basic mechanism stressed by mismatch models.
- Directed search models are readily compatible with the CS evidence, because these models come built-in with an extra recruiting margin, typically in the form of posted offer wages. See Kass and Kircher (2010).

Are All Hires Mediated through Vacancies? A Specification Test

- Number of hires in month *t* accounted for by the flow of new vacancies in *t:*

$$H_t^{NEW} = f_t \theta_t \sum_{s=1}^{\tau} (\tau - s)(1 - f_t - \delta_t + \delta_t f_t)^{s-1}$$

- So, according to the model, the percent of hires in *t* accounted for by establishments with no vacancies at start of month is:

$$E_t^{NoVac} H_t^{NEW} / H_t$$

where the first variable is the employment share at establishments with no vacancies at start of month.

Model Specification Test Results

Percent of Hires in *t* by Establishments with No Vacancies at end of t-1	**41.6**
Percent Implied by Model for Alternative Sectoral Breakdowns	
Size Class (6) by Worker Turnover Rate (6) – 36 cells	**27.0**
Industry (12) by Size Class (2) by Worker Turnover (6) Rate – 144 cells	**26.7**
Industry (2) by Size Class (6) by Worker Turnover Rate (15) – 180 cells	**27.4**

27.4/41.6 = 66% → Our model of daily hiring accounts for about 2/3 of hires at establishments with no vacancies at start of month. So a big share of hires are not mediated through vacancies

Figure B.5: Scatter Plot of the Log Vacancy Rate against the Log Hires Rate across Growth Rate Bins and Hires-Weighted Least Squares Regression Results