THE ESTABLISHMENT-LEVEL BEHAVIOR OF VACANCIES AND HIRING

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NBER Working Paper No. 16265
August 2010, Revised August 2012
JEL No. D21,E24,J63

ABSTRACT

This paper is the first to study vacancies, hires, and vacancy yields at the establishment level in the Job Openings and Labor Turnover Survey, a large sample of U.S. employers. To interpret the data, we develop a simple model that identifies the flow of new vacancies and the job-filling rate for vacant positions. The fill rate moves counter to aggregate employment but rises steeply with employer growth rates in the cross section. It falls with employer size, rises with worker turnover rates, and varies by a factor of four across major industry groups. We also develop evidence that the employer-level hiring technology exhibits mild increasing returns in vacancies, and that employers rely heavily on other instruments, in addition to vacancies, as they vary hires. Building from our evidence and a generalized matching function, we construct a new index of recruiting intensity (per vacancy). Recruiting intensity partly explains the recent breakdown in the standard matching function, delivers a better-fitting empirical Beveridge Curve, and accounts for a large share of fluctuations in aggregate hires. Our evidence and analysis provide useful inputs for assessing, developing and calibrating theoretical models of search, matching and hiring in the labor market.

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1. Introduction

In many models of search, matching, and hiring in the labor market, employers post vacancies to attract job seekers.[1] These models often feature a matching function that requires job seekers and job vacancies to produce new hires. The concept of a job vacancy also plays an important role in mismatch and stock-flow matching models of the labor market.[2] Despite a key role in theoretical models, relatively few empirical studies consider vacancies and their connection to hiring at the establishment level. Even at more aggregated levels, our knowledge of vacancy behavior is very thin compared to our knowledge of unemployment. As a result, much theorizing about vacancies and their role in the hiring process takes place in a relative vacuum.

This study enriches our understanding of vacancy and hiring behavior and develops new types of evidence for assessing, developing, and calibrating theoretical models. We consider vacancy rates, new hires, and vacancy *yields* at the establishment level in the Job Openings and Labor Turnover Survey (JOLTS), a large sample of U.S. employers. The vacancy yield is the flow of realized hires during the month per reported job opening at the end of the previous month. Using JOLTS data, we investigate how the hires rate, the vacancy rate, and the vacancy yield vary with employer growth in the cross section, how they differ by employer size, worker turnover, and industry, and how they move over time.

We first document some basic patterns in the data. In the cross section, the vacancy yield falls with establishment size, rises with worker turnover, and varies by a factor of four

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[1] This description fits random search models such as Pissarides (1985) and Mortensen and Pissarides (1994), directed search models with wage posting such as Moen (1997) and Acemoglu and Shimer (2000), on-the-job search models such as Burdett and Mortensen (1998) and Nagypál (2007), and many others. The precise role of vacancies differs across these models. See Mortensen and Pissarides (1999), Rogerson, Shimer and Wright (2006) and Yashiv (2006) for reviews of research in this area.
[2] See, for example, Hansen (1970) and Shimer (2007) for mismatch models and Coles and Smith (1998) and Ebrahimy and Shimer (2008) for stock-flow matching models.

across major industry groups. We find striking nonlinear relationships of hires, vacancies, and vacancy yields to the growth rate of employment at the establishment level. Among shrinking establishments, the relationship of all three measures to employer growth is nearly flat. Among expanding establishments, all three measures rise steeply with employer growth. Another set of basic facts pertains to the distribution of vacancies and hires across establishments. Employers with no recorded vacancies at month's end account for 45% of aggregate employment. At the same time, establishments reporting zero vacancies at month's end account for 42% of all hires in the following month.

The large share of hires by employers with no reported vacancy at least partly reflects an unmeasured flow of new vacancies posted and filled within the month. This unmeasured vacancy flow also inflates the measured vacancy yield. To address this and other issues, we introduce a simple model of daily hiring dynamics. The model treats data on the monthly flow of new hires and the stock of vacancies at month's end as observed outcomes of a daily process of vacancy posting and hiring. By cumulating the daily processes to the monthly level, we can address the stock-flow distinction and uncover three interesting quantities: the flow of new vacancies during the month, the average daily job-filling rate in the month, and the mean number of days required to fill an open position.

The job-filling rate is the employer counterpart to the much-studied job-finding rate for unemployed workers.[3] Although theoretical models of search and matching carry implications for both job-finding and job-filling rates, the latter has received little attention. Applying our model, we find that the job-filling rate moves counter-cyclically at the aggregate level. In the cross section, the job-filling rate exhibits the same strong patterns as

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[3] Recent studies include Hall (2005a, 2005b), Shimer (2005, 2007b), Yashiv (2007), Petrongolo and Pissarides (2008), Elsby, Michaels, and Solon (2009) and Fujita and Ramey (2009).

the vacancy yield. Vacancy durations are longer for larger establishments, and job-filling rates are an order of magnitude greater at high compared to low turnover establishments. Most striking, the job-filling rate rises very steeply with employer growth in the cross section – from 1-2 percent per day at establishments with stable employment to more than 10 percent per day for establishments that expand by 7% or more during the month.

Looking across industries, employer size classes, worker turnover groups, and establishment growth rate bins, we find a recurring pattern: The job-filling rate exhibits a strong positive relationship to the gross hires rate. The same pattern emerges even more strongly when we isolate changes over time at the establishment level. This pattern suggests that employers rely heavily on other instruments, in addition to vacancies, as they vary the rate of new hires. Other instruments – such as advertising expenditures, screening methods, hiring standards, and compensation packages – influence job-filling rates through effects on applications per vacancy, applicant screening times, and acceptance rates of job offers. Another explanation for the positive relationship between job-filling rates and gross hires in the micro data is increasing returns to vacancies in the employer-level hiring technology.

To evaluate these explanations and extend our analysis in other ways, we consider a generalized matching function defined over unemployed workers, job vacancies, and "recruiting intensity" per vacancy (shorthand for the effect of other instruments). As we show, the corresponding hiring technology implies a tight relationship linking the hires elasticity of job-filling rates in the micro data to scale economies in vacancies and the role of recruiting intensity per vacancy. Partly motivated by this relationship, we devise an approach to estimate the degree of scale economies using JOLTS data. We find evidence of mild increasing returns to vacancies in the employer-level hiring technology. This novel

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result – interesting in its own right – allows us to recover the combined role of other (non-vacancy) recruiting instruments in hiring outcomes from the empirical hires elasticity of job-filling rates. Using this identification strategy, we find that recruiting intensity per vacancy drives the empirical hires elasticity of job-filling rates.

Our analysis and empirical investigation also yield new insights about aggregate labor market fluctuations. Consider a standard CRS matching function defined over job vacancies (*v*) and unemployed persons (*u*): $H = \mu v^{1-\alpha} u^{\alpha}$, where $\mu > 0$ and $0 < \alpha < 1$. The implied vacancy yield is a decreasing function of labor market tightness, as measured by the vacancy-unemployment ratio. Figure 1 plots this implied vacancy yield and shows that it closely tracks the measured vacancy yield in JOLTS data from 2001 to 2007. [4] But the relationship broke down in a major way in the next four years: Conditional on the number of vacant jobs and unemployed workers, new hires are much lower from 2008 to 2011 than implied by a standard matching function. This breakdown is a significant puzzle.

We provide a partial explanation and remedy for the breakdown, building from micro evidence to quantify recruiting intensity per vacancy at the aggregate level. The resulting generalized matching function outperforms the standard matching function in several respects. First, as Figure 1 shows, incorporating a role for recruiting intensity reduces the discrepancy between the measured vacancy yield and the empirical construct implied by the matching function. Second, and closely related, our recruiting intensity measure explains about one quarter of the aggregate time-series residuals produced by the

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[4] The ratio of hires to vacancies is often treated as a measure of the job-filling rate. We reserve the latter term for the measure that adjusts for the stock-flow difference between the monthly flow of gross hires and the end-of-month vacancy stock in JOLTS data. As an empirical matter, the daily fill rate is nearly proportional to the vacancy yield in the aggregate time-series data. So we do not lose much by focusing on the vacancy yield in Figure 1, and we gain simplicity. In the micro data, however, the near proportionality between vacancy yields and job-filling rates fails, and it becomes important to respect the stock-flow distinction.

standard matching function, residuals that other authors interpret in terms of mismatch or fluctuations in matching efficiency. Third, by generalizing the matching function to include a role for recruiting intensity, we obtain a better-fitting empirical Beveridge Curve in national and regional data. Finally, over the period covered by the JOLTS data, our recruiting intensity index accounts for much of the movements in aggregate hires.[5]

Our analysis and results have important implications for search and matching models. Obviously, they point to an important role for other recruiting instruments in the hiring process and the usefulness of the generalized matching function as a device for organizing and interpreting the data. Less obviously, the textbook equilibrium search model extended to include a recruiting intensity margin cannot replicate the observed behavior of job-filling rates. We explain why, discuss modifications to the textbook model that potentially account for the evidence, and briefly consider how the evidence relates to directed search models and mismatch models.

Our work also relates to several previous empirical studies of vacancy behavior. The pioneering work of Abraham (1983, 1987) and Blanchard and Diamond (1989) uses the Help Wanted Index (HWI) to proxy for vacancies, and many other studies follow their lead. The Help Wanted Index yields sensible patterns at the aggregate level (Abraham, 1987; Blanchard and Diamond, 1989; and Shimer, 2005), but it cannot accommodate an employer-level analysis. Several recent studies exploit aggregate and industry-level JOLTS data on hires, separations, and vacancies (e.g., Hall, 2005a; Shimer, 2005, 2007a; Valetta, 2005).

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[5] In follow-on work, we develop additional evidence that the recruiting intensity concept and generalized matching function improve our understanding of aggregate labor market fluctuations. Davis, Faberman and Haltiwanger (2012) show that industry-level movements in job-filling rates are at odds with implications of the standard matching function but consistent with the implications of our generalized matching function. Davis (2011) shows that using our recruiting intensity index in a generalized matching function helps to explain the plunge in job-finding rates during the Great Recession and their failure to recover afterwards.

Earlier studies by Holzer (1994), Burdett and Cunningham (1998) and Barron, Berger, and Black (1999) consider vacancy behavior in small samples of U.S. employers. Van Ours and Ridder (1991) investigate the cyclical behavior of vacancy flows and vacancy durations using periodic surveys of Dutch employers. Coles and Smith (1996), Berman (1997), Yashiv (2000), Dickerson (2003), Andrews et al. (2007) and Sunde (2007) exploit vacancy data from centralized registers of job openings in various countries.

The next section describes our data and measurement mechanics. Section 3 documents basic patterns in the behavior of vacancies and hires. Section 4 sets forth our model of daily hiring dynamics, fits it to the data, recovers estimates for the flow of new vacancies and daily job-filling rate, and develops evidence of how these statistics vary over time and in the cross section. In Section 5, we interpret the evidence and extend the analysis in several ways. We introduce the generalized matching function, and show how to extract information about the role of recruiting intensity and scale economies in the hiring process. We then turn to aggregate implications and relate our evidence to leading search models. In Section 6, we return to our model of daily hiring dynamics and evaluate how well it accounts for the large share of hires at employers with no recorded vacancies. Section 7 concludes with a summary of our main contributions and some remarks about directions for future research.

2. Data Sources and Measurement Mechanics

The Job Openings and Labor Turnover Survey (JOLTS) samples about 16,000 establishments per month. Respondents report hires and separations during the month, employment in the pay period covering the 12$^{\text{th}}$ of the month, and job openings at month's end. JOLTS data commence in December 2000, and our establishment-level sample

continues through December 2006. We drop observations that are not part of a sequence of two or more consecutive observations for the same establishment. This restriction enables a comparison of hires in the current month to vacancies at the end of the previous month, an essential element of our micro-based analysis. The resulting sample contains 577,268 observations, about 93% of the full sample that the BLS uses for published JOLTS statistics. We have verified that this sample restriction has little effect on aggregate estimates of vacancies, hires, and separations.[6] While our JOLTS micro data set ends in December 2006, we consider the period through December 2011 for analyses that use published JOLTS data.

It will be helpful to describe how job openings (vacancies) are defined and measured in JOLTS. The survey form instructs the respondent to report a vacancy when "a specific position exists, work could start within 30 days, and [the establishment is] actively seeking workers from outside this location to fill the position." The respondent is asked to report the number of such vacancies on "the last business day of the month." Further instructions define "active recruiting" as "taking steps to fill a position. It may include advertising in newspapers, on television, or on radio; posting Internet notices; posting 'help wanted' signs; networking or making 'word of mouth' announcements; accepting applications; interviewing candidates; contacting employment agencies; or soliciting employees at job fairs, state or local employment offices, or similar sources." Vacancies are not to include positions open only to internal transfers, promotions, recalls from temporary layoffs, jobs that commence more than 30 days hence, or positions to be filled by temporary help agencies, outside contractors, or consultants.

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[6] There is a broader selection issue in that the JOLTS misses most establishment births and deaths, which may be why our sample restriction has little impact on aggregate estimates. Another issue is the potential impact of JOLTS imputations for item nonresponse, on which we rely. See Clark and Hyson (2001), Clark (2004) and Faberman (2008) for detailed discussions of JOLTS. See Davis, Faberman, Haltiwanger, and Rucker (2010) for an analysis of how the JOLTS sample design affects the published JOLTS statistics.

Turning to measurement mechanics, we calculate an establishment's net employment change in month t as its reported hires in month t minus its reported separations in t. We subtract this net change from its reported employment in t to obtain employment in $t-1$. This method ensures that the hires, separations, and employment measures in the current month are consistent with employment for the previous month. To express hires, separations, and employment changes at t as rates, we divide by the simple average of employment in $t-1$ and t. The resulting growth rate measure is bounded, symmetric about zero and has other desirable properties, as discussed in Davis, Haltiwanger, and Schuh (1996). We measure the vacancy rate at t as the number of vacancies reported at the end of month t divided by the sum of vacancies and the simple average of employment in $t-1$ and t. The vacancy yield in t is the number of hires reported in t divided by the number of vacancies reported at the end of $t-1$.

3. Sectoral and Establishment-Level Patterns

3.A. Cross-Sectional Patterns

Table 1 draws on JOLTS micro data to report the hires rate, separation rate, vacancy rate, and vacancy yield by industry, employer size group, and worker turnover group. Worker turnover is measured as the sum of the monthly hires and separations rates at the establishment. All four measures show considerable cross-sectional variation, but we focus our remarks on the vacancy yield. Government, Health & Education, Information and FIRE have low vacancy yields on the order of 0.8 hires during the month per vacancy at the end of the previous month. Construction, an outlier in the other direction, has a vacancy yield of 3.1. The vacancy yield falls by more than half in moving from establishments with fewer

than 50 employees to those with more than 1,000. It rises by a factor of ten in moving from the bottom to the top turnover quintile.

What explains these strong cross-sectional patterns? One possibility is that matching is intrinsically easier in certain types of jobs. For example, Albrecht and Vroman (2002) build a matching model with heterogeneity in worker skill levels and in skill requirements of jobs. Jobs with greater skill requirements have longer expected vacancy durations because employers are choosier about whom to hire. Barron, Berger, and Black (1999) provide evidence that search efforts and vacancy durations depend on skill requirements. Davis (2001) identifies a different effect that leads to shorter durations in better jobs. In his model, employers with more productive jobs search more intensively because the opportunity cost of a vacancy is greater. Thus, if all employers use the same search and matching technology, more productive jobs fill at a faster rate. Yet another possibility is that workers and employers sort into separate search markets, each characterized by different tightness, different matching technologies, or both. Given the standard matching function described in the introduction, this type of heterogeneity gives rise to differences in vacancy yields across labor markets defined by observable and relevant employer characteristics.

Another explanation recognizes that firms recruit, screen, and hire workers through a variety of channels, and that reliance on these channels differs across industries and employers. For example, construction firms may recruit workers from a hiring hall or other specialized labor pool for repeated short-term work, perhaps reducing the incidence of measured vacancies and inflating the vacancy yield. In contrast, government and certain other employers operate under laws and regulations that require a formal search process for the vast majority of new hires, ensuring that most hiring is mediated through measured

vacancies. More generally, employers rely on a mix of recruiting and hiring practices that differ in propensity to involve a measured vacancy and in vacancy duration. These methods include bulk screening of applicants who respond to help-wanted advertisements, informal recruiting through social networks, opportunistic hiring of attractive candidates, impromptu hiring of unskilled workers in spot labor markets, and the conversion of temp workers and independent contractors into permanent employees. Differences in the mix of recruiting, screening and hiring practices lead to cross-sectional differences in the vacancy yield.

3.B. The Establishment-Level Distribution of Vacancies and Hires

Table 2 and Figure 2 document the large percentage of employers with few or no reported vacancies. In the average month, 45% of employment is at establishments with no reported vacancies. When establishments report vacancies, it is often at very low rates and levels. The median vacancy rate is less than 1% of employment, calculated in an employment-weighted manner, and the median number of vacancies is just one. At the 90th percentile of the employment-weighted distribution, the vacancy rate is 6% of employment and the number of vacancies is 63. Weighting all establishments equally, 88 percent report no vacancies, the vacancy rate at the 90th percentile is 3%, and the number of vacancies at the 90th percentile is just one. The establishment-level incidence of vacancies is highly persistent: only 18% of vacancies in the current month occur at establishments with no recorded vacancies in the previous month.

Establishments with zero hires during the month account for 35% of employment, which suggests that many employers have little need for hires at the monthly frequency. However, Table 2 also reports that 42% of hires take place at establishments with no reported vacancy going into the month. This fact suggests that average vacancy durations

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are very short, or that much hiring is not mediated through vacancies as the concept is defined and measured in JOLTS. We return to this issue in Section 6.

3.C. Hires, Vacancies, and Establishment Growth

We next consider how hires, vacancies, and vacancy yields co-vary with employer growth rates at the establishment level. To estimate these relationships in a flexible nonparametric manner, we proceed as follows. First, we partition the feasible range of growth rates, [-2.0, 2.0], into 195 non-overlapping intervals, or bins, allowing for mass points at -2, 0 and 2. We use very narrow intervals of width .001 near zero and progressively wider intervals as we move away from zero into the thinner parts of the distribution. Next, we sort the roughly 577,000 establishment-level observations into bins based on monthly employment growth rate values. Given the partition and sorting of establishments, we calculate employment-weighted means for the hires rate, the vacancy rate, and the vacancy yield for each bin. Equivalently, we perform an OLS regression of the outcome variables on an exhaustive set of bin dummies. The regressions coefficients on the bin dummies recover the nonparametric relationship of the outcome variables to the establishment-level growth rate of employment. Under the regression approach, it is easy to introduce establishment fixed effects or other controls.

Figures 3, 4, and 5 display the nonparametric regression results.[7] The hires relation must satisfy part of an adding-up constraint, because net growth is the difference between hires and separations. Thus, the minimum feasible value for the hires rate lies along the horizontal axis for negative growth and along the 45-degree line for positive growth. Hiring exceeds this minimum at all growth rates, more so as growth increases.

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[7] We focus on monthly growth rate intervals in the -30 to 30% range because our estimates are highly precise in this range. For visual clarity, we smooth the nonparametric estimates using a centered, five-bin moving average except for bins at and near zero, where we use no smoothing.

Figure 3 shows a highly nonlinear, kinked relationship between the hires rate and the establishment growth rate. The hires rate declines only slightly with employment growth at shrinking establishments, reaching its minimum for establishments with no employment change. To the right of zero, the hire rate rises slightly more than one-for-one with the growth rate of employment. This cross-sectional relationship says that hires and job creation are very tightly linked at the establishment level. Controlling for establishment fixed effects in the regression, and thereby isolating within-establishment time variation, does little to alter the relationship. In fact, the "hockey-stick" shape of the hires-growth relation is even more pronounced when we control for establishment fixed effects.

Figure 4 reveals a qualitatively similar relationship for the vacancy rate. Vacancy rates average about 2% of employment at contracting establishments, dip for stable establishments with no employment change, and rise with the employment growth rate at expanding establishments. The vacancy-growth relationship for expanding establishments is much less steep than the hires-growth relationship. For example, at a 30% monthly growth rate, the vacancy rate is 4.8% of employment compared to 34.2% for the hires rate.

Figure 5 presents the vacancy yield relationship. We report total hires divided by total vacancies in each bin, which is similar to dividing the hires relation in Figure 3 by the vacancy relation in Figure 4.[8] Among contracting establishments, vacancies yield about one hire per month. There is a discontinuity at zero that vanishes when controlling for establishment fixed effects. Among expanding establishments, the vacancy yield increases markedly with the growth rate. Expansions in the 25-30% range yield over five hires per

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[8] It is not identical because the hires and vacancy rates have different denominators. Another alternative is to construct the vacancy yield at the establishment level and then aggregate to the bin level by computing employment-weighted means. This alternative, which restricts the sample to establishments with vacancies, yields a pattern very similar to the one reported in Figure 5.

vacancy. The strongly increasing relation between vacancy yields and employer growth survives the inclusion of establishment fixed effects.

Figure 5 tells us that employers hire more workers per recorded vacancy when they grow more rapidly. This pattern holds very strongly in the cross section of establishments (raw relationship) and when we isolate establishment-level variation over time by controlling for establishment fixed effects.[9] Taken at face value, the finding is starkly at odds with the proposition that (expected) hires are proportional to vacancies. This proposition holds in the textbook search and matching model and most other models with undirected search, as we discuss below. It is unclear, however, whether this finding accurately portrays the underlying economic relationship. It may instead reflect a greater unobserved flow of new vacancies filled during the month at more rapidly growing establishments. The basic point is that, because of time aggregation, we cannot confidently infer the economic relationship between vacancies and hires from raw JOLTS data.

4. Job-Filling Rates and Vacancy Flows

4.A. A Model of Daily Hiring Dynamics

Consider a simple model of daily hiring dynamics where $h_{s,t}$ is the number of hires on day s in month t, and $v_{s,t}$ is the number of vacancies. Denote the daily job-filling rate for vacant positions in month t by f_t, which we treat as constant within the month for any given establishment. Hires on day s in month t equal the fill rate times the vacancy stock:

$$(1) \qquad\qquad h_{s,t} = f_t v_{s-1,t} \, .$$

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[9] We regress the hiring (and vacancy) rates on bin dummies and establishment fixed effects, recovering the coefficients on the bin dummies and adding an equal amount to each coefficient to restore the grand employment-weighted mean. We then take the ratio of resulting hiring and vacancy rates to obtain the curve in Figure 5 with controls for establishment fixed effects. Restricting the sample to establishments with vacancies and running the fixed effects regression directly on the ratio of hires to vacancies yields a very similar plot.

The stock of vacancies evolves in three ways. First, a daily flow θ_t of new vacancies increases the stock. Second, hires deplete the stock. Third, vacancies lapse without being filled at the daily rate δ_t, also depleting the stock. These assumptions imply the daily law of motion for the vacancy stock during month t:

(2) $$v_{s,t} = ((1 - f_t)(1 - \delta_t))v_{s-1,t} + \theta_t.$$

In fitting the model to data, we allow f_t, θ_t and δ_t to vary with industry, establishment size and other observable employer characteristics.

Next, sum equations (1) and (2) over τ workdays to obtain monthly measures that correspond to observables in the data. For vacancies, relate the stock at the end of month $t - 1$, v_{t-1}, to the stock at the end of month t, τ days later. Cumulating (2) over τ days and recursively substituting for $v_{s-1,t}$ yields the desired equation:

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

The first term on the right is the initial stock, depleted by hires and lapsed vacancies during the month. The second term is the flow of new vacancies, similarly depleted.

Hires are reported as a monthly flow in the data. Thus, we cumulate daily hires in (1) to obtain the monthly flow, $H_t = \sum_{s=1}^{\tau} h_{s,t}$. Substituting (2) into (1), and (1) into the monthly sum, and then substituting back to the beginning of the month for $v_{s-1,t}$ yields

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

The first term on the right is hires into the old stock of vacant positions, and the second is hires into positions that open during the month. Given H_t, v_t, v_{t-1}, and δ_t, the system (3) and (4) identifies the average daily job-filling rate, f_t, and the daily flow of vacancies, θ_t.

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4.B. Estimating the Model Parameters

To estimate f_t and θ_t, we solve the system (3) and (4) numerically after first

equating $\tau\delta_t$ to the monthly layoff rate. That is, we assume vacant job positions lapse at the

same rate as filled jobs undergo layoffs. The precise treatment of δ matters little for our

results because any reasonable value for δ is an order of magnitude smaller than the

estimates for f. Thus the job-filling rate dominates the behavior of the dynamic system

given by (1) and (2). We treat all months as having $\tau = 26$ working days, the average

number of days per month less Sundays and major holidays. We calculate the average

vacancy duration as $1/f_t$ and express the monthly vacancy flow as a rate by dividing $\tau\theta_t$ by

employment in month t.[10]

When estimating parameters at the aggregate level, we use published JOLTS

statistics for monthly flows of hires and layoffs and the end-of-month stock of vacancies.

We use the pooled-sample JOLTS micro data from 2001 to 2006 to produce parameter

estimates by industry, size class, turnover category, and growth rate bin.

4.C. Fill Rates and Vacancy Flows over Time

Figure 6 shows monthly time series from January 2001 to December 2011 for the

estimated flow of new vacancies and the daily job-filling rate. The monthly flow of new

vacancies averages 3.6% of employment, considerably larger than the average vacancy stock

of 2.7%. Vacancy stocks and flows are pro-cyclical, with stronger movements in the stock

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[10] We also tried an estimation approach suggested by Rob Shimer. The approach considers steady-state versions of (1) and (2) and sums over τ workdays to obtain $f = (H/v)(1/\tau)$ and $\theta = (f + \delta - f\delta)v$. This system is simple enough to solve by hand. In practice, the method works well on aggregate data, delivering estimates for f_t and θ_t close to the ones implied by (3) and (4). At more disaggregated levels, estimates based on the steady-state approximation often diverge from those implied by (3) and (4), sometimes greatly. Note that the estimated job-filling rate based on the steady-state approximation is simply a rescaled version of the vacancy yield. We stick to the method based on (3) and (4) for our reported results.

measure. The average daily job-filling rate is 5.2% per day. It ranges from a low of 4.0% in February 2001 to a high of 6.9% in July 2009, moving counter cyclically. Mean vacancy duration ranges from 14 to 25 days.[11] Clearly, vacancy durations and job-filling rates exhibit large cyclical amplitudes. [12]

4.D. Results by Industry, Employer Size and Worker Turnover

Table 3 presents cross-sectional results based on the pooled-sample JOLTS micro data from 2001 to 2006. The job-filling rate ranges from about 3% per day in Information, FIRE, Health & Education and Government to 5% in Manufacturing, Transport, Wholesale & Utilities, Professional & Business Services and Other Services, 7% in Retail Trade and Natural Resources & Mining and 12% per day in Construction. Table 3 also shows that job-filling rates decline with employer size, falling by more than half in moving from small to large establishments. The most striking pattern in the job-filling rate pertains to worker turnover categories. The job-filling rate ranges from 1.1% per day in the lowest turnover quintile to 11.4% per day in the highest turnover quintile. These cross-sectional differences have received little attention in the theoretical literature, but they offer a natural source of inspiration for model building and a useful testing ground for theory.[13]

4.E. Vacancy Flows and Fill Rates Related to Establishment Growth Rates

Section 3 finds that the vacancy yield increases strongly with the employment growth rate at expanding establishments. As we explained, this relationship is at least partly driven by time aggregation. To address the role of time aggregation, we now recover the

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[11] Our vacancy duration estimates are similar to those obtained by Burdett and Cunningham (1998) and Barron, Berger, and Black (1999) in small samples of U.S establishments but considerably shorter than those obtained by van Ours and Ridder (1991) for the Netherlands and Andrews et al. (2007) for the U.K.

[12] The online appendix applies our methods to data on new hires from the Current Population Survey and the Conference Board's Help Wanted Index to provide additional evidence on the cyclicality of job-filling rates.

[13] To be sure, there has been some theoretical work that speaks to cross-sectional differences in job-filling rates, including the works by Albrecht and Vroman (2002) and Davis (2001) mentioned above.

job-filling rate as a function of employer growth. Specifically, we sort the establishment-level observations into 195 growth rate bins and then estimate f and θ for each bin using the moment conditions (3) and (4). In this way, we obtain nonparametric estimates for the relationship of the job-filling rate to the establishment growth rate. This estimation exercise also yields the monthly flow of new vacancies by growth rate bin.

Figure 7 displays the estimated relationships. Both the fill rate and the vacancy flow rate exhibit a pronounced kink at zero and increase very strongly with the establishment growth rate to the right of zero. Fill rates rise from 3% per day at establishments that expand by about 1% in the month to 9% per day at establishments that expand by about 5%, and to more than 20% per day at those that expand by 20% or more in the month. The job-filling rate and flow rate of new vacancies are relatively flat to the left of zero.

One important conclusion is immediate from Figure 7: the strong positive relationship between vacancy yields and employer growth rates among expanding establishments is not simply an artifact of time aggregation. If it were, we would not see a positive relationship between the job-filling rate and employer growth to the right of zero. In fact, we see a very strong positive relationship. [14] To check whether unobserved heterogeneity underlies this result, we control for establishment-level fixed effects in fitting the relationship between job-filling rates and establishment-level growth rates.[15] Controlling for heterogeneity actually *strengthens* the relationship between the job-filling

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[14] This is not to say that time aggregation plays no role in the observed vacancy yield relationship to employer growth. On the contrary, Figure 7 shows that the vacancy flow rises strongly with employment growth at expanding establishments, much more strongly than the vacancy rate in Figure 4. This pattern implies that vacancy yields are more inflated by time aggregation at faster growing establishments. In other words, time aggregation is part of the explanation for the vacancy yield relation in Figure 5. But it is not the main story, and it does not explain the fill rate relationship to employer growth in Figure 7.

[15] We solve moment conditions (3) and (4) using the fixed effects estimates from Figures 3 and 4.

rate and the growth rate of employment. Removing time effects (not shown) has negligible impact.

Another possible explanation for the fill-rate relationship in Figure 7 stresses randomness at the micro level. In particular, the stochastic nature of job filling induces a spurious positive relationship between the realized job-filling rate and the realized employer growth rate. Lucky employers fill jobs faster and, as a result, grow faster. To quantify this mechanical luck effect, we simulate hires, vacancy flows and employment paths at the establishment level for fitted values of f, θ, δ, the separation rate and the cross-sectional distribution of vacancies. We let the parameters and the empirical vacancy distribution vary freely across size classes. By construction, the simulation delivers a positive relationship between the realized job-filling rate and the realized growth rate through the luck effect.

Figure 8 overlays the empirical job-filling rates on the simulated rates. We perform the simulations under two polar assumptions for the allocation of new vacancy flows, θ, in each size class: first, by allocating the flows in proportion to the observed distribution of employment in the micro data, and second, by allocating in proportion to the observed distribution of vacancy stocks. Either way, the simulations reveal that the luck effect is much too small to explain the empirical fill-rate relationship. The luck effect produces a fill-rate increase of about 2 to 3 percentage points in moving from 0 to 10 percent monthly growth and up to another 1 point in moving from 10 to 30 percent growth. That is, the luck effect accounts for about one-tenth of the observed positive relationship between job filling and growth at growing employers. We conclude that the vacancy yield and fill rate patterns in Figures 5 and 7 reflect something fundamental about the nature of the hiring process and its relationship to employer growth. We develop an explanation for this pattern below.

4.F. Fill Rates and Gross Hires: A Recurring Pattern

Recalling Figure 3, Figures 7 and 8 also point to a strong relationship across growth rate bins between the job-filling rate and the gross hires rate. Figure 9 shows that this relationship is indeed strong. The nature of the pattern is also noteworthy: as the gross hires rate rises, so does the job-filling rate. The empirical elasticity of the job-filling rate with respect to the gross hires rate is 0.820, which flatly contradicts the view that employers vary vacancies in proportion to desired hires. In the online appendix, we show that a very similar pattern holds across industries, employer size classes, and worker turnover groups. The large positive hires elasticity of job-filling rates is a novel empirical finding and, as we show in the next section, has important implications for theory.

5. Interpretations and Implications

5.A. Hires Are Not Proportional to Vacancies in the Cross Section: Two Interpretations

Standard specifications of equilibrium search and matching models include a constant-returns-to-scale (CRS) matching function defined over job vacancies and unemployed workers. In versions of these models taken to data, the number of vacancies is typically the sole instrument employers use to vary hires. The expected period-*t* hires for an employer *e* with v_{et} vacancies are $f_t v_{et}$, where the fill-rate f_t is determined by market tightness at *t* and the matching function, both exogenous to the employer. That is, hires are proportional to vacancies in the cross section.[16] Since the same job-filling rate applies to all employers, the standard specification implies a zero cross-sectional elasticity of hires (and

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[16] To see the connection to our model of daily hiring dynamics, recall from footnote 10 that steady-state approximations of (1) and (2) yield $H \approx \tau f v$.

the hires rate) with respect to the job-filling rate. This implication fails – rather

spectacularly – when set against the evidence in Figures 7, 8 and 9.[17]

What accounts for this failure? One possibility is that employers act on other

margins using other instruments, in addition to vacancies, when they increase their hiring

rate. They can increase advertising or search intensity per vacancy, screen applicants more

quickly, relax hiring standards, improve working conditions, and offer more attractive

compensation to prospective employees. If employers with greater hiring needs respond in

this way, the job-filling rate rises with the hires rate in the cross section and over time at the

employer level. We are not aware of previous empirical studies that investigate how these

aspects of recruiting intensity per vacancy vary with employer growth. Quantitative search

models also typically omit any role for recruiting intensity per vacancy.

Another class of explanations for the results in Figures 7, 8 and 9 involves scale and

scope economies in vacancies as an input to hiring. It may be easier or less costly to achieve

a given advertising exposure per job opening when an employer has many vacancies rather

than few. Similarly, it may be easier to attract applicants when the employer has a variety of

open positions. Recruiting also becomes easier as an employer grows more rapidly if

prospective hires perceive greater opportunities for promotion and lower layoff risks. These

examples point to potential sources of increasing returns to vacancies at the employer level.

Alternatively, one might try to rationalize the evidence by postulating suitable cross-

sectional differences in matching efficiency. We think an explanation along those lines is

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[17] The online appendix makes this point in a different way. Using the daily model of hiring dynamics, the appendix expresses log gross hires as the sum of two terms – one that depends only on the job-filling rate, and one that depends on the numbers of old and new vacancies. Computing the implied variance decomposition, the vacancy margin (number of vacancies) accounts for half or less of the variance in log gross hires across industries, size classes, turnover groups, and growth rate bins. The proportionality implication says that vacancy numbers are all that matter for cross-sectional hires variation, sharply at odds with the variance decomposition results.

unsatisfactory in two significant respects. First, it offers no insight into why matching

efficiency varies across sectors in line with the gross hire rate, as we document in the online

appendix. Second, sectoral differences in matching efficiency do not explain the key result

in Figure 7 (Figure 9): The job-filling rate is much higher when a given establishment grows

(hires) rapidly, relative to its own sample mean growth (hires) rate, than when it grows

(hires) slowly. A stable CRS hiring technology at the establishment level cannot produce

this pattern when vacancies are the sole instrument employers vary to influence hiring.

5.B. Generalized Matching and Hiring Functions

It will be useful to formalize the role of other recruiting instruments and potential

departures from CRS. Start by writing the standard matching function ($H = \mu v^{1-\alpha} u^{\alpha}$):[18]

$$(5) \qquad \sum_e H_{et} = H_t = \mu \left(\frac{v_t}{u_t} \right)^{-\alpha} v_t = \mu \left(\frac{v_t}{u_t} \right)^{-\alpha} \sum_e v_{et} \equiv f_t \sum_e v_{et}.$$

For an individual employer or group of employers, *e,* (5) implies hires $H_{et} = f_t v_{et}$. Here

and throughout the discussion below, we ignore the distinction between hires and expected

hires by appealing to the law of large numbers when *e* indexes industries, size classes or

worker turnover groups. The simulation exercises reported in Figure 8 indicate that we can

safely ignore the distinction for growth rate bins as well.

Now consider a generalized hiring function that maintains CRS at the aggregate

level, allows for departures from CRS at the micro level, and incorporates a potential role

for employer actions on other recruiting margins using other instruments, *x*:

$$(6) \qquad H_{et} = \mu \left(\frac{v'_t}{u_t} \right)^{-\alpha} q(v_{et}, x_{et}) \equiv \tilde{f}_t q(v_{et}, x_{et}), \qquad \text{where} \sum_e q(v_{et}, x_{et}) = v'_t,$$

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[18] Following customary practice, we use a continuous time formulation in describing the matching functions. We account for the time-aggregated nature of the monthly data in the empirical implementations below.

v'_t is the effective number of vacancies at the aggregate level, and the function $q(\cdot, x)$ captures micro-level scale economies and other margins. When $q(v_{et}, x_{et}) \equiv v_{et}$, aggregation of (6) delivers the standard Cobb-Douglas matching function. For $q(v_{et}, x_{et}) \equiv v_{et}\tilde{q}(x_{et})$ the hiring function includes other margins but satisfies CRS in vacancies at the micro level.[19] More generally, we have increasing, constant or decreasing returns to vacancies at the micro level as $\partial q(\cdot, x_e)/\partial v_e$ is increasing, constant or decreasing in v_e.

For the generalized hiring function (6), the employer's job-filling rate is $f_{et} = \tilde{f}_t q(v_{et}, x_{et})/v_{et}$. Now let $q(v_{et}, x_{et}) \equiv v_{et}^{\gamma}\tilde{q}(x_{et})$, where $\gamma > 0$ governs the degree of micro-level scale economies in vacancies. The job-filling rate becomes

$$(7) \qquad f_{et} = \tilde{f}_t v_{et}^{\gamma-1} \tilde{q}(x_{et}).$$

Taking logs and differentiating with respect to the hiring rate, $\breve{H}_{et}$, we obtain

$$(8) \qquad \frac{d \ln f_{et}}{d \ln \breve{H}_{et}} = \frac{d \ln \tilde{f}_t}{d \ln \breve{H}_{et}} + (\gamma - 1)\frac{d \ln v_{et}}{d \ln \breve{H}_{et}} + \frac{d \ln \tilde{q}(x_{et})}{d \ln \breve{H}_{et}}$$

Recall from Figure 9 that a hires-weighted regression yields a tightly estimated value of 0.820 for the hires elasticity on the left side of (8). The first elasticity on the right side of (8) is zero, because all employers face the same aggregate conditions at a point in time. The second term on the right side of (8) captures the contribution of departures from CRS to the empirical elasticity on the left side. The last term captures the contribution of employer actions on other margins, i.e., the role of recruiting intensity per vacancy.

According to (8), the contribution of scale economies depends partly on the empirical elasticity of vacancies with respect to the gross hires rate. To obtain evidence on this elasticity, we fit a hires-weighted regression of log vacancies per establishment on the

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[19] See Chapter 5 in Pissarides (2000) for analysis of a search equilibrium model with a similar hiring function. Pissarides speaks of an employer's recruiting or advertising intensity, but his specification is like ours when we impose CRS in vacancies at the micro level.

log gross hires rate in the bin-level data. We use the same approach as in Figure 9 to control for establishment fixed effects. The resulting estimate for $d \ln v_{et}/d \ln \breve{H}_{et}$ is -0.128 (s.e. = 0.13). Although not significantly different from zero, the implication of the point estimate is that scale economies cannot rationalize the strong departure from proportionality in the empirical hires-vacancy relationship. Even if we set $d \ln v_{et}/d \ln \breve{H}_{et}$ to 0.13, two standard errors above the point estimate, substituting into (8) yields $0.820 = (\gamma - 1)(0.13) + d \ln \tilde{q}(x_{et})/d \ln H_{et}$. To explain the behavior of job-filling rates in Figure 9 with this vacancy elasticity value, we must invoke strong increasing returns to vacancies at the employer level (i.e., $\gamma = 6.3$), a major role for employer actions on other margins, or some combination of the two.

Based on these calculations in equation (8), we conclude that variation in recruiting intensity per vacancy is a major factor – possibly the central factor – in the employer-level relationship between the job-filling rate and the hiring rate.[20] To sharpen this point, we next develop evidence on the parameter γ in the employer-level hiring technology.

5.C. Estimating Returns to Vacancies in the Hiring Technology

To estimate the returns to vacancies in the employer-level hiring technology, we fit a regression derived from (7) on JOLTS data aggregated to the level of industry × employer size cells and pooled over the 2001-2006 sample period.[21] We select the aggregation level and specify the regression model to isolate variation in the scale of employer hiring activity, as reflected in the average number of vacancies per establishment, while controlling for

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[20] The reader might worry that this conclusion relies on vacancy data unadjusted for time aggregation. To address this concern, the online appendix derives an alternative version of (8) expressed in terms of vacancy flows, adjusted for time aggregation. As the appendix shows, working with the alternative version of (8) yields results even less congenial to the hypothesis that Figure 9 reflects scale economies in vacancies.

[21] We use 12 major industry sectors and 6 size classes. For two industries, the largest size classes have very sparse cells. We therefore aggregate these cells into the next largest size class, providing us with 70 observations.

market tightness, recruiting intensity per vacancy, and differences in matching efficiency by industry and employer size. We use this conditional variation in the scale of employer-level hiring activity as leverage to estimate γ.

Letting i and s index industries and size classes and taking logs in (7) yields

$$\ln f_{is} = \ln \tilde{f} + (\gamma - 1) \ln v_{is} + \ln \tilde{q}(x_{is}) + \epsilon_{is},$$

where $\ln \tilde{f}$ is a constant that absorbs the average level of market tightness during our sample period, $\ln \tilde{q}(x_{is})$ is average recruiting intensity per vacancy in the industry-size cell, and ϵ_{is} is an error term that captures sampling error in the cell-level statistics and unobserved differences in matching efficiency and market tightness by industry and size. To control for these differences, we include industry and size class fixed effects. We also include the average employment growth rate in the industry-size cell during the sample period, g_{is}, to control for any differences in recruiting intensity per vacancy not captured by the fixed effects. Thus, our empirical regression specification becomes

$$\ln f_{is} = \ln \tilde{f} + (\gamma - 1) \ln v_{is} + \psi g_{is} + I_i + I_s + \xi_{is},$$

We fit this regression model by OLS to recover an estimate for γ. Identification requires that the error ξ_{is} be uncorrelated with $\ln v_{is}$ conditional on the controls.

Estimation by OLS may lead to a form of division bias. To see the issue, recall the steady-state approximation $f \approx H/v$ implied by our model of daily hiring dynamics. This approximation indicates that measurement errors in v enter into our model-based estimates of f derived from (3) and (4). To address this issue, we run a two-stage least squares regression, instrumenting $\ln v_{is}$ with the log of total employment in the industry-size cell. The employment data are not used in constructing our estimates of f.

Another potential concern is the regression model's specification in terms of the vacancy stock, v, which is subject to time aggregation. To address this concern, we consider a second regression model specified in terms of vacancy flows, θ, measured as the average vacancy flow per establishment in the industry-size cell. Using the steady-state relation, $v_{is} = \theta_{is}/f_{is}$, and substituting, our second regression model has the same form as above but with θ_{is} replacing v_{is} and a coefficient of $(\gamma - 1)/\gamma$ on $\ln \theta_{is}$. We estimate both regression specifications by OLS and two-stage least squares.

Table 4 presents the results. Three of the four estimates for γ provide statistically significant evidence of mild increasing returns to vacancies. In light of our remarks above about division bias and time aggregation, our preferred estimate is based on 2SLS estimation of the specification with vacancy flows, which yields $\gamma = 1.33$.

Returning to equation (8), we can now assess the role of increasing returns to vacancies as an explanation for the empirical relationship in Figure 9. Multiplying $\gamma - 1 = 0.33$ by the upper end estimate of .13 for $d \ln v_{et}/d \ln \breve{H}_{et}$ yields a value of about 0.04 – a tiny fraction of the empirical elasticity on the left side of (8). Therefore, our evidence and calculations imply that employer-level scale economies in vacancies do not explain the pattern in Figure 9. Rather, Figure 9 reflects employer variation in recruiting intensity per vacancy, as they vary the hiring rate. As a corollary, the strong relationship between job-filling rates and employer growth rates in Figure 7 also reflects the role of recruiting intensity per vacancy.

We should add that we do not see Table 4 as the final word on scale economies in employer-level hiring technologies. Our results say nothing about scale economies in the *creation* of job vacancies; they speak only to the effect of vacancy numbers on job-filling

rates. Likewise, they say nothing about scale economies in the use of non-vacancy recruiting instruments. There is much room for additional investigations into the employer-level hiring technology using micro data.

5.D. Aggregate Implications

We now draw out several aggregate implications of our findings. Our study of (8) reveals that recruiting intensity, not scale economies, drives the cross-sectional variation in job-filling rates. Thus we work with CRS at the micro level, implying $f_{et} = \tilde{f}_t \tilde{q}(x_{et})$. Aggregating (6) then yields a generalized matching function defined over unemployment, vacancies and recruiting intensity per vacancy:

$$(9) \qquad H_t = \sum_e H_{et} = \mu \left(\frac{v'_t}{u_t} \right)^{-\alpha} \sum_e v_{et} \tilde{q}(x_{et}) = \mu \left(\frac{v'_t}{u_t} \right)^{-\alpha} v'_t = \mu v_t^{1-\alpha} u_t^{\alpha} \bar{q}_t^{1-\alpha},$$

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

Here, $\bar{q}_t$ is the vacancy-weighted mean impact of employer actions on other recruiting margins. If $\bar{q}_t$ is time invariant, it folds into the efficiency parameter μ and (9) reduces to the standard matching function. However, we just established that employers adjust on other recruiting margins as they vary the gross hires rate, i.e., $\tilde{q}_{et}$ varies strongly with the hires rate in the cross section. It stands to reason that $\bar{q}_t$, the vacancy-weighted cross-sectional mean of $\tilde{q}_{et}$, varies with the aggregate hires rate.

How important are employer actions on other recruiting margins for the behavior of aggregate hires? Dividing by employment and taking log differences in (9) yields $\Delta \ln \breve{H} = \alpha \Delta \ln \breve{u} + (1-\alpha)\Delta \ln \breve{v} + (1-\alpha)\Delta \ln \bar{q}$. Thus to answer the question, we need to know how $\bar{q}_t$ varies with $\breve{H}_t$ over time. As a working hypothesis, we posit that $\bar{q}_t$ varies with $\breve{H}_t$ over time in the same way as $\tilde{q}_{et}$ varies with $\breve{H}_{et}$ in the cross section. That is, we set the

elasticity of $\bar{q}_t$ with respect to $\breve{H}_t$ to 0.82. Given a value for α of about one-half, this working hypothesis yields the tentative conclusion that $\bar{q}_t$ accounts for about 40% of movements in the aggregate hires rate. Of course, $\bar{q}$ is correlated with $\breve{u}$ and $\breve{v}$ in the time series, so we cannot attribute 40% of the movements in aggregate hires uniquely to recruiting intensity. Nevertheless, this calculation suggests that recruiting intensity is an important proximate determinant of fluctuations in aggregate hires.

Figure 10 displays the monthly index for recruiting intensity per vacancy implied by the working hypothesis over the period covered by published JOLTS data. The index exhibits sizable movements and, most notably, falls by about 20% from early 2007 to late 2009. This large drop in recruiting intensity had a material effect on the evolution of job-filling rates over this period. To see this point, recall that the job-filling rate is nearly proportional to the vacancy yield in aggregate data and use (9) to obtain $\Delta \ln(H/v) = -\alpha \Delta \ln(v/u) + (1 - \alpha)\Delta \ln \bar{q}$. The vacancy yield rose by 33.5 log points from its average value in 2007 to its average value in 2009. Given $\alpha = 0.5$ and the recruiting intensity index in Figure 10, we calculate that the vacancy yield would have risen by 42 log points over this period had recruiting intensity remained at its 2007 level. In other words, the recruiting intensity drop from 2007 to 2009 substantially repressed the rise in job-filling rates.

Applying the generalized matching function (9) again, we can perform the same type of calculation for the job-finding rate of unemployed workers. The literature measures this rate in various ways, so we calculate its log change from 2007 to 2009 in three ways: the unemployment-to-employment transition rate in gross flows data from the Current Population Survey (CPS) fell by 49 log points; the unemployment escape rate calculated using CPS data on unemployment spell durations fell by 64 log points; and the job-finding

rate calculated as *H/u* fell by 90 log points. The contemporaneous fall in recruiting intensity per vacancy accounts for about 10% to 20% of the decline in the job-finding rate over this period, depending on the job-finding rate measure. Given that the recruiting intensity index remains low through 2011, it continues to contribute to the historically low job-finding rates for unemployed workers in recent years.

Summarizing: Under our working hypothesis, recruiting intensity accounts for sizable cyclical movements in aggregate hires, job-filling rates, and job-finding rates. To develop this conclusion, we built on micro evidence to motivate and construct our index of recruiting intensity. We recognize, however, that our working hypothesis involves a bit of a leap because it calibrates a time-series elasticity from cross-sectional evidence. We now evaluate this working hypothesis and consider several checks of our conclusions about the importance of recruiting intensity for aggregate fluctuations. Along the way, we develop additional evidence that the generalized matching function (9) and the recruiting intensity index in Figure 10 improves our understanding of aggregate outcomes.

As a first check, if $\bar{q}$ moves as posited with the aggregate rate of hires, the standard matching function suffers from a particular form of misspecification. Specifically, the standard function says that the aggregate vacancy yield obeys a simple relationship to market tightness given by $(H/v) = \mu(v/u)^{-\alpha}$. In contrast, the generalized matching function (9) yields $(H/v) = \mu(v/u)^{-\alpha}\bar{q}^{1-\alpha}$. Thus, if employers cut back on recruiting intensity per vacancy in weak labor markets, (9) implies a decline in the vacancy yield relative to $\mu(v/u)^{-\alpha}$. Returning to Figure 1, we evaluate this implication for $\alpha = 0.5$. The vacancy yield falls well short of the benchmark implied by the standard matching function after early 2008, and it typically exceeds this benchmark in the stronger labor markets before

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2008. This pattern supports the view that employers cut back on average recruiting intensity per vacancy, $\bar{q}$, in a weak labor market with a low hires rate.

As a second check, we plug aggregate data on hires, vacancies and unemployment into the standard matching function (5) to back out a "Solow residual" or macro $\bar{q}$ series, which we then compare to the micro-founded $\bar{q}$ recruiting intensity measure in Figure 10. Figure 11 carries out this comparison for $\alpha = 0.5$ and reveals that the two measures are very highly correlated over time.[22] Note that our micro-based recruiting intensity index varies much less than one-for-one with the macro-based Solow residual measure. Perhaps random errors in the data or the matching function (9) attenuate the estimated relationship in Figure 11, but the macro-based residual series also captures other forms of cyclical misspecification in the matching function. For example, if search intensity per unemployed worker declines in weak labor markets along with recruiting intensity per vacancy, then fluctuations in the macro-based series will exhibit greater amplitude. Davis (2011) reports evidence along these lines. Thus, we see our analysis of recruiting intensity as providing only a partial explanation for the matching function breakdown highlighted by Figure 1.

Our third check finds the elasticity value that maximizes the fit of a Beveridge curve relationship augmented by recruiting intensity. Specifically, we regress the log of the aggregate unemployment rate on the log of the effective vacancy rate $\breve{v}'_t = \breve{v}_t \bar{q}_t$, where $\ln \bar{q}_t = \varepsilon \ln \breve{H}_t$ and ε is the fill rate elasticity with respect to hires. Estimation by nonlinear least squares yields $\hat{\varepsilon} = .836$ in this approach based entirely on time-series variation, very close to the value of .820 from the cross-sectional evidence. This result shows that the

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[22] We have verified that the pattern in Figure 11 holds for all values of the matching function elasticity α in the range from 0.3 to 0.7. The R-squared values never fall below 0.61 for α in this range, and they exceed 0.9 for $\alpha \in [0.4, 0.7]$. The goodness of fit between the two measures is maximized at $\alpha = 0.51$. The slope coefficient in a regression of the micro-based $\bar{q}$ on the macro-based $\bar{q}$ is always less than one-half.

recruiting intensity index we constructed using micro evidence performs well in capturing the aggregate effects of fluctuations in employers' use of other recruiting instruments.

Our fourth check considers whether our micro-based generalized matching function improves the fit of national and regional Beveridge Curves compared to the standard matching function. Our fit metric is the residual RMSE in a time-series regression of the log unemployment rate on the log of the observed vacancy rate (standard) or the log effective vacancy rate (generalized). As reported in Table 5, the generalized matching function yields a better fitting Beveridge Curve in all cases. The RMSE is 21% smaller for the specification implied by the standard matching function in the national data and 13-24% smaller across the four Census regions. We stress that the generalized matching function considered here does not nest the standard matching function, because it entails a specific time-series path for recruiting intensity per vacancy.[23]

5.E. Additional Implications for Theoretical Models

We have now developed several pieces of evidence that point to an important role for employer actions on other recruiting margins in the hiring process. Obviously, this evidence presents a challenge to search and matching models that treat vacancies as the sole or chief instrument that employers manipulate to vary hires. Our evidence and analysis also present a deeper and less obvious challenge for the standard equilibrium search model: adding a recruiting intensity margin is not enough, by itself, to reconcile the standard theory with the evidence. This conclusion follows by considering a version of the standard theory due to Pissarides (2000, chapter 5) and confronting it with our evidence.

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[23] In an analogous exercise, the online appendix reports that the effective labor market tightness ratio more accurately tracks fluctuations in the job-finding rate in national and regional data.

Pissarides analyzes a search equilibrium model with a free entry condition for new jobs, variable recruiting intensity, and a generalized matching function similar to (9).[24] In his model, the job-filling rate rises with recruiting intensity in the cross section, and recruiting costs per vacancy are increasing and convex in the employer's intensity choice. Wages are determined according to a generalized Nash bargain. Given this setup, Pissarides proves that optimal recruiting intensity is insensitive to aggregate conditions *and* takes the same value for all employers (given that all face the same recruiting cost function). As Pissarides explains, this result follows because employers use the vacancy rate as the instrument for attracting workers, and they choose recruiting intensity to minimize cost per vacancy.[25] The cost-minimizing intensity choice depends only on the properties of the recruiting cost function.

This invariance result implies that the textbook search equilibrium model – extended to incorporate variable recruiting intensity – cannot account for the evidence in Figures 8 and 9. Those figures show that job-filling rates rise sharply with employer growth rates and gross hires rates in the cross section. Moreover, the invariant result precludes a role for recruiting intensity per vacancy in the behavior of aggregate hires. Thus, the standard theory cannot account for the evidence in Figures 10 and 11 that average recruiting intensity varies over time and matters for aggregate hires and the job-finding rate. In sum, both the cross-sectional and time-series evidence are inconsistent with the standard theory.

We do not see this inconsistency as fatal to standard search equilibrium models with random matching. Rather, we think the evidence calls for a re-evaluation of some of the building blocks in these models. One candidate for re-evaluation is the standard free entry

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[24] His generalized matching function also allows for variable search intensity by unemployed workers, but that aspect of his model is inessential for the discussion at hand.
[25] See the discussion related to his equations (5.22) and (5.30).

condition for new jobs. This condition ensures that vacancies have zero asset value in equilibrium. In turn, the zero asset value condition plays a key role in leading all employers to choose the same recruiting intensity. More generally, when job creation costs rise at the margin and job characteristics differ among employers, the optimal recruiting intensity and the job-filling rate increase with the opportunity cost of unfilled positions.[26] The free entry condition for new jobs is widely adopted in search and matching models because it simplifies the analysis of equilibrium. Our evidence indicates that the simplicity and analytical convenience come at a high cost. Stepping further away from the textbook model with random matching, there are other mechanisms that potentially generate heterogeneity in job-filling rates.[27] Our evidence is also informative about other theoretical models of hiring behavior. Figures 8 and 9, for example, are hard to square with simple mismatch models. In these models, an employer fills vacancies quickly if its hiring requirements do not exhaust the pool of unemployed workers in the local labor market. That is, an employer with modest hiring needs enjoys a high job-filling rate. In contrast, a rapidly expanding employer is more likely to exhaust the local pool of available workers. Thus, employers with greater hiring needs tend to fill vacancies more slowly and experience lower job-filling rates. In short, the basic mechanism stressed by mismatch models pushes towards a negative cross-sectional relationship between job-filling rates and employer growth rates.

Directed search models are readily compatible with the evidence in Figures 8 and 9. These models come with a built-in extra recruiting margin, typically in the form of the

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[26] Davis (2001) analyzes an equilibrium search model with these features and shows that it delivers heterogeneity in recruiting intensity per vacancy and job-filling rates. See his equations (14) and (15) and the related discussion.
[27] For example, Faberman and Nagypál (2008) show that a model with search on the job, a convex vacancy creation cost, and productivity differences among firms can deliver a positive relationship between the job-filling rate and employer growth rates in the cross section.

employer's choice of a wage offer posted along with a vacancy announcement. The wage offer influences the arrival rate of job applicants and the job-filling rate. An employer that seeks to expand more rapidly both posts more vacancies and offers a more attractive wage. As a result, the job-filling rate rises with employer growth rates in the cross section. See Kass and Kircher (2010) for an explicit analysis of this point.

6. Hires by Establishments with No Reported Vacancies

Table 2 reports that 41.6% of hires in the JOLTS data occur at establishments with no reported vacancies at month's start. Some of these hires reflect vacancies posted and filled within the month. Other hires may not be mediated through vacancies, as the concept is defined and measured in JOLTS data. To shed some light on these matters, we return to the model of daily hiring dynamics and calculate the model-implied quantity of hires at establishments with no reported vacancies. We compare this model-implied quantity to the corresponding observed quantity in the JOLTS data.

Recalling equation (3), the model-implied flow of hires due to vacancies newly posted during the month is given by

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

Multiplying this expression by the observed share of employment at establishments with no reported vacancies at month's start and dividing by total hires yields the model-implied percent of hires at establishments with no reported vacancies. We calculate this model-implied quantity and compare to the 41.6% figure from Table 2. In computing the model-implied quantity, we disaggregate by industry, employer size, and worker turnover to capture the heterogeneity in job-filling rates and vacancy flow rates seen in Table 3. That is,

we first calculate the model-implied share of hires at establishments with no reported vacancies by sector and then take the hires-weighted mean over sectors.

Table 6 reports the results of the comparison. When we slice the data by 6 employer size categories crossed with (up to) 15 worker turnover categories and a broad division into goods-producing and service-producing industries, our model of daily hiring dynamics implies that 27.4% of all hires occur at establishments with no recorded vacancies. This quantity is about two-thirds of the 41.6% figure observed directly in the data. The other classifications reported in Table 6 produce somewhat smaller figures for hires at establishments with no reported vacancies. We do not consider finer classifications because of concerns about sparsely populated cells and imprecise cell-level estimates of f and θ.

Table 6 tells us that time aggregation accounts for most, but by no means all, hires at establishments with no reported vacancies. The unexplained hires may reflect a failure to adequately capture cross-sectional heterogeneity in f and θ or some other form of model misspecification. Perhaps the most natural interpretation, however, is that many hires are not mediated through measured vacancies. For example, JOLTS definitions exclude vacancies for positions that could not begin within 30 days. Certain other hires are unlikely to be captured by the JOLTS vacancy measure, because they involve hires into positions with zero prior vacancy duration. Using data on job applications and hires in the 1982 wave of the Employment Opportunity Pilot Project Survey, Faberman and Menzio (2010) report that 20% of all new hires involve no formal vacancy or recruiting time by the employer

Based on Table 6 and our discussion here, we think the topic of hires not mediated through vacancies warrants attention in future research and in surveys of hiring practices. In line with our broader theme about the importance of non-vacancy recruiting instruments, we

think of hires not mediated through vacancies as arising through an alternative hiring technology exploited that is relevant for at least some employers.

7. Concluding Remarks

This study is the first to examine the behavior of vacancies, hires, and vacancy yields at the establishment level in the Job Openings and Labor Turnover Survey, a large sample of U.S. employers. We find strong patterns in hiring and vacancy outcomes related to industry, employer size, the pace of worker turnover, and employer growth rates.

Our study also innovates in several other respects. First, we develop a model of daily hiring dynamics and a simple moment-matching method that, when applied to JOLTS data, identifies the flow of new vacancies and the job-filling rate for vacant positions. Second, we show that job-filling rates rise steeply with the gross hires rate across industries, employer size classes, worker turnover groups, and employer growth rates – a novel finding with important implications for theory. Third, we show how to interpret the evidence through the lens of a generalized matching function and, in particular, how to extract information about employer-level scale economies in the use of vacancies to hire and how to identify the role of other recruiting instruments used by employers to affect the pace of hiring. Fourth, we develop evidence that employer actions on other recruiting margins account for a large share of movements in aggregate hires. We also show that our micro-founded generalized matching function fares better than the standard matching function in accounting for aggregate movements in job-filling rates and job-finding rates. The effective vacancy concept embedded in our generalized matching function also leads to a more stable Beveridge curve in national and regional data. Finally, we show that the standard search equilibrium model cannot explain the cross-sectional and time-series evidence, even when

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the model is extended to incorporate a recruiting intensity margin. We also discuss possible modifications to the standard theory to help account for the evidence.

Much work remains to explain the patterns in vacancy and hiring behavior we uncover using JOLTS micro data. One partly unresolved issue involves the 42 percent of hires that occur at establishments with no reported vacancies at the start of the month. Our model of daily hiring dynamics accounts for two thirds of these hires. The remaining one-third reflects some combination of model misspecification, systematic underreporting of vacancies by JOLTS respondents, and hires not mediated through vacancies. As we discussed in Section 6, evidence from other sources points to an important role for hires not mediated through vacancies. A fuller analysis of such hires will require information beyond what is currently available in JOLTS data. We plan to pursue this topic in future work.

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**Figure 1. Measures of Inverse Market Tightness, January 2001 to December 2011**
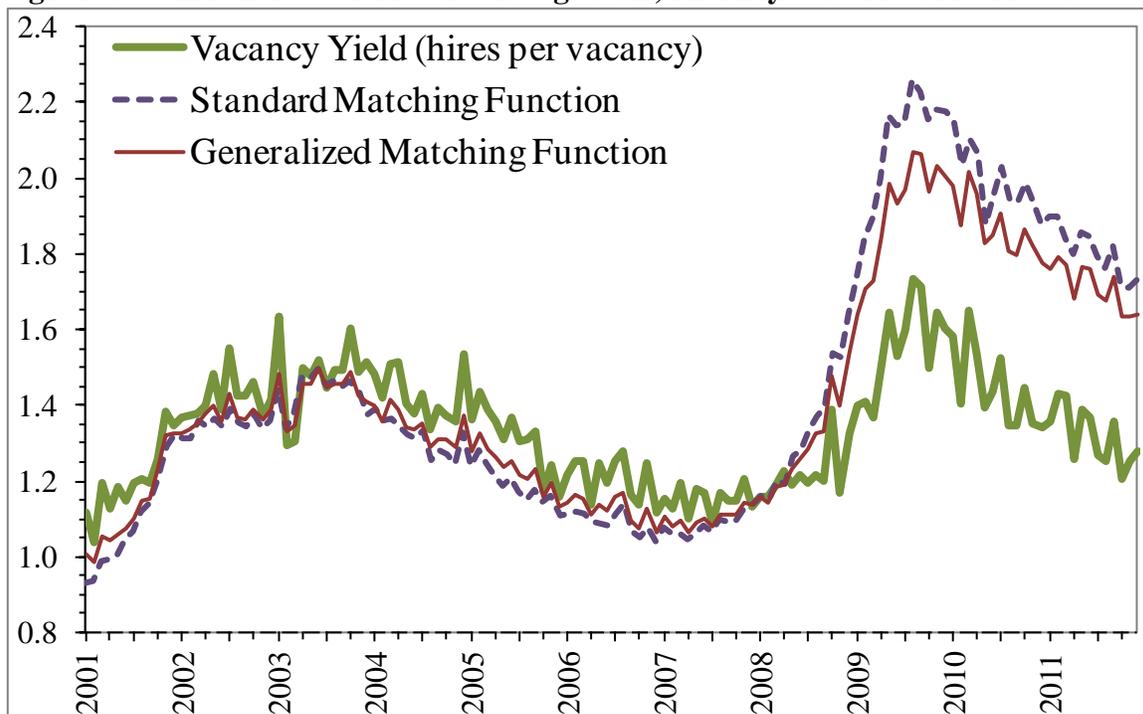
Note: Authors' calculations using published JOLTS data for nonfarm hires and vacancies and CPS data for civilian unemployment.

Figure 2. Distribution of Vacancies over Establishments, Employment-Weighted
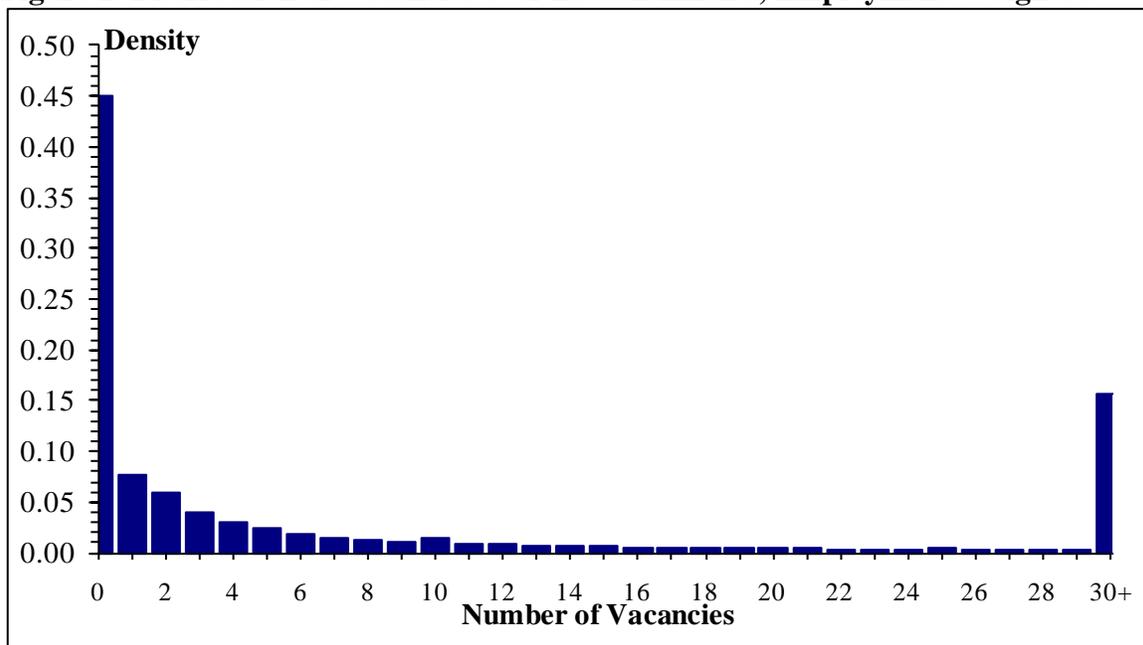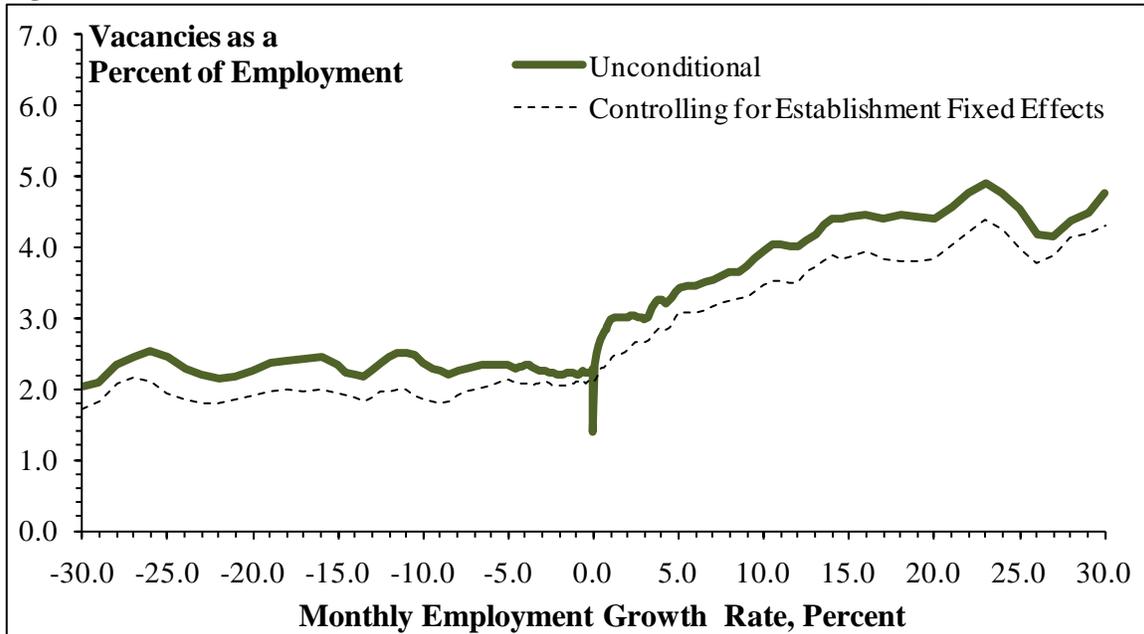

Note: Calculated from approximately 577,000 monthly establishment-level observations in JOLTS data from January 2001 to December 2006.

Figure 3. Hires and Establishment Growth in the Cross Section, JOLTS Data
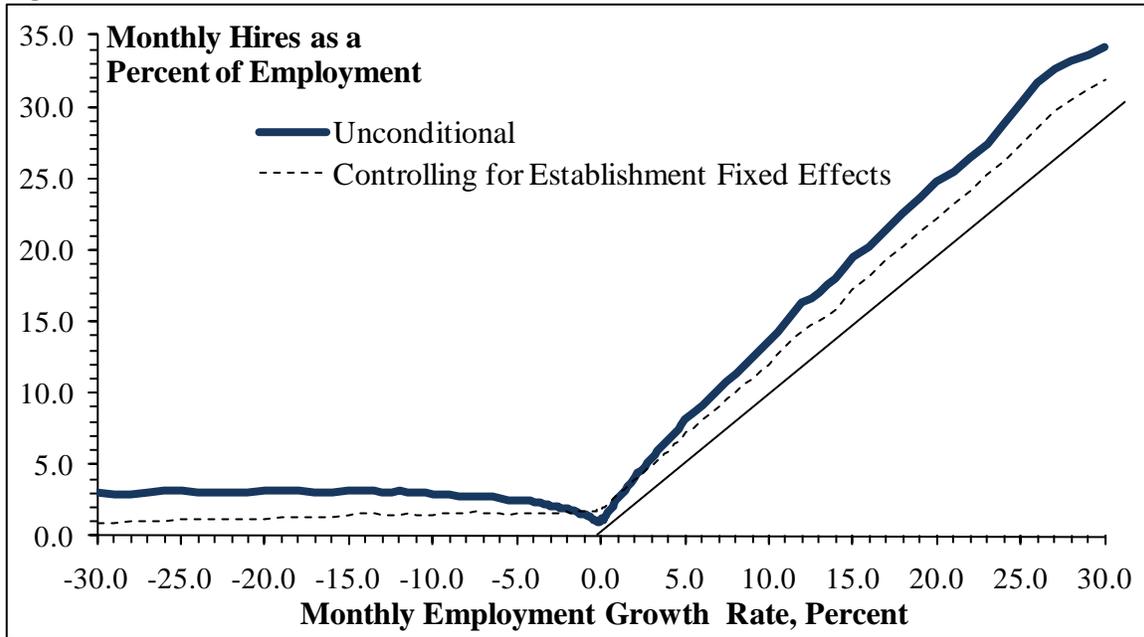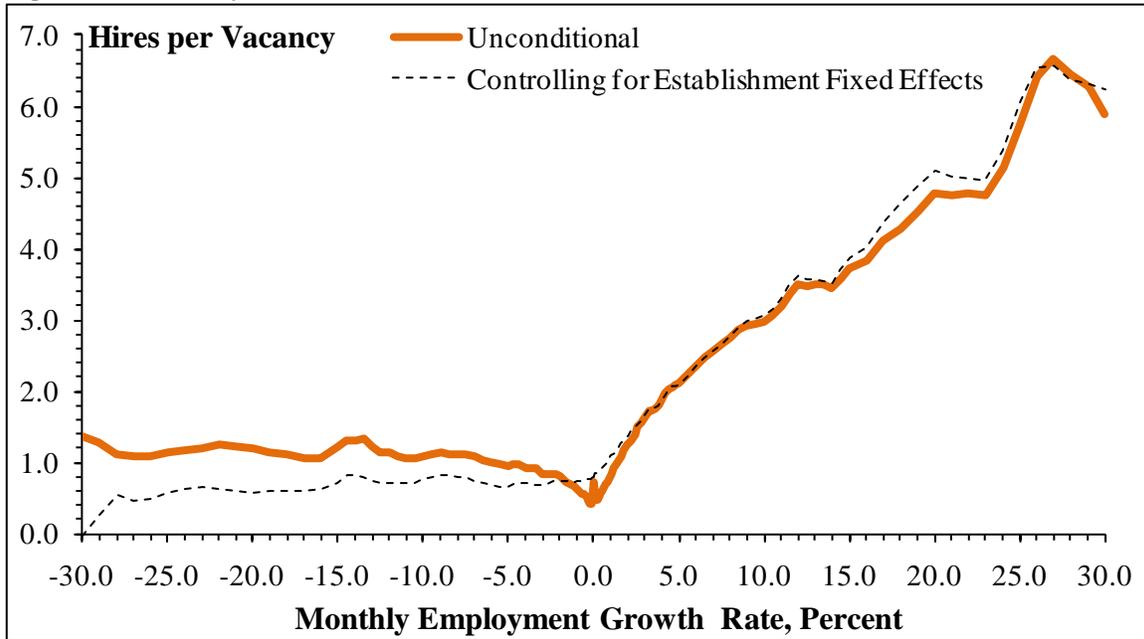

Note: The figure shows the cross-sectional relationship of the hires rate to the establishment growth rate, as fitted by nonparametric regression to approximately 577,000 monthly observations from 2001 to 2006. See text for details. The straight thin line emanates from the origin at 45 degrees.

**Figure 4. Vacancies and Establishment Growth in the Cross Section, JOLTS Data**

Note: The figure shows the cross-sectional relationship of the vacancy rate to the establishment growth rate, as fitted by nonparametric regression to approximately 577,000 monthly observations. See text for details.

Figure 5. Vacancy Yields and Establishment Growth in the Cross Section, JOLTS Data


Note: The figure shows the cross-sectional relationship of the vacancy yield, as fit by nonparametric regression to approximately 577,000 monthly establishment-level observations. See text for additional details.

Figure 6. New Vacancy Flows and Daily Job-Filling Rate, Model-Based Estimates Using Published JOLTS Data, January 2001 to December 2011
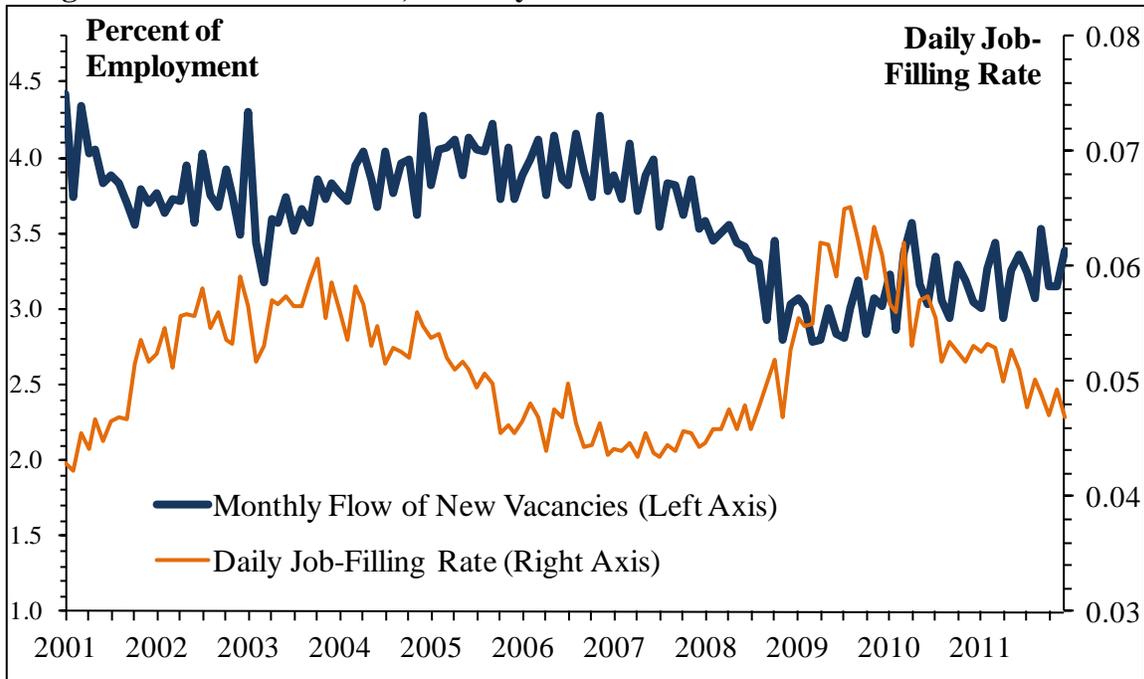

Note: The figure displays the monthly flow of new vacancies and the average daily job-filling rate in the month, as estimated from published JOLTS data using the moment conditions (3) and (4) in the text.

Figure 7. Fill Rates and Vacancy Flows as Functions of Establishment Growth
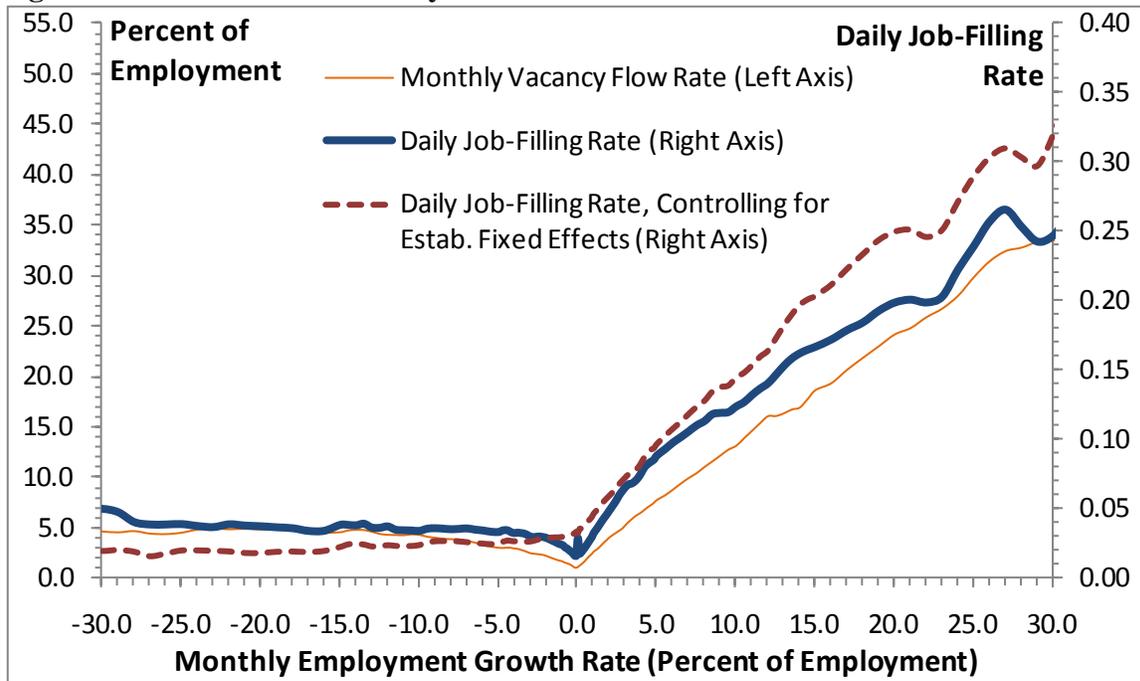
Note: The figure displays the vacancy flow rate as a percent of employment and the daily job-filling rate as functions of the monthly establishment growth rate, as estimated from JOLTS micro data using the moment conditions (3) and (4).

Figure 8: Empirical and Simulated Job-Filling Rates Compared
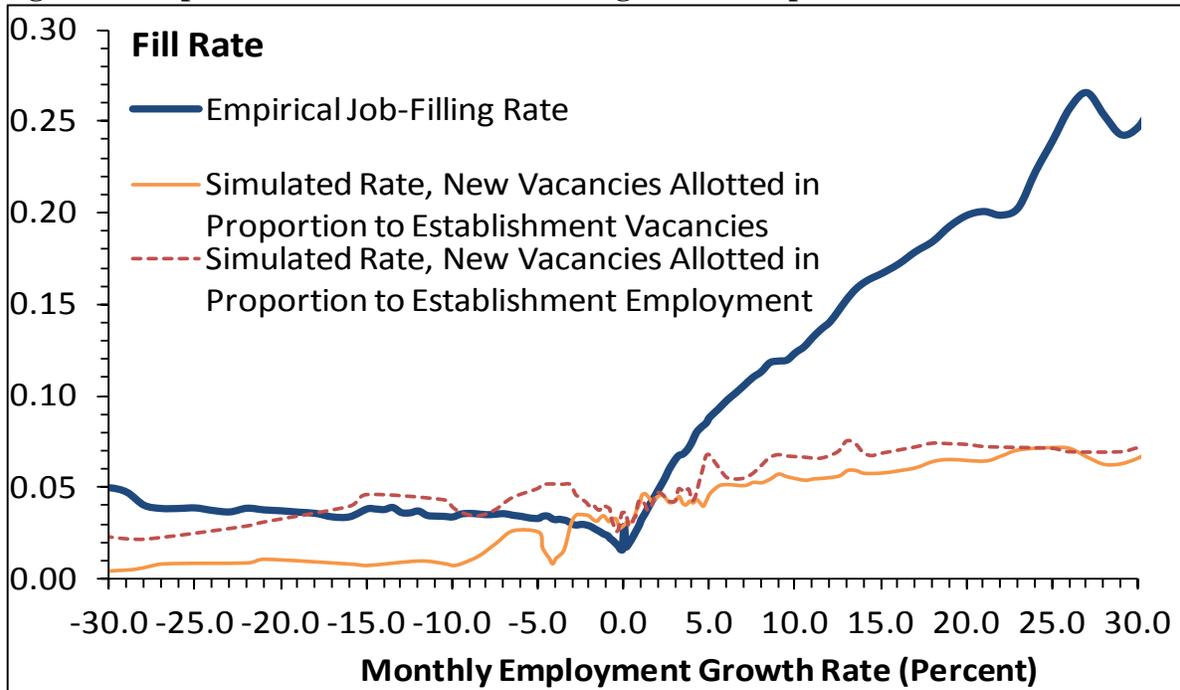
Note: Simulated job-filling rates are constructed under two polar assumptions about the allocation of new vacancy flows – in proportion to an establishment's stock of vacancies at the beginning of the month or in proportion to its employment. See text for details.

Figure 9. Job-Filling Rates and Gross Hires Rates by Growth Rate Bin
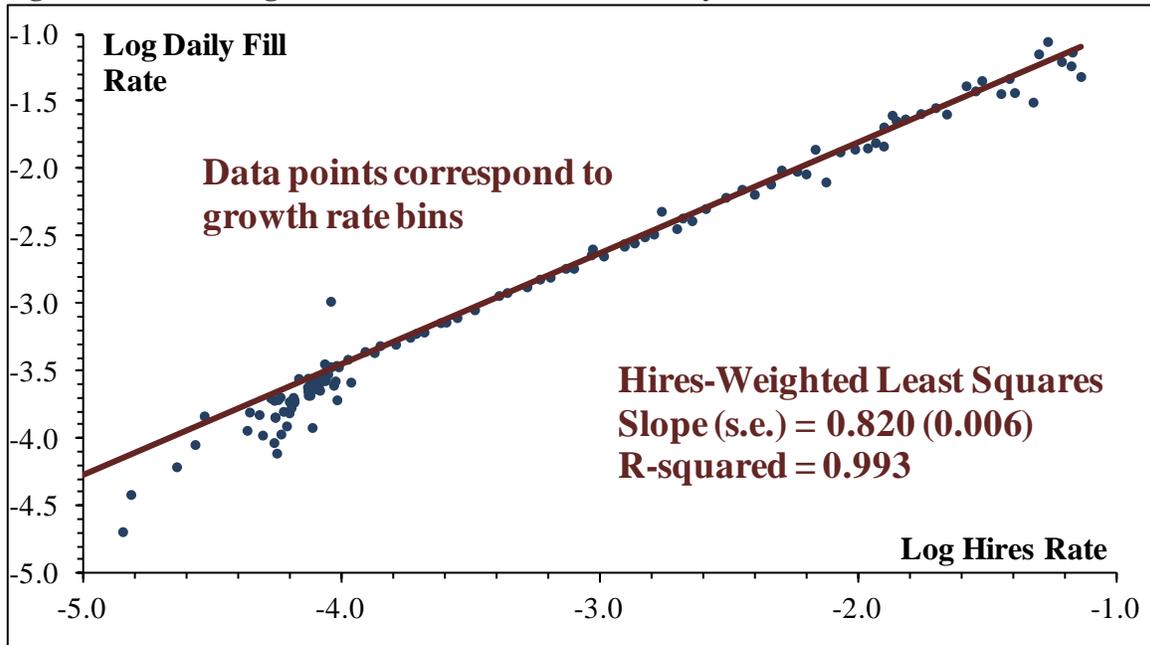
Note: The figure plots the relationship of the log daily job-filling rate to the log gross hires rate across growth rate bins i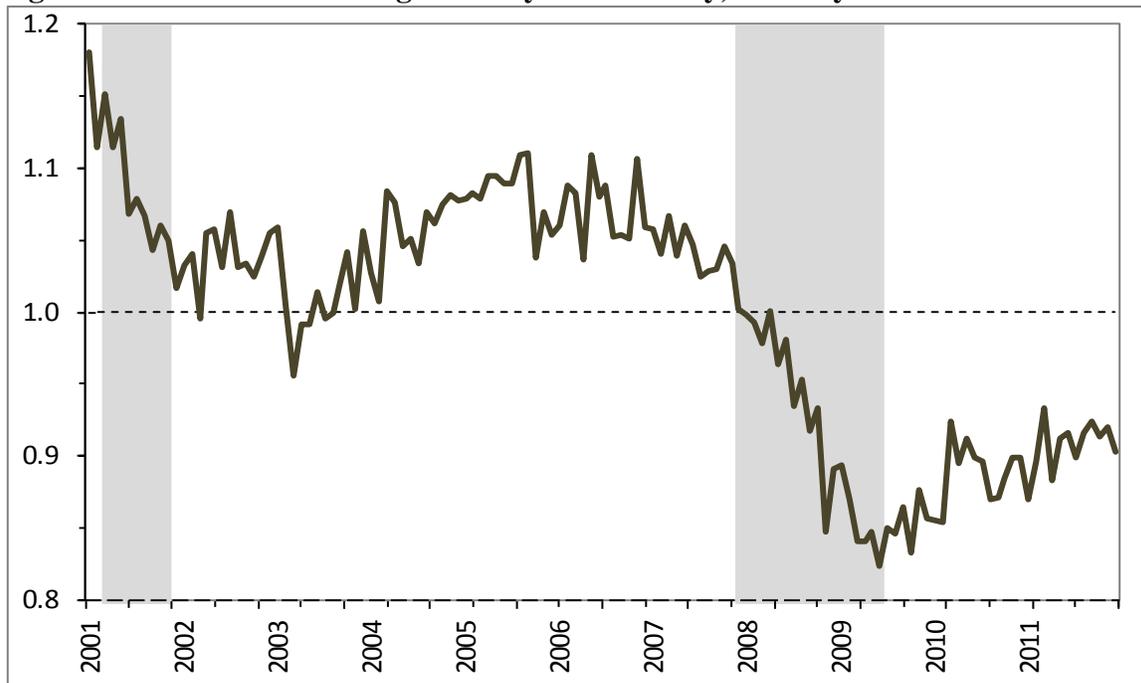n [-.3, .3] and the hires-weighted least squares regression fit of the bin-level data. Bin-level fill rates estimated from establishment-level data sorted into bins after removing mean establishment growth rates.

Figure 10. Index of Recruiting Intensity Per Vacancy, January 2001 to December 2011

Note: The figure displays the monthly time-series index for (the effects of) recruiting intensity per vacancy. See text for an explanation of the index construction.

Figure 11. Recruiting Intensity Index (Micro *q*) Related to Solow Residual Implied by Standard Matching Function (Macro *q*), January 2001 to December 2011
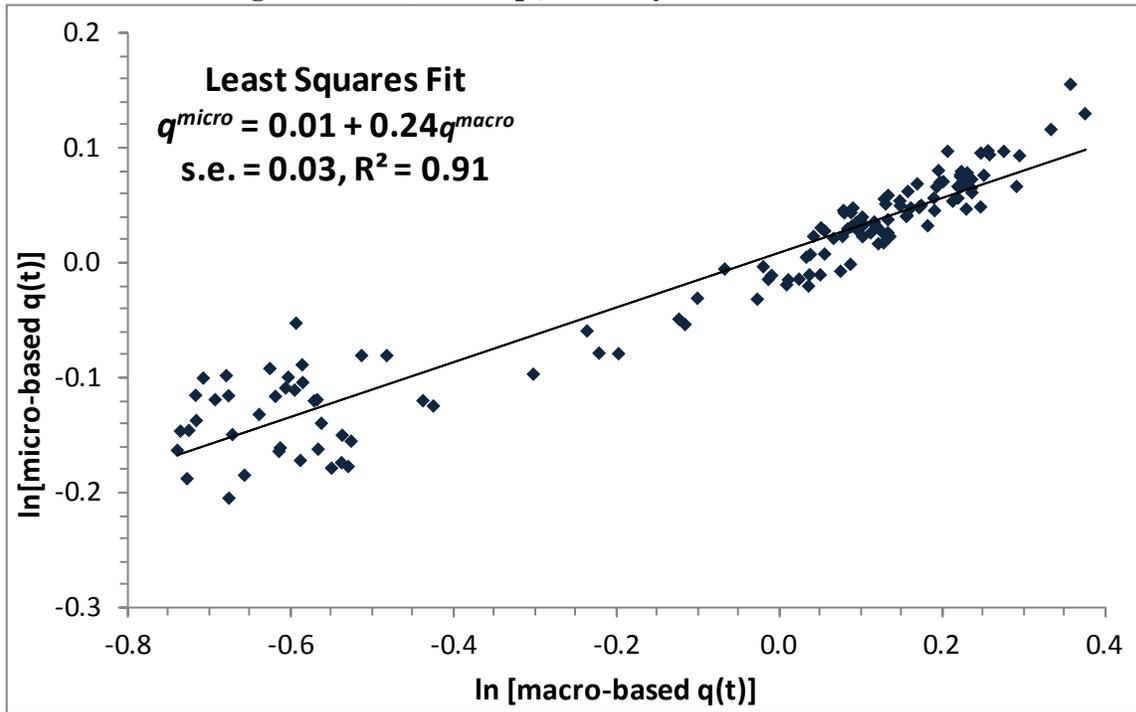
Note: Macro-based q(t) measure computed as residuals from equation (5) with $\alpha = 0.5$ after plugging in data on hires, unemployment and vacancies. The micro-based q(t) measure is the index of recruiting intensity per vacancy plotted in Figure 10.

Table 1. Worker Flows, Vacancies and Yields by Industry, Size, and Turnover

	Hires Rate	Separations Rate	Vacancy Rate	Vacancy Yield	Employment Share
Nonfarm Employment	3.4	3.2	2.5	1.3	---
Major Industry					
Natural Resources & Mining	3.1	3.0	1.5	2.0	0.5
Construction	5.4	5.4	1.7	3.1	5.3
Manufacturing	2.3	2.6	1.7	1.3	11.3
Transport, Wholesale, Utilities	2.7	2.7	1.9	1.4	8.0
Retail Trade	4.5	4.4	2.3	1.9	11.4
Information	2.2	2.4	2.6	0.8	2.4
FIRE	2.3	2.2	2.5	0.9	6.1
Prof. & Business Services	4.6	4.2	3.5	1.3	12.4
Health & Education	2.7	2.3	3.5	0.7	12.7
Leisure & Hospitality	6.3	6.0	3.4	1.8	9.3
Other Services	3.3	3.2	2.3	1.4	4.1
Government	1.6	1.3	1.9	0.8	16.5
Establishment Size Class					
0-9 Employees	3.4	3.3	2.0	1.6	12.1
10-49 Employees	4.0	4.0	2.3	1.7	23.2
50-249 Employees	4.0	3.8	2.6	1.5	28.3
250-999 Employees	3.1	2.9	2.8	1.1	17.1
1,000-4,999 Employees	2.1	1.9	3.0	0.7	13.0
5,000+ Employees	1.7	1.5	2.4	0.7	6.4
Worker Turnover Category					
No Turnover	0	0	1.1	0	24.4
First Quintile	0.5	0.6	1.7	0.3	15.1
Second Quintile	1.3	1.2	2.6	0.5	15.1
Third Quintile	2.4	2.2	2.9	0.8	15.1
Fourth Quintile	4.5	4.3	3.1	1.4	15.1
Fifth Quintile (highest)	13.5	13.0	4.4	3.1	15.1

Notes: Estimates tabulated from our sample of JOLTS micro data, containing 577,268 monthly establishment-level observations from 2001 to 2006. Rates as defined in the text. Turnover defined by the sum of the hires rate and the separations rate for the monthly establishment-level observation.

Table 2. Additional Statistics on Hires and Vacancies

Statistic	Percent
Employment at Establishments with No Hires in t	34.8
Employment at Establishments with No Vacancies at end of t-1	45.1
Vacancies at end of t at Establishments with No Vacancies at end of $t-1$	17.9
Hires in t at Establishments with No Vacancies at end of $t-1$	41.6

See Table 1 for notes. Statistics are for nonfarm establishments.

Table 3. Results of Hiring Dynamics Model by Industry, Size, and Turnover

	Daily Job-Filling Rate, f_t	Monthly Vacancy Flow Rate, $\tau \cdot \theta_t$ (pct. of empl.)	Mean Vacancy Duration, $1/f_t$ (in days)
Nonfarm Employment	0.050	3.4	20.0
Major Industry			
Natural Resources & Mining	0.078	3.1	12.8
Construction	0.121	5.4	8.3
Manufacturing	0.052	2.3	19.3
Transport, Wholesale, Utilities	0.052	2.7	19.1
Retail Trade	0.073	4.5	13.7
Information	0.031	2.2	32.0
FIRE	0.034	2.3	29.0
Prof. & Business Services	0.049	4.6	20.4
Health & Education	0.028	2.7	35.4
Leisure & Hospitality	0.069	6.3	14.6
Other Services	0.053	3.3	18.8
Government	0.032	1.6	31.4
Establishment Size Class			
0-9 Employees	0.061	3.3	16.5
10-49 Employees	0.066	4.0	15.2
50-249 Employees	0.059	4.0	17.1
250-999 Employees	0.041	3.1	24.1
1,000-4,999 Employees	0.026	2.1	37.9
5,000+ Employees	0.026	1.7	38.9
Worker Turnover Category			
First Quintile (lowest turnover)	0.011	0.4	87.9
Second Quintile	0.019	1.3	52.8
Third Quintile	0.030	2.4	32.8
Fourth Quintile	0.054	4.6	18.4
Fifth Quintile (highest turnover)	0.114	14.0	8.7

See notes to Table 1.

Table 4. Estimates of Returns to Scale in Vacancies in the Employer Hiring Technology Regression Dependent Variable: Log Daily Job-Filling Rate in the Industry-Size Cell

Explanatory Variable	Beginning-of-Month Vacancies, v_{t-1}		Monthly Vacancy Flow, θ_t	
	OLS	IV	OLS	IV
Coefficient	0.072	0.227	0.272	0.247
(std. error)	(0.082)	(0.086)	(0.057)	(0.080)
R^2	0.779	0.764	0.850	0.818
First-stage R^2	---	0.996	---	0.996
Implied γ, (Scale Economies)	1.072	1.227	1.374	1.328

Notes: The table reports results for regressions of the log daily job-filling rate on the log of the variable in the top row, using data pooled over the 2001-2006 period at the industry-size class level ($N = 70$). All regressions contain industry and establishment size class fixed effects and include the mean employment growth rate in the industry-size cell as an additional control. IV estimates are from a two-stage least squares regression that instruments the variable in the top row with the log total employment in the industry-size cell. The coefficient (standard error) is for the (second-stage) estimate on the indicated explanatory variable.

Table 5. Beveridge Curve Fits for Standard and Generalized Matching Functions, Monthly Data from January 2001 to December 2011

Aggregation Level of Unemployment and Vacancy Data	Time-Series Standard Deviation, Log Unemployment Rate	RMSE of Residuals in Regression on Log Vacancy Rate, Standard Matching Function	Percent Reduction in RMSE Using Log Effective Vacancy Rate, Generalized Matching Function
National Data	0.30	0.13	20.7
Northeast	0.27	0.17	17.2
Midwest	0.28	0.14	13.0
South	0.30	0.16	18.4
West	0.34	0.19	23.8

Notes: The table reports summary statistics and regression results for national and regional Beveridge Curves. The dependent variable is the log unemployment rate, and the right-side variable is either the log vacancy rate (standard matching function) or the log effective vacancy rate (generalized matching function). The effective vacancy rate equals the product of the measured vacancy rate and our index of recruiting intensity per vacancy plotted in Figure 10. As reported in the last column, the effective vacancy rate yields a better fitting Beveridge Curve at the national level and in all four Census regions.

Table 6. Accounting for Hires at Establishments with No Reported Vacancy

Percent of Hires at Establishments with No Vacancy at End of Previous Month	
From Data	41.6
Percent Implied by Model of Daily Hiring Dynamics	
Industry (12) × Size (6) Disaggregation	25.2
Industry (12) × Turnover (6) Disaggregation	26.0
Size (6) × Turnover (6) Disaggregation	27.0
Industry (12) × Size (2) × Turnover (6) Disaggregation	26.7
Industry (2) × Size (6) × Turnover (up to 15) Disaggregation	27.4

Notes: The table compares the percent of hires at establishments with no reported vacancy at the end of the previous month in the JOLTs data (top panel) to the percent implied by versions of the daily hiring dynamics model (lower panel). Model versions differ in the sector-level parameter heterogeneity allowed, as indicated in the row descriptions. Numbers in parentheses indicate the level of disaggregation for the indicated category (e.g., 12 industries, 6 size classes, etc.) In the bottom row, turnover quintiles are disaggregated into as many as 15 categories for the smaller employer size groups, where cell counts permit. The total number of cells used in the bottom row is 111. To compute the model-implied percent of hires at establishments with no reported vacancy, we apply the model sector by sector and then compute the hires-weighted mean across sectors of model-implied values.

Appendix Material for
"The Establishment-Level Behavior of Vacancies and Hiring"

21 August 2012

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Appendix A: A Model-Based Variance Decomposition for Gross Hires

As discussed in the main text, a standard specification of the matching function implies that hires are proportional to vacancies in the cross section. We identified three reasons why this implication could fail in the data: differences in matching efficiency across sectors, differences in recruiting intensity per vacancy, and departures from constant returns to scale in employer or sectoral hiring functions. Because sectoral differences in matching efficiency cannot explain the evidence in Figures 7 and 9, we focused on recruiting intensity differences and scale economies as potential explanations for the failure of the proportionality implication. Using a generalized matching function, we showed that recruiting intensity per vacancy varies with employer growth rates in the cross section, and that they drive much of the cross-sectional variation in gross hires.

This appendix considers an alternative approach to quantifying departures from proportionality. Specifically, we exploit a closed-form solution for the gross hires rate in our empirical model of job-finding behavior. The solution allows us to quantify the fraction of cross-sectional variation in the log of gross hires accounted for by vacancies alone. Implementing the decomposition, we find that vacancies account for no more than half of the variation in log hires across industries, size classes, worker turnover categories, and growth rate bins. We now turn now to the details.

Recall the solution for hires given by equation (4) in the main text,

$$
\begin{aligned}
H_t &= f_t v_{t-1} \sum_{s=1}^{\tau} (1 - f_t - \delta_t + \delta_t f_t)^{s-1} + f_t \theta_t \sum_{s=1}^{\tau} (\tau - s)(1 - f_t - \delta_t + \delta_t f_t)^{s-1} \\
&\equiv f_t v_{t-1} \sum_{s=1}^{\tau} x_t^{s-1} + f_t \theta_t \sum_{s=1}^{\tau} (\tau - s) x_t^{s-1}.
\end{aligned}
$$

Note that

$$\sum_{s=1}^{\tau} x_t^{s-1} = \frac{1-x^\tau}{1-x} \equiv B \text{ and}$$

$$\sum_{s=1}^{\tau} (\tau-s)x_t^{s-1} = \frac{\tau(1-x)-(1-x^\tau)}{(1-x)^2} = \tau B\left[\frac{1}{1-x^\tau} - \frac{(1/\tau)}{1-x}\right]$$

where we use the fact that

$$\sum_{i=1}^{n} ix^i = \frac{x-(n+1)x^{n+1}+nx^{n+2}}{(1-x)^2}.$$

Therefore, and suppressing time subscripts, we can rewrite the solution for hires as

(A.1)
$$H = Bf\left\{v_{-1} + \left[\frac{1}{1-x^\tau} - \frac{1/\tau}{1-x}\right]\tau\theta\right\} \equiv Bf\left\{v_{-1} + A\tau\theta\right\}$$

where $x \equiv 1 - f - \delta + \delta f$, $B \equiv (1-x^\tau)/(1-x)$. The term in braces is the sum of old vacancies and A times the flow of new vacancies, where A converges to unity as $\tau \to \infty$.

For a given value of τ and δ, we can calculate A as a function of the daily job-filling rate, f. Figure A.1 displays this function for $\tau = 26$ and $\delta = (.0117)/26$, where .0117 is the mean monthly layoff rate in the JOLTS data. The figure shows that A ranges from .504 to .872 as f ranges from .01 to .30, and it varies in a narrow range near .6 in the aggregate time series. Evaluating at sample means for f and δ yields $\bar{A} = 0.5916$.

Taking logs in (A.1) yields:

(A.2)
$$\log H \approx \log(Bf) + \log\left\{v_{-1} + \bar{A}(\tau\theta)\right\}.$$

Using (A.2) with $\bar{A} = 0.5916$, Table A.1 reports the percentage of the cross-sectional variance in log hires accounted for by vacancies. The table also reports variance decomposition results based on the "exact" log version of (A.1), which involves no approximation but is not a true decomposition because of A's dependence on f. The

rightmost column in Table A.1 uses the steady-state approximation of (2) and (3) in the main text, which yields $\log H \approx \log \tau + \log f + \log v$.

If hires are proportional to vacancies in the cross section, then all explanatory power in the variance decompositions loads onto the vacancy term. Contrary to this implication, vacancies account for half or less of the cross-sectional variance in log hires. This conclusion holds for all three variants of the cross-sectional variance decomposition for log hires. Thus, the variance decomposition results in Table A.1 confirm the conclusion we drew in the main text that there are large departures from a proportional relationship between vacancies and hires in the cross section. Moreover, the failure of the proportionality implication across growth rate bins rules out an explanation that rests on sectoral differences in matching efficiency. That leaves recruiting intensity and scale economies as potential explanations for the failure of the proportionality implication.

The variance decomposition results developed in this appendix cannot discriminate between these two explanations. In that respect, the variance decomposition is less informative than the generalized matching function analysis in the main text. Nevertheless, we think the variance decomposition approach is a useful check, because it imposes fewer assumptions. It is reassuring that the variance decomposition results are consistent with the matching function analysis in the main text.

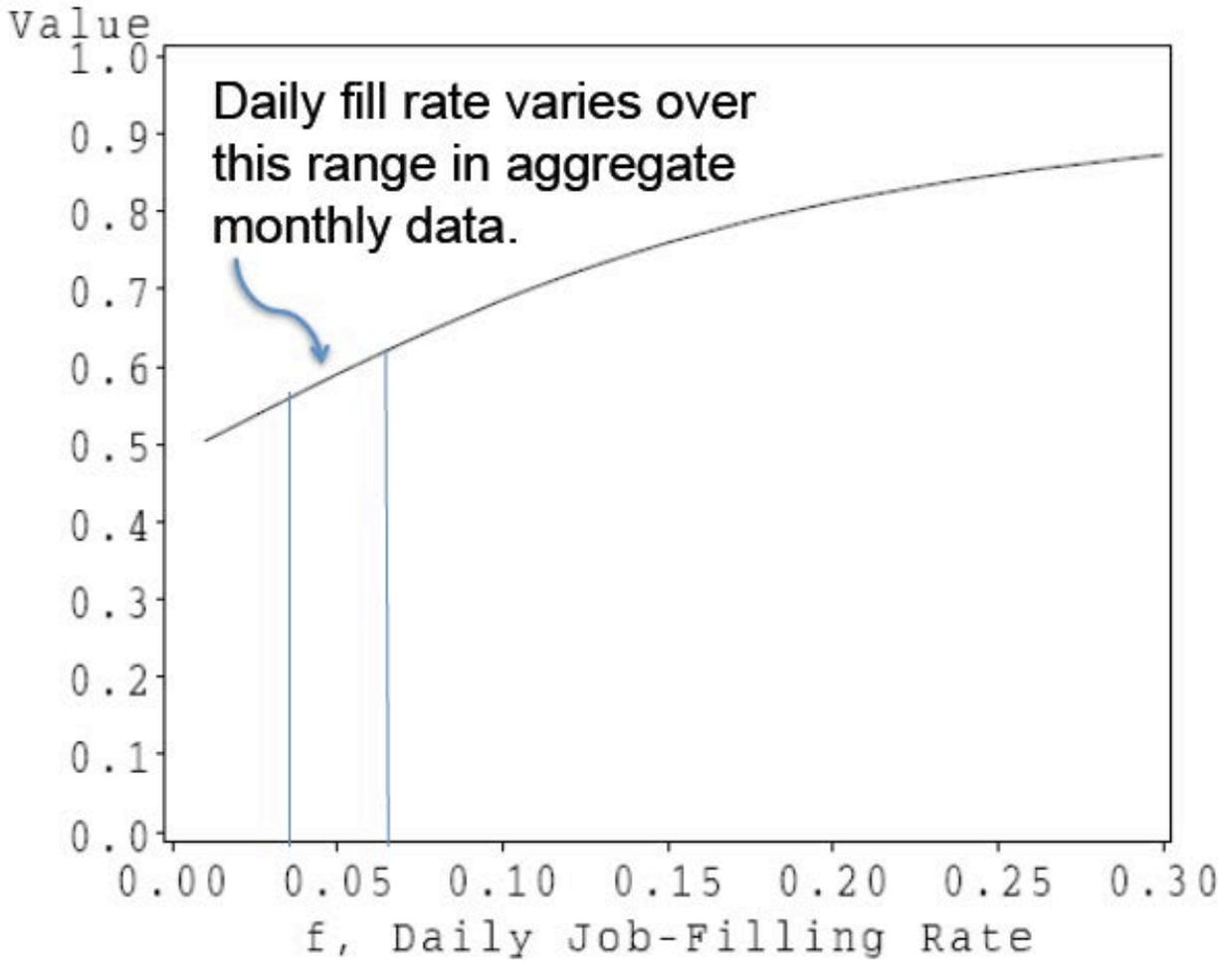**Figure A.1: Evaluating _A_ as a Function of the Job-Filling Rate, _f_**

Daily fill rate varies over this range in aggregate monthly data.

Table A.1. Cross-Sectional Variance Decomposition Results for the Gross Hires Rate

Classification	Variance of log(*H*)	Percentage of log(*H*) Variance Accounted for by Vacancies		
		Using Eq. (A.2)	*Using Exact Expression*	*Using SS Approximation*
Industry	0.17	47.0	51.7	53.3
Size Class	0.13	13.9	16.7	15.0
Turnover	1.52	29.8	34.9	6.9
Growth Bin	0.95	37.9	50.7	9.5

Notes: Table entries report unweighted variance decomposition results for the log of the gross hires rates based on equation (A.2), the log version of equation (A.1) ("Exact"), and the expression for hires based on the steady-state approximation to (2) and (3). Employment-weighted variance decompositions are similar.

Appendix B: Additional Empirical Results

Hires, Vacancies and Job-Filling Rates Back to 1976

We supplement our evidence from the JOLTS data with other sources that yield longer time series for aggregate outcomes. To obtain hires and separations, we rely on two related sources of data on gross worker flows, both of which derive from the Current Population Survey (CPS). First, using data from Shimer (2007b), we compute the aggregate hires rate at t as the gross flow of persons who transit from jobless status in $t-1$ (unemployed or out of the labor force) to employed status in t divided by employment at t. We detrend the resulting hires rate using a Hodrick-Prescott filter with a smoothing parameter of 10^5. This filter removes low-frequency movements in the series, including movements induced by CPS design changes, and it facilitates a comparison to the Help Wanted Index described below. Second, using data from Fallick and Fleischman (2004), we compute the aggregate hires rate as the sum of gross flows from joblessness to employment and direct job-to-job transitions. Thus, the Fallick-Fleischman data yield a more inclusive measure of the hires rate. However, their series runs from 1994, whereas the Shimer series begins in 1976.[1] Both series are quarterly averages of monthly values.

The Conference Board's Help Wanted Index (HWI) is a monthly measure of help-wanted advertising volume in a sample of U.S. newspapers. The HWI has significant shortcomings as a proxy for vacancies, but it is the only vacancy-related measure for the U.S. economy that provides a long, high-frequency time series. We detrend the HWI using the same HP filter as before, then rescale the deviations to match the mean JOLTS

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[1] Direct job-to-job transitions by workers cannot be identified under the pre-1994 CPS design.

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vacancy rate in the overlapping period.[2] We use the detrended rescaled HWI in the first month of each quarter as a proxy for vacancies and match it to the monthly average CPS-based hires rates in the same quarter when computing the HWI-CPS vacancy yield.

Figures B.1 and B.2 draw on JOLTS, CPS, and HWI sources to plot aggregate hires, vacancies and vacancy yields. Figure B.1 shows the aggregate hiring and vacancy rates, expressed as percentages of employment. The HWI and the JOLTS-based measures show strong pro-cyclical patterns for hires and vacancies.[3] In contrast, the CPS-based measures show little cyclicality in the hires rate. HP filtering in the Shimer measure removes a secular decline in hiring observed in other research (e.g., Faberman, 2008b and Davis et al., 2006). The correlation between the log vacancy yield and log tightness is -0.85 in the detrended CPS and HWI data from 1975Q2 to 2007Q2 and -0.88 in the JOLTS data from 2001Q1 to 2011Q4.

We also estimate the job-filling rate using CPS data on new hires and the detrended Help Wanted Index. These data are less suitable for our methods, but they provide longer time series for drawing inference about cyclical patterns. Figure B.3 reports the results and shows pronounced counter-cyclical variation in the job-filling rate, with sharp increases during recessions. All three sources show increasing fill rates during the recession of 2001, but the increase is less abrupt in the JOLTS data, and it extends for an additional two years beyond the NBER-dated recession end. (Aggregate employment continued to contract through the middle of 2003.) In short, the available evidence

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[2] This approach to the HWI follows Abraham (1987) and Shimer (2007b), who discuss the measurement issues in detail. See also Kroft and Pope (2008).
[3] The economy was in recession from March to November 2001 according to NBER dating, but employment continued to contract until the middle of 2003.

clearly points to strongly counter-cyclical movements in job-filling rates – in line with the view that employers find it easier to recruit suitable workers in weak labor markets.

Nevertheless, the JOLTS and CPS-HWI series for the job-filling rate are rather imperfectly correlated during the period of overlap. These discrepancies between JOLTS and CPS-HWI measures are noteworthy, because quantitative analyses of search and matching models have relied heavily on CPS-HWI data. One potential explanation is cyclical variation in the recruiting channels used by employers to hire workers. Recall that the HWI reflects help-wanted advertising volume in a sample of U.S. newspapers. In contrast, the JOLTS program elicits information about a broader concept of vacancies and is not confined to a single recruiting method. Russo, Gorter and Schettkat (2001) report that Dutch employers alter the mix of recruitment methods as labor market tightness varies and, in particular, that they rely less heavily on paid advertisements in weak labor markets.

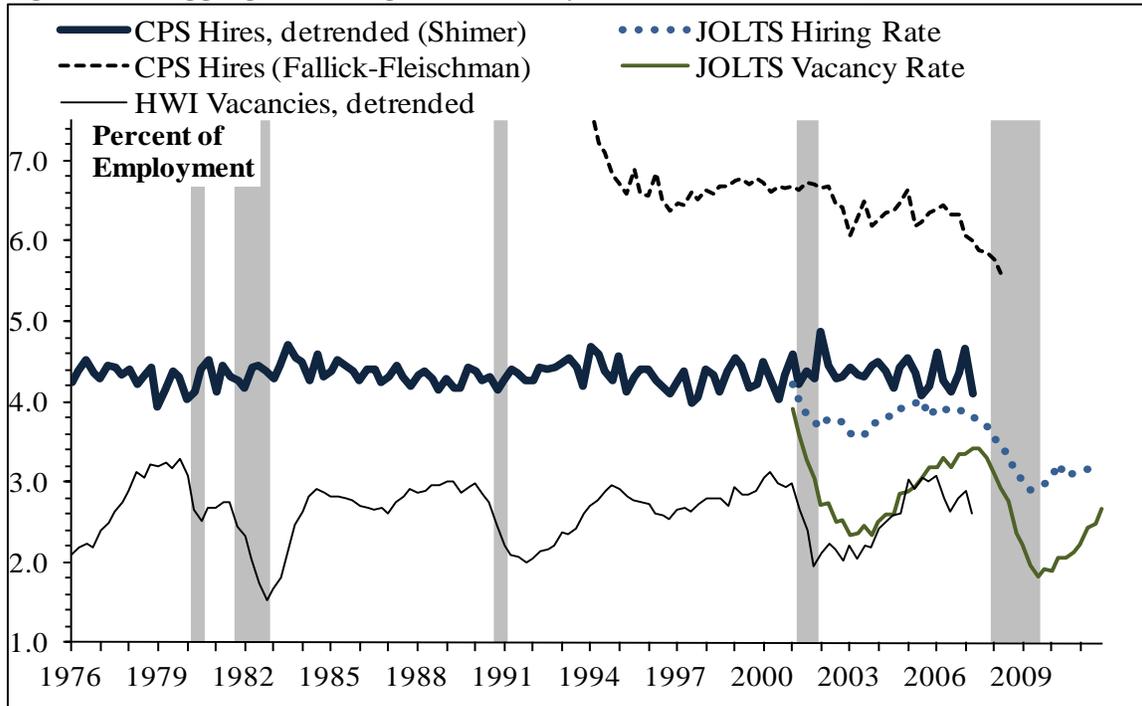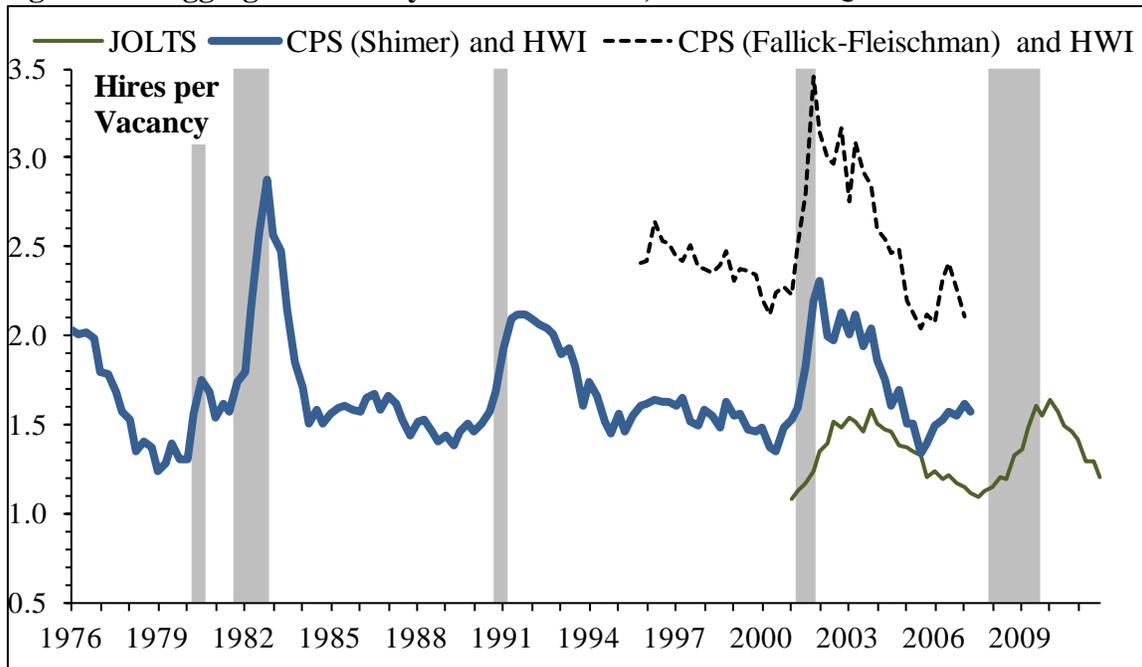**Figure B.1. Aggregate Hiring and Vacancy Rates, 1976 to 2011Q4**

Figure B.2. Aggregate Vacancy Yield Measures, 1976 to 2011Q4

Notes: CPS Hires from Shimer (2007a) for 1976-2007q2 and from Fallick and Fleischman (2004, updated) for 1994-2007q2. Help Wanted Index from the Conference Board from 1976-2007q2. JOLTS data from 2001-2011q4 from the BLS. CPS (Shimer) and HWI series are detrended using an HP filter with smoothing parameter of $\lambda = 10^5$. See text for the vacancy yield calculations. Shaded regions depict NBER recessions.

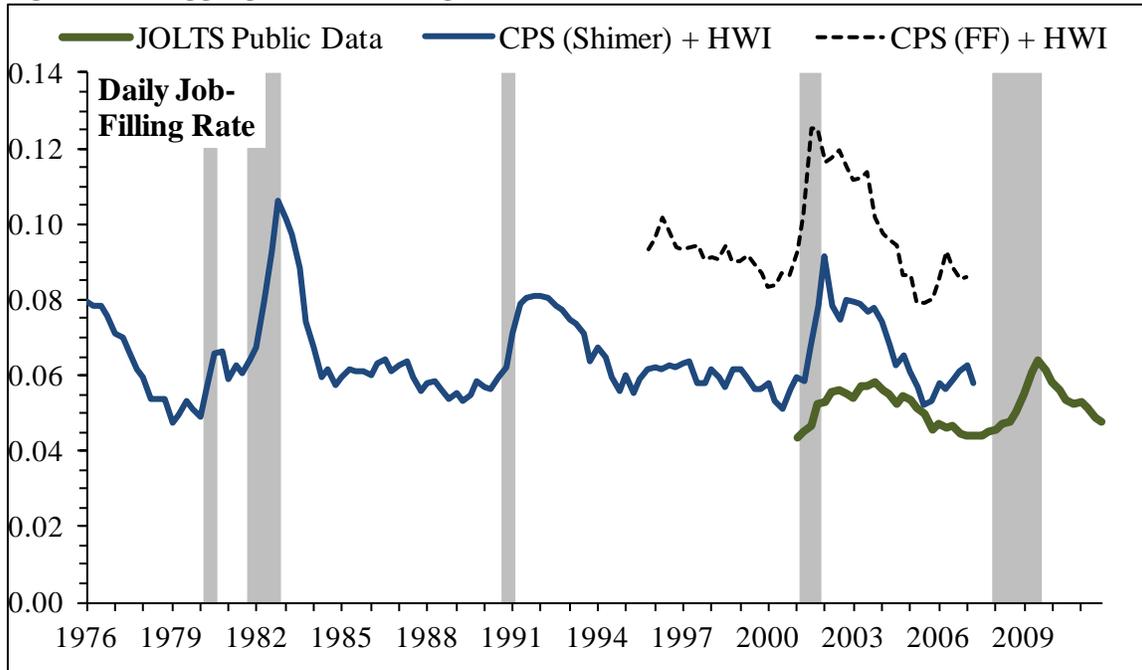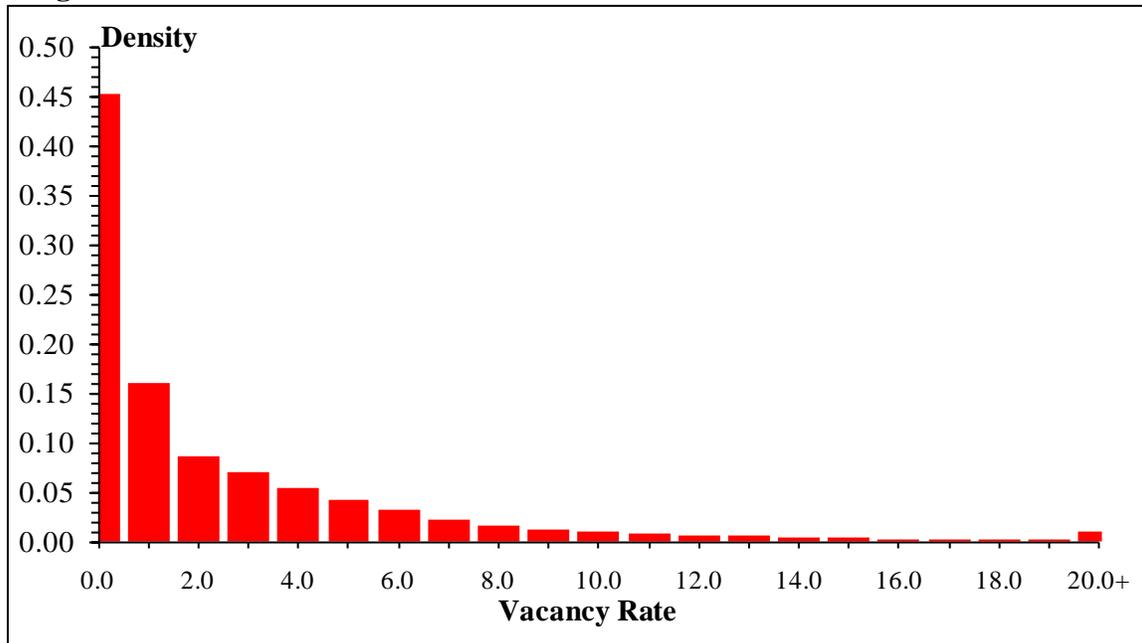**Figure B.3. Aggregate Job-Filling Rate Measures, 1976 to 2011Q4**

Figure B.4. The Distribution of Vacancy Rates across Establishments, Employment-Weighted

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<u>Additional Cross-Sectional Statistics and Results</u>

Figure B.4 plots the employment-weighted distribution of vacancy rates in the establishment-level JOLTS data. See Figure 2 in the main text for the corresponding distribution of vacancy numbers.

As reported in Table B.1, there is much variation in the frequency of hires and vacancies across industries, employer size classes, and worker turnover groups. Industries with the highest worker turnover rates (Table 1) have the highest employment-weighted incidence of establishments with no reported vacancies. The same pattern holds across worker turnover quintiles, setting aside establishments with no worker turnover. In addition, nearly half of all hires by employers in the top worker turnover quintile occur at establishments with no reported vacancies going into the month. Recall from Table 1 that worker turnover is 26.5% of employment per month for establishments in this group. Given these results, it must be the case that vacancy durations are extremely short for these employers, or that a large fraction of their hires are not mediated through vacancies.

Figure B.5 displays the relationship between the fill rate and the gross hires rate across industries, size classes and worker turnover categories.   The fitted relationship is very similar to the one across growth rate bins in Figure 9. In short, the job-filling rate displays a strong positive relationship to the gross hires rate across industries, size classes, worker turnover groups and employer growth rate bins. This is a novel finding and, as we show in the main text, it has important implications for theoretical models.

Table B.1. Additional Statistics on Hires and Vacancies by Industry, Size, and Turnover

	Pct. of Employment in t at Establishments with:		Pct. of Vacancies in t at Estabs. with $v_{t-1} = 0$	Pct. of Hires in t at Establishments with $v_{t-1} = 0$
	No Hires during t	No Vacancies at end of t-1		
Nonfarm Employment	34.8	45.1	17.9	41.6
Major Industry				
Natural Resources & Mining	40.1	59.2	22.5	57.8
Construction	46.3	73.7	36.3	67.2
Manufacturing	33.0	43.3	15.4	41.3
Transport, Wholesale & Utilities	43.2	51.2	20.2	41.5
Retail Trade	39.4	59.3	30.5	49.1
Information	32.6	34.3	13.7	29.5
FIRE	44.6	48.8	16.9	40.3
Professional & Business Services	34.7	41.9	14.8	31.9
Health & Education	27.5	31.6	8.3	26.0
Leisure & Hospitality	33.1	54.2	25.6	47.7
Other Services	61.6	70.6	30.9	54.5
Government	21.6	25.7	7.8	20.2
Establishment Size Class				
0-9 Employees	87.0	91.6	43.2	76.9
10-49 Employees	60.0	73.6	33.3	60.3
50-249 Employees	27.7	43.6	16.5	36.5
250-999 Employees	11.9	18.7	6.2	17.3
1,000-4,999 Employees	3.7	7.1	2.4	6.3
5,000+ Employees	1.1	8.8	3.0	8.0
Worker Turnover Category				
No Turnover	100.0	85.2	27.7	---
First Quintile	20.7	22.5	7.6	18.2
Second Quintile	12.3	22.6	7.2	19.7
Third Quintile	11.8	28.4	10.8	25.9
Fourth Quintile	12.1	38.4	18.5	35.6
Fifth Quintile (highest)	12.0	49.0	27.4	49.2

See notes to Table 1 in the main text.

Figure B.5 Job-Filling Rates and Gross Hires Rates in the Cross Section
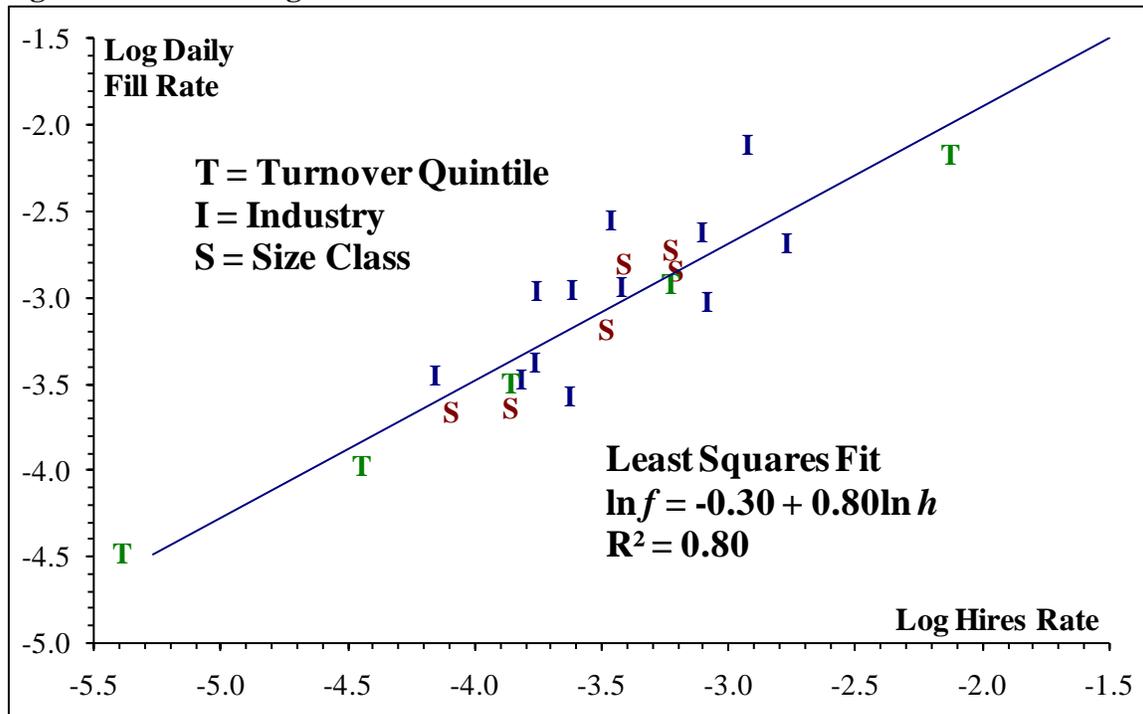
Notes: The figure plots the relationship between the daily job-filling rate and the hiring rate across worker turnover, industry, and establishment size class categories, along with the fit from a least squares regression of the log fill rate on the log hires rate.

Vacancy Stock and Vacancy Flow Elasticity with Respect to the Hires Rate

Section 5.B uses an estimate for the empirical elasticity of vacancies per establishment with respect to the hires rate. We obtain this estimate from the hires-weighted regression of log vacancies per establishment on the log hires rate using data at the level of growth rate bins. To obtain the number of establishments, we divide bin-level employment by average establishment size in the bin. We obtain the empirical elasticity of the vacancy flows per establishment with respect to the hires rate in the same way. Table B.2 reports the regression results with and without controls for establishment fixed effects. The table also reports results for the corresponding regression with the job-

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filling rate as the dependent variable. The regression reported in the lower panel for $\ln f$

corresponds to the scatterplot in Figure 9 in the main text.

Equation (8) in the main text describes the relationship of the job-filling rate

elasticity to the vacancy stock elasticity and other variables. The analogous relationship

expressed in terms of the vacancy flow elasticity is given by

$$\frac{d \ln f_{et}}{d \ln \breve{H}_{et}} = \left(\frac{1}{\gamma}\right)\frac{d \ln \tilde{f}_t}{d \ln \breve{H}_{et}} + \left(\frac{\gamma - 1}{\gamma}\right)\frac{d \ln \theta_{et}}{d \ln \breve{H}_{et}} + \left(\frac{1}{\gamma}\right)\frac{d \ln \tilde{q}(x_{et})}{d \ln \breve{H}_{et}}.$$

Table B.2: Estimates of the Elasticity of Job-Filling Rates, Vacancies and Vacancy Flows with respect to the Hiring Rate

Dependent Variable:	$\ln f$	ln Vacancy Per Establishment	ln Vacancy Flow Per Establishment
No Controls			
ln H	0.722	-0.039	0.604
	(0.013)	(0.111)	(0.105)
R-squared	0.962	0.001	0.203
Controlling for Establishment Fixed Effects			
ln H	0.820	-0.128	0.559
	(0.006)	(0.130)	(0.133)
R-squared	0.993	0.008	0.121

Note: The table reports coefficients for regression of the indiicated dependent variable on the log of the hiring rate across growth rate bins in the [-0.30, 0.30] interval. The top set of results includes no controls, while the bottom set of results use variables that condition out establishment fixed effects. Standard errors are in partentheses. To control for establishment fixed effects in the regressions involving vacancies and vacancy flows, we first remove establishemnt fixed effects for hiring rates, vacacny rates and vacancy flow rates. We then multiply the result vacancy rates and vacancy flow rates by employment in the bin and and divide by the number of establishments in the bin.

Estimating Scale Economies at the Employer Level

Section 5.C reports OLS and 2SLS regression estimates for the specification

$$\ln f_{is} = \ln \tilde{f} + (\gamma - 1) \ln v_{is} + \psi g_{is} + I_i + I_s + \xi_{is}$$

fit to JOLTS data aggregated to the level of industry × employer size cells and pooled

over the 2001-2006 sample period. The $\ln v_{is}$ measure on the right side of this regression

is the (natural) log of vacancies per establishment in the industry × employer size cell.

Because we do not have JOLTS data on the number of establishments for these cells, we

use County Business Patterns data for 2004 and 2005 on the number of establishments in

each industry × employer size cell. These years are the only available overlapping years

that have establishment counts by size and industry. Specifically, we calculate

establishment shares for each industry-size cell from County Business Patterns data and

then multiply these shares by the total number of establishments in the JOLTS sample to

get our figure for the number of establishments in each cell. We calculate the average

vacancy stock per establishment in the cell as total vacancies in the cell divided by

number of establishments in the cell. We take the same approach to calculate the average

vacancy flow per establishment in the cell.

Tracking the Job-Finding Rate Using Standard and Generalized Matching Functions

Table 5 in the main text compares Beveridge Curve fits using observed vacancies

to our measure of effective vacancies. We repeat the same type of exercise here using the

job-finding rate as the dependent variable and the market tightness ratio as the

explanatory variable. Specifically, we regress the log of the job-finding rate measured as

JOLTS hires per unemployed worker on the log of one of two measures of labor market

tightness: the (v/u) ratio implied by the standard matching function, or the ratio of

effective vacancies to unemployment (v'/u) implied by the generalized matching

function. Here $v' = \bar{q}v$, where $\bar{q}$ is the recruiting intensity index in Figure 10. Our goal

is to assess which tightness measure performs better in tracking the job-finding rate.

Table B.3 reports the results and shows that the effective market tightness

measure corresponding to the generalized matching function outperforms the standard

market tightness measure at the national level and in all four Census regions. The residual

RMSE is 17.7 percent lower at the national level using the effective market tightness

measure and 15.3 to 28.0 percent lower across the four Census regions.

Table B.3 Trackng the Job-Finding Rate Using Market Tightness Measures Implied by the Standard and Generalized Matching Functions, Monthly Data from January 2001 to December 2011

Dependent variable: job-finding rate measured as *H/u*,

Aggregation Level	Time-Series Standard Deviation of Log Job-Finding Rate	Residual RMSE in Regression on (*v/u*), Standard Matching Function	Percent Reduction in RMSE Using (*v'/u*), Generalized Matching Function
National Data	0.40	0.08	17.7
Northeast	0.34	0.12	28.0
Midwest	0.37	0.08	21.3
South	0.42	0.11	15.3
West	0.47	0.12	17.3

Notes: The regressions reported in Table B.3 parallel the ones reported in Table 5 except for the use of the job-finding rate as the dependent variable and the market tightness ratio as the explanatory variable.