The Establishment-Level Behavior of Vacancies and Hiring

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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 job-filling 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 constant returns and that at the employer level, and that employers rely heavily on other instruments, in addition to vacancies, as they vary hires. We also develop evidence that effective recruiting intensity per vacancy varies over time, accounting for about 41% of movements in aggregate hires in the 2007 to 2009 period. Our evidence and analysis provide useful inputs for assessing, developing and calibrating theoretical models of search, matching and hiring in the labor market.

Keywords: vacancies, vacancy yield, job-filling rate, hiring, labor market search, generalized matching function, recruiting intensity, establishment data
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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.

[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.

We first document some basic patterns in the data. The aggregate vacancy yield moves counter-cyclically, in line with standard matching functions.[3] To see this point, consider a standard constant returns to scale 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 shows that the measured vacancy yield closely tracks the empirical construct implied by the standard matching function from 2001 to 2007, but the relationship broke down more recently. We provide a partial explanation and remedy for this breakdown. Our explanation and remedy flow from a generalized matching function that incorporates a role for recruiting intensity per vacancy. We develop a method to quantify the behavior of recruiting intensity per vacancy, and we show that the resulting generalized matching function outperforms the standard matching function in several respects. As Figure 1 illustrates, incorporating a role for recruiting intensity per vacancy reduces the discrepancy between the empirical vacancy yield and the matching function.

In the cross section, the vacancy yield falls with establishment size, rises with worker turnover, and varies by a factor of four across major industry groups. We also document 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. Stable establishments with no

[3] The ratio of hires to vacancies is often used as a measure of the job-filling rate. We reserve the latter label for the measure that adjusts for the stock-flow differences between monthly flow of hires and end-of-month stock of vacancies in JOLTS. In the aggregate, the daily fill rate is essentially proportional to the vacancy yield (so they are effectively equivalent) but this does not hold in the micro or cross sectional data.

employment change have the smallest rates for hires and vacancies and the lowest vacancy yields.

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 percentage of hires by employers with no reported vacancy partly reflects an unmeasured flow of new vacancies that are posted and filled within the month. This also inflates the vacancy yield. To address this and other issues, we consider 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.[4] 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 the vacancy yield. Vacancy durations are longer for larger establishments, and job-filling rates are an order of magnitude greater at the highest turnover establishments relative to the

[4] 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).

lowest turnover establishments. Perhaps most striking, the job-filling rate rises very steeply with employer growth in the cross section– from about 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. This pattern suggests that employers rely heavily on other instruments, in addition to vacancies, as they vary the rate of new hires. Other employer instruments with potentially important roles in the hiring process include advertising, screening methods, wage offers and their effects on application and acceptance rates, and hiring standards for new employees.

We characterize the role of other employer instruments with a generalized matching function defined over unemployed workers, job vacancies, and "recruiting intensity" per vacancy (shorthand for the effect of other instruments). This characterization yields three additional results. First, the data imply that employers rely heavily on other recruiting instruments, the hiring technology exhibits strong increasing returns to vacancies at the establishment-level, or both. We present evidence that rules out increasing returns to vacancies. Second, variations in recruiting intensity per vacancy have important aggregate consequences. We show that these variations account for about 40% of movements in the aggregate hiring rate in the 2007 to 2009 period and that augmenting a standard matching function to account for these variations substantially improves its ability to match the aggregate evidence. For instance, it produces a notably better fit of the empirical Beveridge curve. Third, 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 how to modify the textbook search model to account for the evidence, and briefly consider how the evidence relates to directed search models and mismatch models.

Our work is related 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 a firm-level or establishment-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). 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 sources 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, and recovers estimates for the flow of new vacancies, the daily job-filling rate, and mean vacancy duration. Section 4 also develops evidence of how the job-filling rate varies 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 recover information about the role of recruiting intensity and scale economies in the hiring process. We then turn to aggregate implications and quantify the role of other instruments in the behavior of aggregate hires over time. Lastly, we relate our evidence to leading search models. Section 6 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 12th 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.[5] While our JOLTS micro data set ends in December 2006, we consider the period through December 2010 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

[5] 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 (2008a) for detailed discussions of JOLTS. See Davis, Faberman, Haltiwanger, and Rucker (2008) for an analysis of how the JOLTS sample design affects the published JOLTS statistics.

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.

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 $t-1$.

In the appendix, we supplement our evidence from the JOLTS data with other sources that yield longer time series for aggregate outcomes. There, we present estimates of the aggregate vacancy yield and job -filling rate back to 1976.

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 the 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 vacancy 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 are very short, or that much hiring is not mediated through vacancies as the concept is defined and measured in JOLTS. Below, we return to this statistic to quantify the relative importance of these two channels.

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.[6] 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, one can 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.

[6] Previous research finds a wide distribution of growth rates at the establishment level at any point in time (e.g., Davis, Haltiwanger, and Schuh, 1996). Earlier research also finds highly nonlinear relationships between the hires rate and the establishment growth rate in the cross section (Abowd, Corbel, and Kramarz, 1999; Davis, Faberman, and Haltiwanger, 2006).

[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, and thereby isolating the 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

[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. 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 presents an accurate picture of the underlying economic relationship between hires and vacancies. 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 we cannot confidently infer the economic relationship between vacancies and hires from the raw JOLTS data, because the relationship is obscured by time aggregation. The model developed in the next section addresses this and other issues.

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. We assume the latter is constant within the month for any given establishment. Hires on day s in month t equal the fill rate times the vacancy stock:

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

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.

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 experience 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*.[9]

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

[9] 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 in Section 3. 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.[10]

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.[11]

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 job-filling rate as a function of employer growth. Specifically, we sort the establishment-

[10] 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.

[11] 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.

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. To check whether unobserved heterogeneity accounts for this result, we remove each establishment's sample mean growth rate before sorting observations into growth rate bins. Controlling for establishment fixed effects in this manner, and thereby isolating within-establishment time variation, actually *strengthens* the positive relationship between the job-filling rate and the growth rate of employment.[12]

Another possible explanation for this relationship stresses randomness at the micro level. In particular, the stochastic nature of job filling induces a spurious positive relationship between the job-filling rate and the employer growth rate. Lucky employers fill

[12] Adding controls for time effects as well has little impact.

jobs faster and, as a result, grow faster. To quantify this mechanical luck effect, we simulated 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 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.[13]

The empirical job-filling rate is overlain on the simulation results in Figure 8. We present results of the simulation performed two ways: one where the allocation of the draws of θ are based on the distribution of employment observed in the data and one where the allocation is based on the distribution of the initial vacancy stock observed in the data. The simulations show that the luck effect is much too small to explain the empirical fill-rate relationship in Figure 8. The luck effect produces an increase of about 2 to 3 percentage points in the fill rate in moving from 0 to 10 percent monthly growth and up to another 1 percentage point increase in moving from 10 to 30 percent growth. Thus, 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 in the Cross Section: A Recurring Pattern

Recalling Figure 3, Figure 8 also points 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. In the appendix, we show that a very similar pattern holds

[13] See the appendix for a full presentation of the simulation results.

across industries, employer size classes, and worker turnover groups. 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 0.821, which flatly contradicts the view that employers vary vacancies in proportion to desired hires.

The appendix contains a supplementary analysis that reinforces this point and makes it in another way. Using the daily model of hiring dynamics, we show how to express 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 the log gross hires rate across industries, size classes, turnover groups, and growth rate bins.

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 that employers manipulate 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 of which are exogenous to the employer. That is, hires are proportional to vacancies in the cross section.[14] Since the same job-filling rate applies to all employers, the standard specification implies a zero cross-

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

sectional elasticity of hires (and 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.

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. 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.[15] We are not aware of previous empirical studies that investigate how these aspects of "recruiting intensity" per vacancy vary with the employer's growth rate. Quantitative theoretical models of search, matching and hiring 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 advertising and recruiting. It may cost less 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.

[15] Employers may also alter job characteristics to better fit the locations, skills, and other attributes of potential hires. To the extent that employers tailor job openings in this way, it becomes easier to fill vacancies. If rapidly expanding employers are more prone to tailor jobs in this way, it generates a positive relationship between the fill rate and the growth rate.

5.B. Generalized Matching and Hiring Functions

It will be useful to formalize the role of other recruiting instruments and potential departures from CRS.[16] Start by writing the standard matching function ($H = \mu v^{1-\alpha} u^{\alpha}$) as:

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

The corresponding employer-level fill rate is $f_{et} = H_{et}/v_{et}$, which equals the aggregate when using the standard matching function in (5). 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 exercise in Section 4.E indicates 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) $$H_{et} = \mu \left(\frac{v_t'}{u_t}\right)^{-\alpha} q(v_{et}, x_{et}) \equiv \tilde{f}_t q(v_{et}, x_{et}), \qquad \text{where } \sum_e q(v_{et}, x_{et}) = v_t',$$

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 $q(x_{et}, v_{et}) \equiv v_{et}$, the 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 satisfies CRS in vacancies at the micro level.[17] More

[16] For the development of the generalized matching function, we follow the standard practice of using a continuous time representation. In empirical implementation below, we take into account the monthly data and time aggregation issues as we have earlier in the paper.

[17] 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 formally identical to our specification when we impose CRS in vacancies at the micro level.

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.

Several important observations follow. First, the employer's job-filling rate now takes the form $f_{et} = \tilde{f}_t q(v_{et}, x_{et})/v_{et}$, which reduces to $f_{et} = \tilde{f}_t \tilde{q}(x_{et})$ when the hiring function is CRS in vacancies at the micro level. Second, our evidence soundly rejects the case of decreasing returns to vacancies at the micro level with no role for other instruments, because this case implies that the job-filling rate declines with the vacancy rate in the cross section. Comparing Figures 4 and 7 reveals very much the opposite pattern. Third, the positive cross-sectional relationship between the vacancy rate and the job-filling rate implies strong increasing returns to v_e in the hiring function (6), a major role for other recruiting instruments, or both.

To develop the third point, 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 now takes the form,

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

Taking logs and differentiating with respect to hires, we obtain,

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

Recall from Figure 9 that a cross-sectional hires-weighted regression yields an estimate of 0.821 for the elasticity on the left side of (8). Estimating the vacancy rate elasticity in the same way yields 0.270 for $d \log v_{et}/d \log H_{et}$.[18] The first elasticity on the right on the right of (8) is zero, because all employers face the same aggregate conditions at a point in time. Substituting, $0.821 = (\gamma - 1)(0.270) + d \log \tilde{q}(x_{et})/d \log H_{et}$. Thus, to explain the cross-sectional behavior of job-filling rates, we must invoke strong increasing returns to vacancies

[18] The standard error of the elasticity estimate is 0.011. See the appendix for the scatter plot.

at the employer level, a major role for employer actions on other margins, or both. To preclude a role for other margins would require $\gamma = 4.04$.

The vacancy elasticity input in (8) relies on vacancy stock data not adjusted for time aggregation. To address this concern, consider an alternative calculation that accounts for the flow of vacancies. Ignoring lapsed vacancies, the steady-state vacancy rate equals the ratio of vacancy flows to job filling, $v_{et} = \theta_{et}/f_{et}$. In this case, equation (8) now becomes

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

The estimate of the vacancy flow elasticity from a cross-sectional regression is 0.957.[19] In this case, precluding a role for other recruiting margins would require $\gamma = 5.35$, which is even larger than the value we obtained directly from (8). We think such high degrees of increasing returns are empirically implausible, which leads us to conclude that employers rely importantly on other recruiting margins as they vary the gross hires rate.

We now estimate the returns to vacancies using the relationship specified in (7), in logs, and data aggregated into industry × size-class cells.[20] Across *i* industries and *s* size classes, the regression is

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

where ϵ_{is} is an error term and $\ln \tilde{f}$ becomes the constant term. Since we do not have an observable measure of $\ln \tilde{q}(x_{is})$, we proxy for it using the average employment growth rate of the industry-size cell. The use of industry-size cells is useful in this context since we avoid residual variation over time in $\ln \tilde{q}(x_{is})$ that is likely not well captured by an

[19] The standard error of the elasticity estimate is 0.01. See the appendix for the scatter plot.
[20] The regressions 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.

employment growth rate proxy. Estimating this equation with OLS also raises concerns of a form of division bias (in the daily model $f = H/v$ and, while more complicated, related concerns carry over to the monthly model (3) and (4)). To deal with this, we also run a two-stage least squares regression where we instrument ln v_{is} with the log of total employment in the industry-size cell. Finally, to account for time aggregation, we repeat the exercise using the log of vacancy flows rather than the vacancy stock. The two specifications are related through the steady-state relation $v_{is} = \theta_{is}/f_{is}$.

Table 4 presents our results. The estimates strongly support constant returns to scale in vacancies at the employer level. The implied estimate of γ from the IV estimates of the two specifications is 1.001 in both cases. Hence, we interpret this analysis as providing compelling evidence that employers rely heavily on other recruiting instruments, in addition to vacancies, to vary hires. In this regard, it is worth remarking that the negative relationship between employer size and job-filling rates in Table 3 also cuts against the view that scale economies dominate the cross-sectional variation in job-filling rates.

5.C. Aggregate Implications

We now use the generalized hiring function (6) to draw out some aggregate implications of our findings. We work with CRS at the micro level so that $f_{et} = \tilde{f}_t \tilde{q}(x_{et})$. Aggregating (6) then yields a generalized matching function defined over unemployment, vacancies and recruiting intensity per vacancy:

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

where $\bar{q}_t = \sum_e \left(\frac{v_{et}}{v_t}\right) \tilde{q}(x_{et})$ 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 gross hires, 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 aggregate hires? Taking log differences in (9) yields $\Delta \ln H = \alpha \Delta \ln u + (1-\alpha)\Delta \ln v + (1-\alpha)\Delta \ln \bar{q}$. Thus, to answer the question, we need to know how $\bar{q}_t$ varies with H_t over time. We adopt the working hypothesis that $\bar{q}_t$ varies with H_t in the same way as $\tilde{q}_{et}$ varies with H_{et} in the cross section. That is, we set the elasticity of $\bar{q}_t$ with respect to H_t to 0.821. 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 from 2007 to 2009. Of course, $\bar{q}$ is correlated with u and v in the time series, so we cannot allocate 41% of the movements in hires uniquely to recruiting intensity.

We can perform a similar decomposition for the job-filling and job-finding rate. For the job-finding rate, taking log differences of (9) and dividing by u yields $\Delta \ln(H/u) = (1-\alpha)\Delta \ln(v/u) + (1-\alpha)\Delta \ln \bar{q}$. For the job-filling rate, the same procedure yields $\Delta \ln(H/v) = -\alpha \Delta \ln(v/u) + (1-\alpha)\Delta \ln \bar{q}$. The literature uses several empirical measures of the job finding rate, so we perform the decomposition with three of them: the job-finding rate of the unemployed (measured from their unemployment-to-employment transitions), JOLTS hires per unemployed individual, and the unemployment escape rate (measured based on changes in the short-term and total unemployed). For this exercise, we measure the job-filling rate as hires per vacancy (recall that the steady state approximation of $H \approx \tau f v$ works well in the aggregate data). In the exercise, we find that aggregate movements in $\bar{q}_t$ account for between 10.5% and 20.2% of the movement in the job-finding rate and they reduce movements in the job-filling rate by 30.5% between 2007 and 2009.

The above analyses rely on the working hypothesis that $\bar{q}_t$ varies with H_t in the same way as $\tilde{q}_{et}$ varies with H_{et} in the cross section. We check this conclusion in three ways. First, if $\bar{q}_t$ moves with aggregate hires, it implies a particular form of misspecification in the standard matching function. According to the standard matching function, the aggregate vacancy yield obeys a simple relationship to inverse 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 can evaluate this implication for α = 0.5 and μ chosen so that both curves have the same mean. 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 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. Maintaining our assumption that the elasticity of $\bar{q}$ with respect to aggregate hiring is equal to its cross-sectional estimate (0.821), we can derive a time series of recruiting intensity from the published JOLTS hiring rate. We present this series in Figure 10. Our measure of recruiting intensity declines sharply, 17 percent, after early 2008, and remains low thereafter.

In our second check, we plug aggregate data on hires, vacancies and unemployment into (8) to back out a "macro-based" $\bar{q}_t$ series, and compare it to the micro-based $\bar{q}_t$ series. Figure 11 carries out this comparison for α = 0.5.[21] Two results stand out. First, the two measures of average recruiting intensity per vacancy are very highly correlated over time, and both show large fluctuations. This result lends added support to the conclusion that recruiting intensity per vacancy is an important source of movements in the aggregate hires rate. Second, the micro-based measure varies much less than one-for-one with the macro-based measure. Perhaps random errors in the data or the matching function specification (9) attenuate the estimated relationship. But the macro-based $\bar{q}$ 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 that supports this inference. For this reason, we think our micro-based series for $\bar{q}_t$ is better suited for isolating the effects of employer actions on other recruiting margins.

Our third check examines what elasticity value would maximize the fit of a Beveridge curve relationship augmented by our recruiting intensity measure. Specifically, we regress the log of the aggregate unemployment rate on the log of v'_t, where $v'_t = v_t\bar{q}_t$, where $\ln \bar{q}_t = \varepsilon \ln H_t$ and ε is the cross-sectional elasticity of the fill rate with respect to hires. We repeat this regression over a range of values for the elasticity of recruiting intensity with respect to hiring. We consider the fit of the Beveridge curve maximized at the

[21] 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 of $\bar{q}_t$ 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.

elasticity value that minimizes the mean squared error of the regression. This exercise produces a unique minimum when the elasticity equals 0.836, which is very close to the 0.821 estimate obtained from the cross-section. We take this as further evidence that our micro-based $\bar{q}_t$ measure does well in capturing employers' use of other recruiting margins.

We conclude the section with a final evaluation of the aggregate implications of fluctuations in $\bar{q}_t$. The preceding exercise shows that we can evaluate how much our augmented measure of vacancies, v'_t, improves the fit of the Beveridge curve relative to the case where we ignore aggregate movements in recruiting intensity. We evaluate the fit of the Beveridge curve at the national level and in each of the four Census regions. We examine the percentage reduction in the root mean squared error (RMSE) of using the augmented vacancy series relative to the base case where we impose $\bar{q}_t = 1$. As above, we estimate the Beveridge curve by regressing the log of the unemployment rate on the log of v'_t.

Our results are in Table 5.[22] All specifications suggest that accounting for our recruiting intensity measure improves the fit of the Beveridge curve. The RMSE is reduced by 21 percent at the national level. Across the four Census regions, the improvement in RMSE is between 13 and 24 percent.

5.D. 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

[22] We report results of alternative specifications of the Beveridge Curve in Table B.2 in the appendix. The results in the latter are similar qualitatively and quantitatively with those in Table 5. Note that we also conducted a non-nested test of the two alternative models (one with vacancies only and one with effective vacancies). We find that the tests always reject both models implying that there is predictive power from effective vacancies when only including actual vacancies and vice versa. This pattern likely reflects the instability of the Beveridge Curve so that additional information is useful in capturing variation.

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.

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).[23] 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.[24] 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 nature of the optimal intensity choice 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

[23] 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.
[24] See the discussion related to his equations (5.22) and (5.30).

average recruiting intensity varies over time and matters for aggregate hires. 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 condition for new jobs. This condition ensures that vacancies have zero asset value in equilibrium. In turn, the zero asset value plays a key role in driving 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 leaving the position unfilled.[25] 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. For example, Faberman and Nagypál (2008) show that a model with search on the job and productivity differences among firms can deliver a positive relationship between the job-filling rate and employer growth rates in the cross section.

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 his 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

[25] 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.

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 built-in with an extra recruiting margin, typically in the form of the 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. A Specification Test for Hires at Establishments with No Observed Vacancies

As a final point, we return to the finding in Table 2 that 41.6% of hires in the JOLTS data were at establishments that did not begin the month with a reported vacancy. Many of these hires may have come from vacancies that were posted and filled during the month. Therefore, a fraction of this statistic is due to time aggregation. The hiring framework in Section 4 allows us to quantify how much hiring one should observe, given our estimates of f_t and θ_t, at establishments that begin the month without a reported vacancy. Recall from equation (3), that if $v_{t-1} = 0$, all hiring will be from the flow of new vacancies during the month. We denote this as

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

The amount of hiring from the flow that occurs at employers with $v_{t-1} = 0$ is H_t^{θ} multiplied by the fraction of employment at these employers, which we denote λ_t^0. The fraction of hires that should occur at employers with $v_{t-1} = 0$ is therefore $\lambda_t^0 H_t^{\theta} / H_t$. We can calculate H_t^{θ} directly from the estimates obtained from the hiring framework. We can obtain an empirical measure of $\boldsymbol{\lambda_t^0}$ from the micro data. Table 2 shows that this fraction averages 0.451in the JOLTS data.

Performing this exercise with our national-level estimates of the hiring model implies that time aggregation alone would only produce 19.8% rather than 41.6% of hires at establishments that began a month with no vacancies. Table 3, however, shows that there exists a large amount of heterogeneity in vacancy flow and fill rates, so a more accurate measure of the role of time aggregation would account for as much of this heterogeneity as possible. Therefore, we repeat the exercise using data disaggregated by establishment size, employee turnover, and industry. We then take the employment-weighted average of the industry, size class, and turnover results to obtain an aggregate estimate comparable to the 41.6% statistic. Our results are in Table 6. Since the data for some cells become too sparse at certain levels of disaggregation, we perform the exercise with several two-way and three-way slices by industry, size, and turnover. Results by detailed size and turnover categories, split into goods-producing and service-producing industries, account for the highest fraction of hiring at establishments who start with zero vacancies, at 27.4%. This accounts for roughly two-thirds of the statistic observed in the data. Thus, our hiring framework manages to account for most of the hiring observed at establishments that start the month without a vacancy. Nevertheless, the results in Table 7 indicate that a nontrivial share of hires are not mediated through vacancies, as the concept is defined and measured in JOLTS.

7. Concluding Remarks

This paper 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 document strong patterns in hiring and vacancy outcomes related to industry, employer size, the pace of worker turnover, and employer growth rate.

Our study also innovates in several other respects. First, we develop an empirical 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 the job-filling rate rises steeply with the gross hires rate across industries, employer size classes, worker turnover groups, and employer growth rates. Third, we show how to interpret the evidence through the lens of a generalized matching function that includes a role for other recruiting instruments, in addition to vacancy numbers. Fourth, we develop evidence that employer actions on other recruiting margins account for about 40% of movements in aggregate hires. We also show that the standard matching function is misspecified in a cyclically varying manner, as predicted by our micro evidence and our analysis of recruiting intensity. Consistent with the latter, we show that aggregate patterns of job-filling rates, job-finding rates, and the Beveridge curve are better accounted for by effective vacancies. Finally, we show that the standard search equilibrium model cannot explain the cross-sectional and time-series evidence, even when the model is extended to incorporate a recruiting intensity margin. We also discuss how to modify the standard theory to account for the evidence.

Much work remains to explain the patterns in vacancy and hiring behavior that we uncover using JOLTS micro data. One issue is how well our model of daily hiring dynamics accounts for the extent of hiring by employers with no recorded vacancies. We find that 42 percent of hires occur at establishments that start the month with zero vacancies. Our daily hiring model that takes into account time aggregation can account for roughly two thirds of such hires through vacancies that are posted within any given month. While our model accounts for most of hires by establishments that begin the month with zero vacancies, the remaining fraction is of considerable interest. We think a promising area for future research is to explore the role of hires not mediated through vacancies. Guidance for such analysis will require information beyond what is available in the JOLTS data. We plan to explore these questions in future work.

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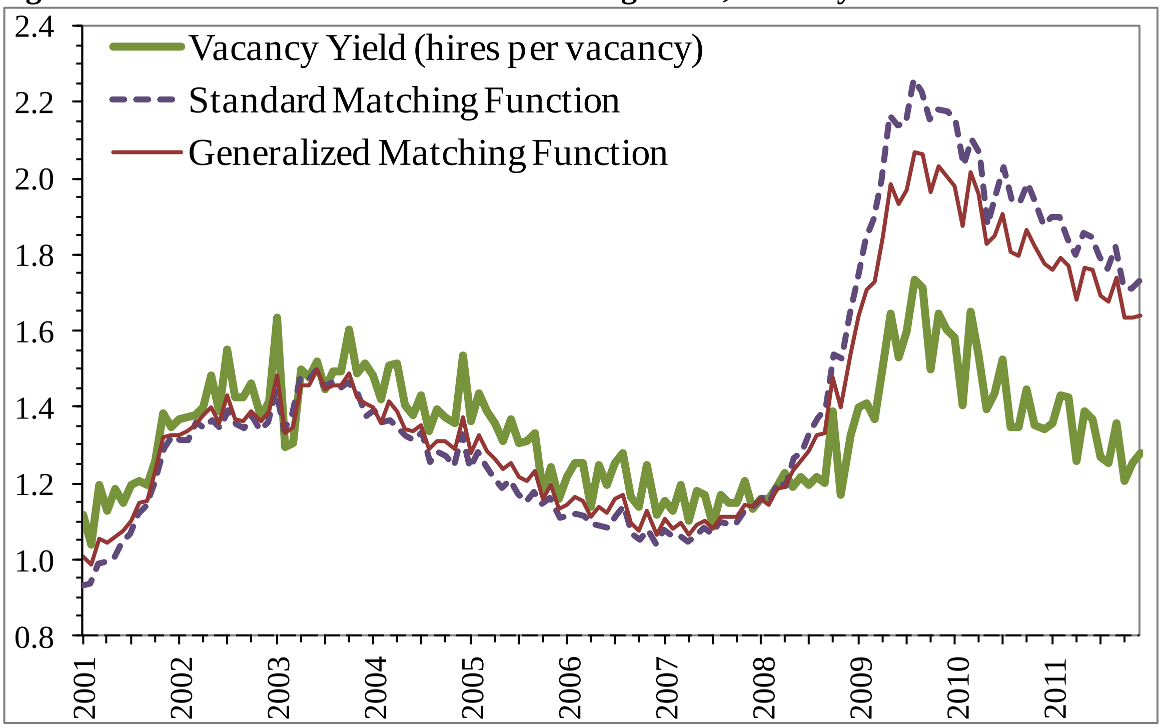
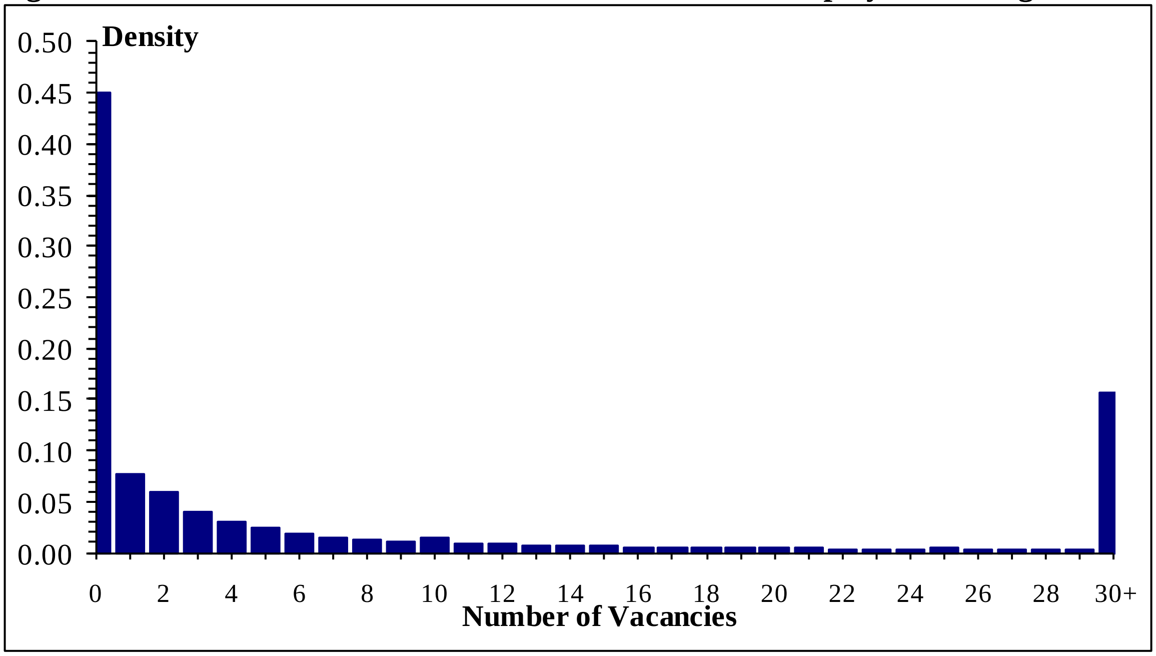
Figure 1. Two Measures of Inverse Market Tightness, January 2001 to December 2011



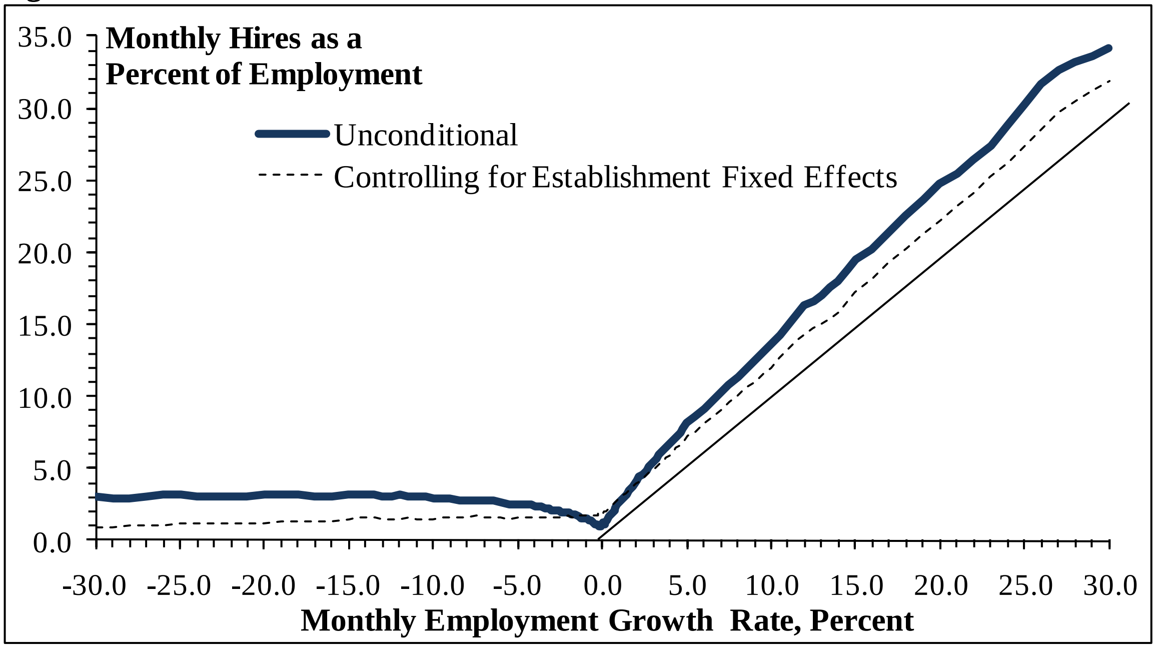
Note: Authors' calculations using published JOLTS data for nonfarm hires and vacancies and CPS data for civilian unemployment.

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



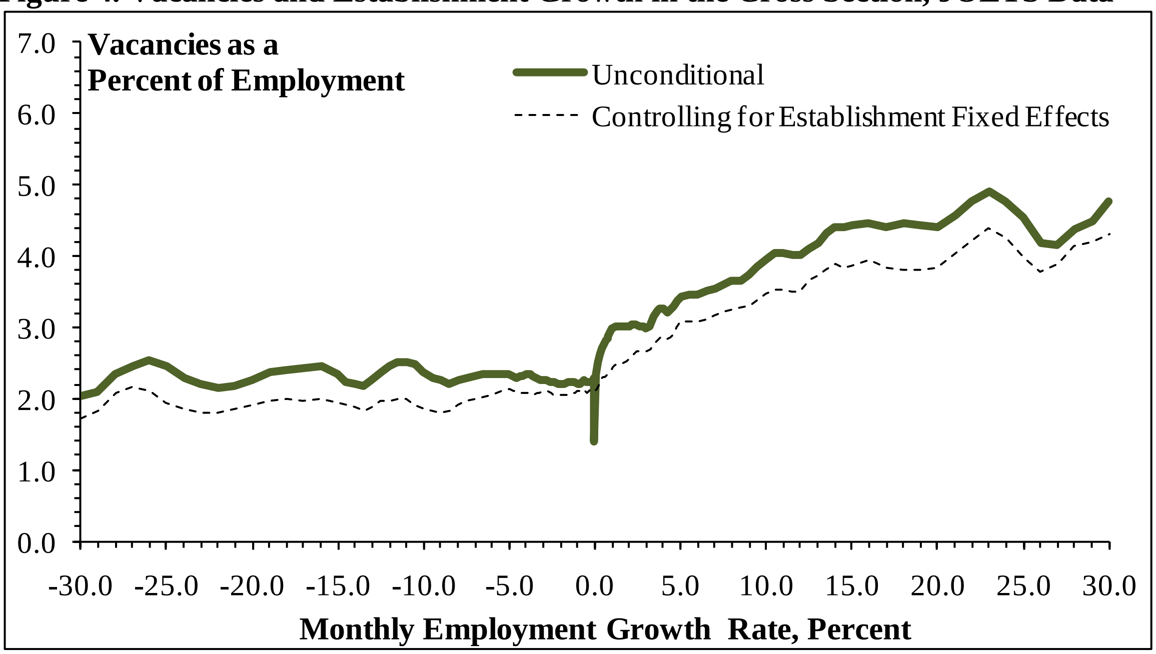
Note: Calculated from approximately 577,000 monthly establishment-level observations in JOLTS data from January 2001 to December 2006.

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



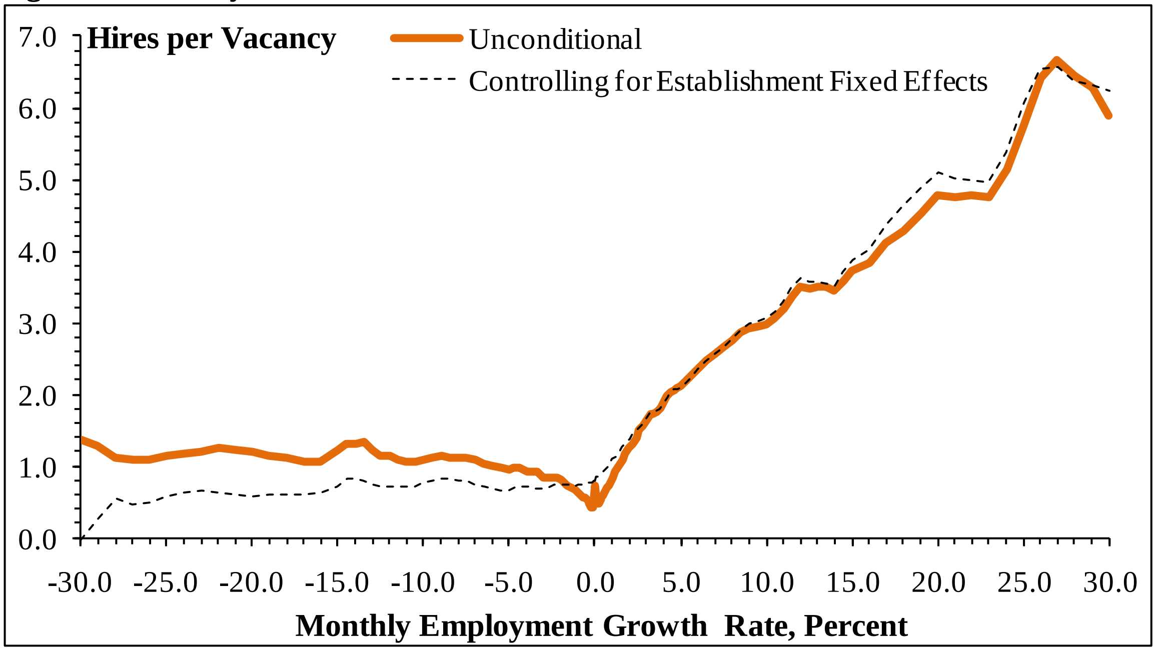
Note: The figure shows the cross-sectional relationship of the hires rate to the establishment growth rate, as fitted by nonparametric regression to approximately 577,000 monthly observations from 2001 to 2006. See text for details. The straight thin line emanates from the origin at 45 degrees.

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



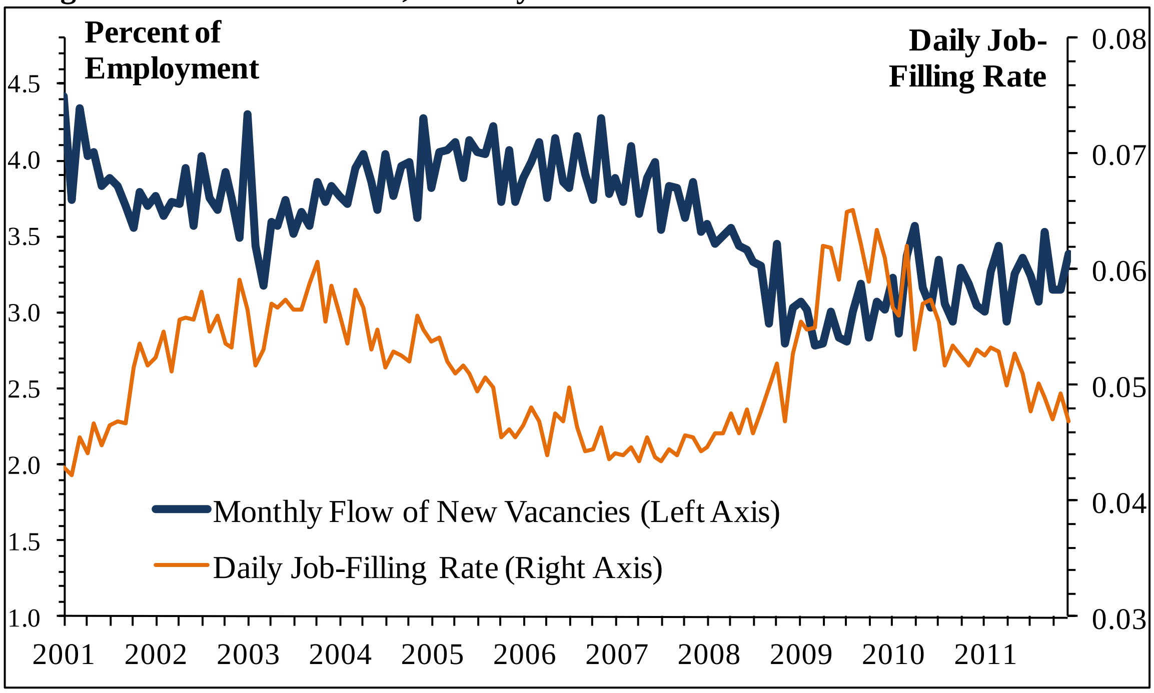
Note: The figure shows the cross-sectional relationship of the vacancy rate to the establishment growth rate, as fitted by nonparametric regression to approximately 577,000 monthly observations. See text for details.

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



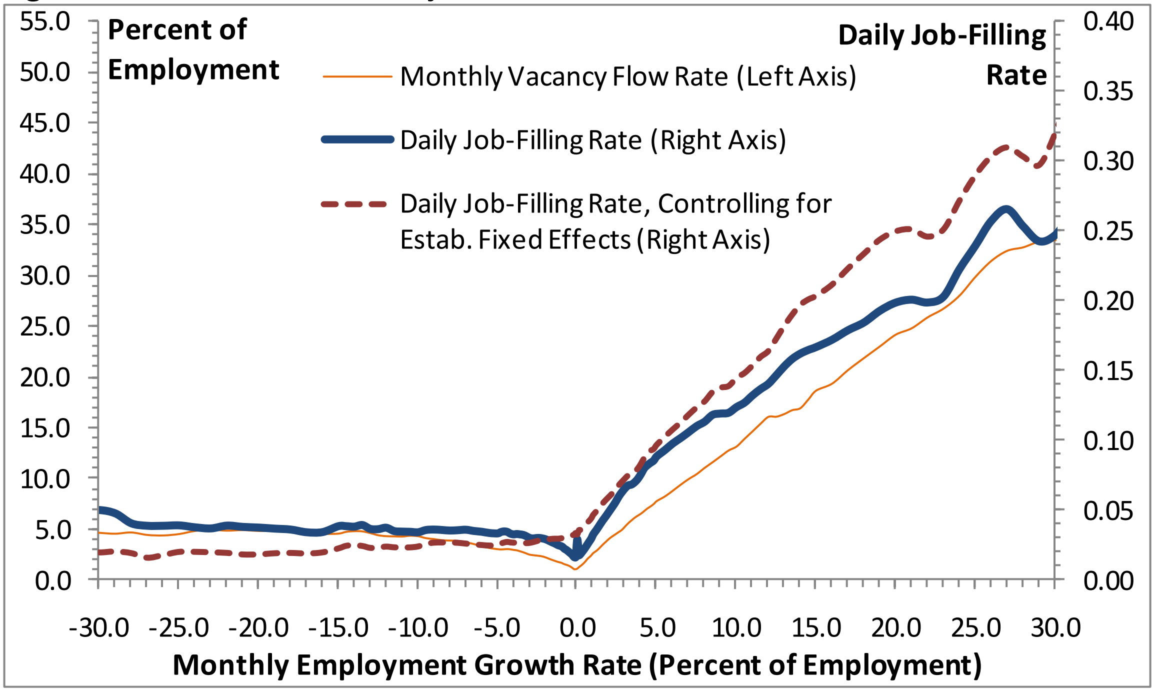
Note: The figure shows the cross-sectional relationship of the vacancy yield, as fit by nonparametric regression to approximately 577,000 monthly establishment-level observations. See text for additional details.

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



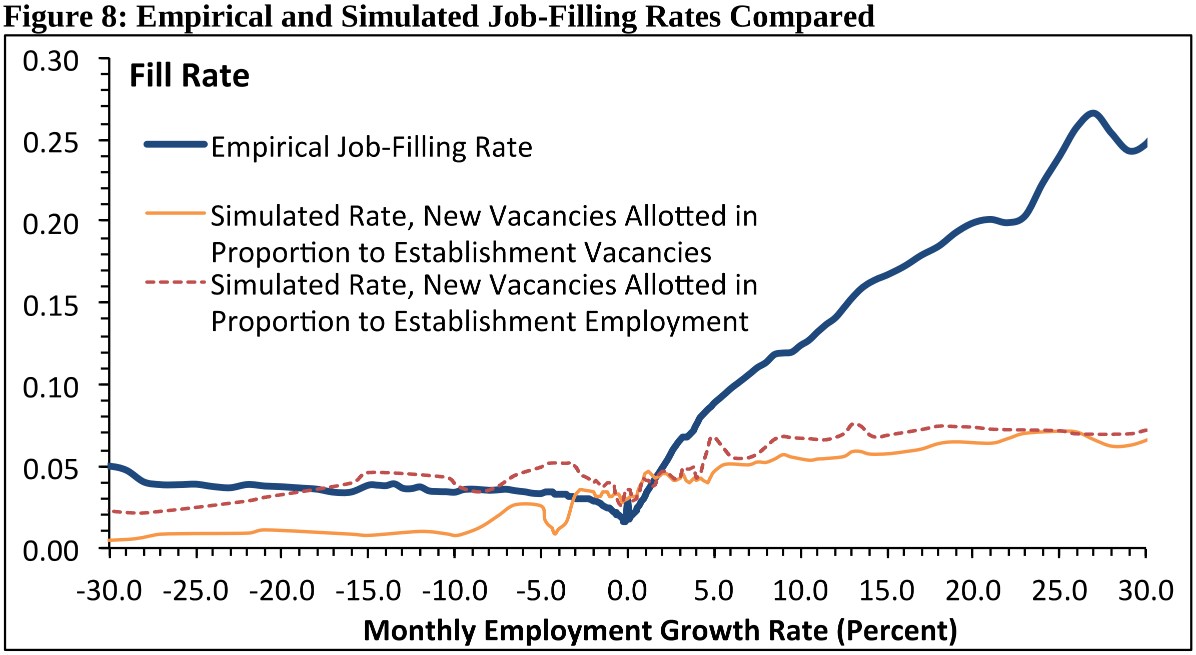
Note: The figure displays the monthly flow of new vacancies and the average daily job-filling rate in the month, as estimated from published JOLTS data using the moment conditions (4) and (5) in the text.

Figure 7. Fill Rates and Vacancy Flows as Functions of Establishment Growth



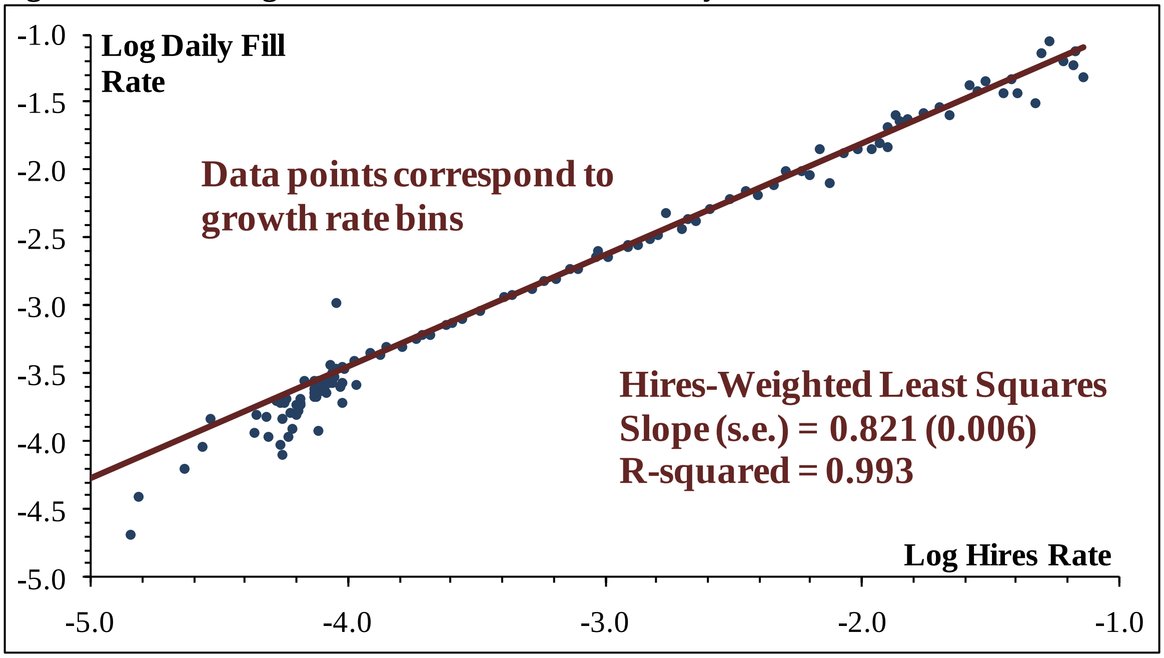
Note: The figure displays the vacancy flow rate as a percent of employment and the daily job-filling rate as functions of the monthly establishment growth rate, as estimated from micro JOLTS data using the moment conditions (4) and (5).

Figure 8: Empirical and Simulated Job-Filling Rates Compared



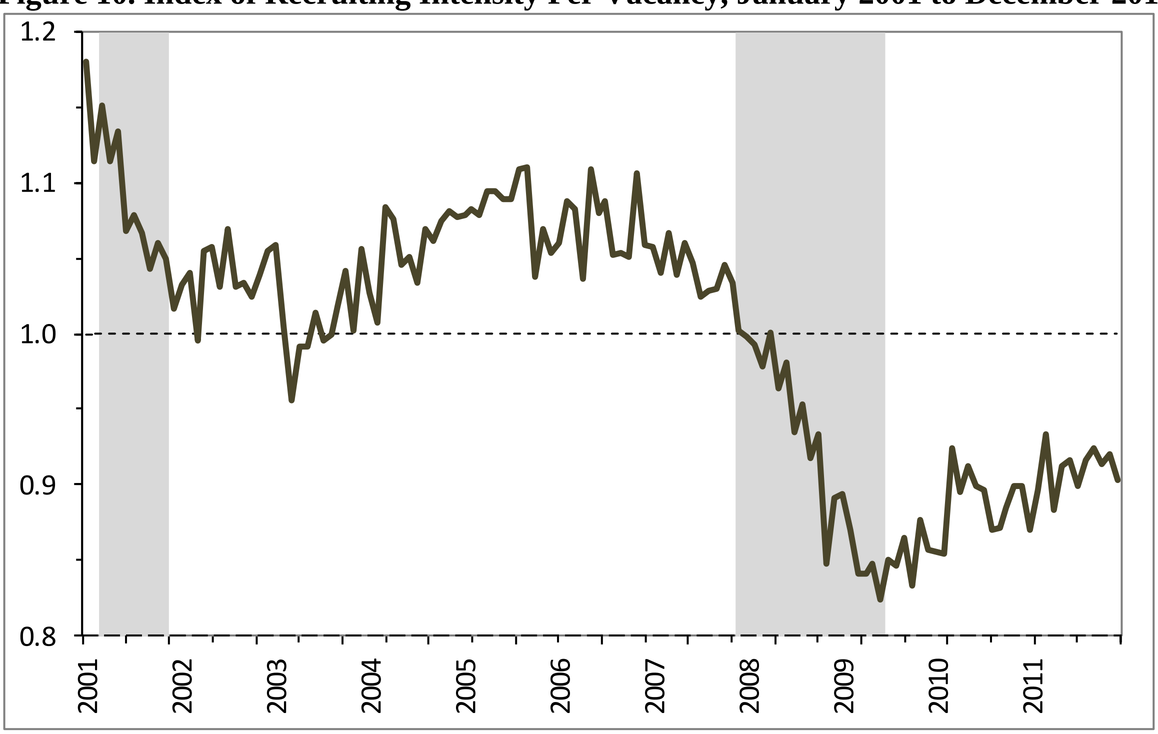
Note: Simulated job-filling rates are constructed under two alternative assumptions about the allocation of new vacancy flows – in proportion to an establishment's stock of vacancies or at the beginning of the month or in proportion to its employment. See text for additional details about the simulations.

Figure 9. Job-Filling Rates and Gross Hires Rates by Growth Rate Bin



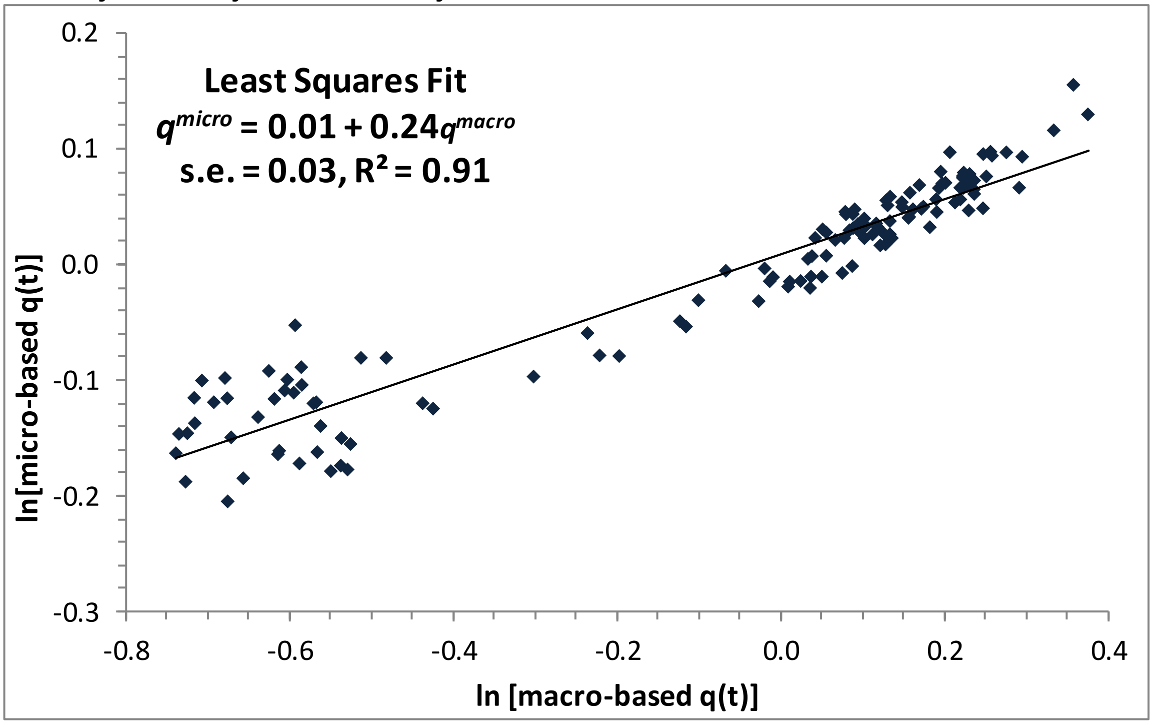
Note: The figure plots relationship between the log daily job-filling rate and the log gross hires rate across growth rate bins in the interval [-.3, .30] and the hires-weighted least squares regression fit. The bin-specific fill rates are estimated with controls for establishment fixed effects, as explained in the text, and displayed in Figure 7.

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



Note: The figure displays the monthly time series of our micro-based index of recruiting intensity per vacancy. See the text for details of the index construction.

Figure 11. The Relationship between Two Measures of Recruiting Intensity Per Vacancy, Monthly Data, January 2001 to December 2011



Note: See text for an explanation of how the two measures are constructed.

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
Professional & 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	Percentage
Pct. of Employment at Establishments with No Hires in t	34.8
Pct. of Employment at Establishments with No Vacancies at the end of t–1	45.1
Pct. of Vacancies at the end of t at Establishments with No Vacancies at the end of $t-1$	17.9
Pct. of Hires in t at Establishments with No Vacancies at the end of $t-1$	41.6

See Table 1 for notes. All statistics are for aggregate 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
Professional & 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 Recruiting

Explanatory Variable	**Beginning-of-Month Vacancies, v_{t-1}**		**Monthly Vacancy Flow, θ_t**	
	OLS	IV	OLS	IV
Coefficient	-.059	.001	.065	.001
(std. error)	(.049)	(.051)	(.049)	(.051)
R^2	.779	.772	.780	.772
First-stage R^2	---	.985	---	.986
Implied γ	0.941	1.001	1.069	1.001

Notes: Results are from the regression, at the industry-size class level (*N* = 70), of the log of the daily job-filling rate on the log of the variable listed in the top row, major industry and establishment size class fixed effects, and the net employment growth rate of the industry-size observation. IV estimates are from a two-stage least squares regression that instruments the variable listed in the top row with the log of total employment in the industry-size observation. The coefficient (standard error) is for the (second-stage) estimate on the listed explanatory variable.

Table 5. Test of Beveridge Curve Fit, Standard and Generalized Matching Functions

Specification	**Std. Deviation, Dependent Variable**	**RMSE, Standard Model**	**Pct. Reduction in RMSE, Generalized Model**
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: Table lists results from the regressions that include the listed variables using time-series data for either the nation or one of the four Census regions. Each row reports statistics from regression run on two versions of the independent variable: one with v equal to the vacancy rate (standard model), and one with v' equal to the product of $\bar{q}$ and the vacancy rate (generalized model). The columns report, the time-series standard deviation of the dependent variable, the root mean-squared error of the regression of the standard model, and the percent reduction in RMSE when moving from the standard to the generalized model. See text for details.

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

Percent of Hires in *t* at Establishments with No Vacancies at the end of *t* – 1	
From Data	41.6
Percent Implied by Baseline Model Using Disaggregated Data	
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 (15*) Disaggregation	27.4

Notes: Table reports the percentage of total hires at establishments that start the month with no reported vacancies calculated from JOLTS micro data and implied from aggregated data by the basic framework characterized by equations (4) and (5). Percentages implied by the disaggregated data are obtained by taking the hires-weighted average percentage predicted by the basic framework estimated at the listed level of disaggregation. Numbers in parentheses indicate the level of disaggregation for the listed category (e.g., 12 industries, 6 size classes, 6 turnover classes, etc.)

* : Turnover quintiles are disaggregated into 5 percentile categories for the smaller size classes, where cell size permits. The total number of cells used in this exercise is 111.