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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 show that (a) employers rely heavily on other instruments, in addition to vacancy numbers, as they vary hires, (b) the hiring technology exhibits strong increasing returns to vacancies at the establishment level, or both. We also develop evidence that effective recruiting intensity per vacancy varies over time, accounting for about 35% of movements 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. To obtain longer time series, we draw on the Conference Board's Help Wanted Index and data on hires from the Current Population Survey.

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 Nagypal (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 Ebrahimi 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. 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 rates. Stable establishments with no 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, and those with exactly one vacancy account for another 7%. Nevertheless, many establishments with zero reported vacancies at month's end hire new employees in the following month. Establishments reporting zero vacancies at month's end account, on average, 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 unmeasured vacancy flow also inflates the vacancy yield. For both measures, the observed values are partly an artifact of time aggregation and the distinction between point-in-time stocks (vacancies) and monthly flows (hires). 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 daily processes for vacancy flows and new hires. 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 the vacancy yield. Perhaps most striking, the job-filling rate rises very steeply with employer growth – 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. Vacancies take longer to fill at larger employers, averaging 15-17 days at establishments with fewer than 250 workers and about 38 days at those with 1000 or more. The job-filling rate for employers in the highest worker turnover quintile is ten times greater than in the lowest turnover quintile.

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 vacancy numbers, as they vary the rate of new hires. To sharpen this point, we again exploit our model of daily hiring dynamics. According to the model, we can 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

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).

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. 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.

To more fully characterize the role of other employer instruments, we introduce a generalized matching function defined over unemployed workers, job vacancies, and “recruiting intensity” per vacancy (shorthand for the effect of other instruments). Interpreting our evidence through the lens of this matching function, we obtain three additional results. First, the data imply that (a) employers rely heavily on other instruments, in addition to vacancy numbers, as they vary hires, (b) the hiring technology exhibits strong increasing returns to vacancies at the establishment level, or both. Second, 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. Third, employer actions on other margins have important aggregate consequences. Specifically, we develop evidence that recruiting intensity per vacancy accounts for about 35% of movements in the aggregate hires rate. We also show that the standard matching function applied to aggregate data suffers from a form of misspecification implied by our evidence and analysis.

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 implement the variance decomposition for log hires, introduce the generalized matching function, and show how to recover information about the role of other instruments 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.⁴ While our JOLTS micro data set ends in December 2006, we consider the period through March 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 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;

⁴ 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.

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 $t - 1$.

We supplement 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 1976.⁵ 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 vacancy rate in the overlapping period.⁶ 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.

3. Aggregate, Sectoral, and Establishment-Level Patterns

3.A. Cyclical Behavior of the Aggregate Vacancy Yield

Figure 1 draws on JOLTS, CPS, and HWI sources to plot three measures of the aggregate vacancy yield. The JOLTS-based measure plots quarterly averages of monthly vacancy yields, calculated as the flow of hires during month t divided by the stock of

⁵ Direct job-to-job transitions by workers cannot be identified under the pre-1994 CPS design.

⁶ This approach to the HWI follows Abraham (1987) and Shimer (2007b), who discuss the measurement issues in detail. See also Kroft and Pope (2008).

vacancies at the end of month $t-1$.⁷ The Fallick-Fleischman measure of hires captures job-to-job transitions, which is why it produces a greater vacancy yield than the Shimer measure. While there are notable differences across the measures in Figure 1, all three show that the aggregate vacancy yield exhibits a strong pattern of counter-cyclical movements.⁸

This counter-cyclical pattern is very much in line with standard specifications of the matching function in models of frictional unemployment. To see this point, let hires be determined by a 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 $0 < \alpha < 1$. Rearranging,

$$(1) \quad \frac{H}{v} = \mu \left(\frac{v}{u} \right)^{-\alpha}.$$

Thus, the vacancy yield is a log-linear decreasing function of labor market tightness, as measured by the vacancy-unemployment ratio (v/u). 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 2010Q1.

3.B. 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

⁷ JOLTS data are downloadable at www.bls.gov/jlt. To maintain consistency with our micro dataset, we rely on historical JOLTS statistics published before the March 2009 revisions and splice them to post-revision data. Specifically, we estimate log linear regressions of pre-revision on post-revision data in the pre-revision period. We use the regression estimates and post-revision data to obtain fitted values for the post-revision period. Taking anti-logs yields our adjusted data for the post-revision period.

⁸ The economy was in recession from March to November 2001 according to NBER dating, but employment continued to contract until the middle of 2003. For plots of the vacancy and hires rates that underlie Figure 1, see the appendix. On the large gap in average hires (and average vacancy yields) between CPS-based and JOLTS-based measures of aggregate hires, see Davis et al. (2008).

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. Inspecting (1), 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.C. 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.

There is considerable variation in the frequency of hires and vacancies across industries, employer size classes, and worker turnover groups. Perhaps counter-intuitively, 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.

3.D. Hires, Vacancies, and Establishment Growth

We next consider how hires, vacancies, and vacancy yields co-vary with employer growth rates at the establishment level.⁹ To estimate these relationships in a flexible nonparametric manner, we proceed as follows. First, partition the feasible range of growth rates, $[-2.0, 2.0]$, into 195 non-overlapping intervals, or bins, allowing for mass points at -2,

⁹ 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).

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, sort the roughly 577,000 establishment-level observations into bins based on monthly employment growth rate values. Given the partition and sorting of establishments, calculate employment-weighted means for the hires rate, the vacancy rate, and the vacancy yield for each bin. Equivalently, 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.¹⁰ 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.

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

¹⁰ 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.

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 4.¹¹ 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 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. It is unclear,

¹¹ 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 6.

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 . Hires on day s in month t equal the fill rate times the vacancy stock:

$$(2) \quad h_{s,t} = f_t v_{s-1,t}.$$

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 according to (2). 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 :

$$(3) \quad v_{s,t} = ((1 - f_t)(1 - \delta_t))v_{s-1,t} + \theta_t.$$

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 (2) and (3) 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 (3) over τ days and recursively substituting for $v_{s-1,t}$ yields the desired equation:

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

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 (2) to obtain the monthly flow, $H_t = \sum_{s=1}^{\tau} h_{s,t}$. Substituting (3) into (2), and (2) into the monthly sum, and then substituting back to the beginning of the month for $v_{s-1,t}$ yields

$$(5) \quad H_t = f_t v_{t-1} \sum_{s=1}^{\tau} (1 - f_t - \delta_t + \delta_t f_t)^{s-1} + f_t \theta_t \sum_{s=1}^{\tau} (\tau - s + 1) (1 - f_t - \delta_t + \delta_t f_t)^{s-1}.$$

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 (4) and (5) 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 (4) and (5) 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 (2) and (3). 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 .

We also tried an estimation approach suggested by Rob Shimer. The approach considers steady-state versions of (2) and (3) 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 (4) and (5). At more disaggregated levels, estimates based on the steady-state approximation often diverge from those implied by (4) and (5), 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 (4) and (5) for our reported results.

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. To obtain longer time series, we use the HWI for vacancies, CPS data on the monthly flow of hires, and CPS flows from employment to unemployment as our measure of the layoff rate. 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 2001:1 to 2010:3 for the estimated flow of new vacancies, the daily job-filling rate, and the measured vacancy stock. The monthly flow of new vacancies averages 3.3% of employment, considerably larger than the average vacancy stock of 2.5%. Vacancy stocks and flows are pro-cyclical, with stronger movements in the stock 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.¹²

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 7 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. (As we remarked previously, aggregate employment continued to contract through the middle of 2003.) In short, the available evidence 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.

¹² 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.

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 first turnover quintile to 11.4% per day in the fifth quintile. These 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 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 (4) and (5). 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 new vacancy flows by growth rate.

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.

Figure 8 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, but they actually decline with the growth rate of employment.

One important conclusion is immediate from Figure 8: 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.¹⁴

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 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

¹⁴ Adding controls for month effects as well has no visible impact.

construction, the simulation delivers a positive relationship between the realized job-filling rate and the realized growth rate through the luck effect.¹⁵

The simulations show that the luck effect is much too small to explain the fill rate relationship in Figure 8. The luck effect produces an increase of about 2 percentage points in the fill rate in moving from 0 to 10 percent monthly growth and 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 8 reflect something more fundamental about the nature of the hiring process and its relationship to employer growth.¹⁶ We return to this issue 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. 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 0.72, which flatly contradicts the view that employers vary vacancies in proportion to desired hires.

¹⁵ To simulate establishment-level paths, we must take a stand on the allocation of new vacancy flows and separations to establishments. We allocate separations in proportion to an establishment's employment (within its size class). For new vacancy flows, we considered two alternatives: allocation in proportion to employment and allocation in proportion to beginning-of-month vacancy stocks. These two alternatives yield very similar results. See the appendix for a full presentation of the simulation results.

¹⁶ This is not to say that time aggregation plays no role in the observed vacancy yield relationship to employer growth. On the contrary, Figure 8 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 an important 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 8.

Figure 9 reflects a recurring cross-sectional pattern in the data. To highlight this point, Figure 10 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 summary, we have shown that 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 next section, it has important implications for theoretical models.

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 exogenous to the employer. That is, hires are proportional to vacancies with the same constant of proportionality for all units in the cross section.¹⁷ Since the same job-filling rate applies to all employers, the standard specification implies a zero cross-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 8, 9 and 10.

¹⁷ To see the connection to our model of daily hiring dynamics, recall that steady-state approximations of (2) and (3) yield $H \approx \tau f v$.

What accounts for this failure? One possibility is that employers act on other margins using other instruments, in addition to vacancy numbers, when they raise the hires 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.¹⁸ 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 8, 9 and 10 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.

5.B. A Model-Based Variance Decomposition for Hires

Employer actions on other margins and increasing returns to vacancies at the micro level share the implication that vacancy numbers alone do not fully account for cross-sectional differences in the gross hires rate. Motivated by this observation, we now use our empirical model of daily hiring dynamics to quantify how fully the vacancy instrument

¹⁸ 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.

accounts for cross-sectional differences in the gross hires rate. Consider a closed-form expression for the hires solution (5) derived in the appendix:

$$(6) \quad H = Bf \left\{ v_{-1} + \left[\frac{1}{1-x^\tau} - \frac{1/\tau}{1-x} \right] \tau \theta \right\} \equiv Bf \{ v_{-1} + A\tau\theta \}$$

where $x \equiv 1 - f - \delta + \delta f$, $B \equiv (1 - x^\tau) / (1 - x)$, and we suppress the time subscript t . The Bf term in this expression is independent of vacancies. The term in braces is the sum of old vacancies and A times the flow of new vacancies, which depends on f only through A .

Evaluating at $\tau = 26$ and sample mean values for f and δ yields $\bar{A} = .5916$. Substituting into (6) and taking logs yields an approximate expression for log gross hires:

$$(7) \quad \log H \approx \log(Bf) + \log \{ v_{-1} + \bar{A}(\tau\theta) \}.$$

Using (7), Table 4 reports the percentage of the cross-sectional variance in log hires accounted for by vacancies. Table 4 also reports variance decomposition results based on the “exact” log version of (6), which involves no approximation but is not a true decomposition because of A ’s dependence on f . The rightmost column in Table 4 uses the steady-state approximation of (2) and (3), which yields $\log H \approx \log \tau + \log f + \log v$. If hires are proportional to vacancies, then all explanatory power in the variance decompositions should load 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.

One could try to rationalize this evidence by postulating suitable differences in matching efficiency. We think an explanation along those lines is unsatisfactory in at least two major respects. First, it offers no insight into why matching efficiency varies across sectors in line with the gross hire rate (Figure 10). Second, sectoral differences in matching

efficiency do not explain the patterns in Figures 8 and 9: The job-filling rate is much higher when an establishment grows (hires) rapidly than when the same establishment grows (hires) slowly. As we discussed, one interpretation is that employers significantly increase recruiting intensity per vacancy, as well as vacancy numbers, when they increase hiring. Another interpretation is that the hiring technology exhibits increasing returns to vacancies at the level of sectors and individual employers. We now show how to map these two interpretations to the evidence in a tight way.

5.C. Generalized Matching and Hiring Functions

It will be useful to formalize the role of other recruiting instruments and potential departures from CRS. Start by rewriting the standard matching function (1):

$$(1) \quad \sum_e H_{et} = H_t = \mu \left(\frac{v_t}{u_t} \right)^{-\alpha} v_t = \mu \left(\frac{v_t}{u_t} \right)^{-\alpha} \sum_e v_{et} \equiv f_t \sum_e v_{et}.$$

For an individual employer or group of employers, e , (1) implies hires at t of $H_{et} = f_t v_{et}$.

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 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 margins using other instruments, x :

$$(8) \quad H_{et} = \mu \left(\frac{v'_t}{u_t} \right)^{-\alpha} q(v_{et}, x_{et}), \text{ where } \sum_e q(v_{et}, x_{et}) = v'_t,$$

where 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 $q(v_{et}, x_{et}) \equiv v_{et}$, (8) reduces to the hiring function implied by (1), and aggregation 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.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 .

Several important observations follow. First, the 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 it implies that the job-filling rate declines with the vacancy rate in the cross section. Comparing Figures 4 and 8 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 (8), 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

$f_{et} = \tilde{f}_t v_{et}^{\gamma-1} \tilde{q}(x_{et})$. Taking logs and differentiating, we obtain

$$(9) \quad \frac{d \log(f_{et})}{d \log(H_{et})} = \frac{d \log(\tilde{f}_t)}{d \log(H_{et})} + (\gamma - 1) \frac{d \log(v_{et})}{d \log(H_{et})} + \frac{d \log(\tilde{q}(x_{et}))}{d \log(H_{et})}.$$

Recall from Figure 9 that a cross-sectional hires-weighted regression yields an estimate of 0.722 for the elasticity on the left side of (9). Estimating the vacancy rate elasticity in the

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

same way yields 0.336 for $d \log(v_{et}) / d \log(H_{et})$.²⁰ The first elasticity on the right is zero, because all employers face the same aggregate conditions at a point in time. Substituting, $0.722 = (\gamma - 1)(0.336) + [d \log(\tilde{q}(x_{et})) / d \log(H_{et})]$. Thus, to explain the cross-sectional behavior of job-filling rates, we must invoke strong increasing returns to vacancies at the employer level, a major role for employer actions on other margins, or both. To preclude a role for other margins requires a value for the scale economy parameter γ of about 3.15.

A possible concern here is that our estimate for the vacancy elasticity in (9) relies on vacancy stock data that are not adjusted for time aggregation. To address this concern, consider an alternative version of (9). Ignoring lapsed vacancies, the steady-state vacancy rate equals the ratio of vacancy flows to job filling, $v_{et} = \theta_{et} / f_{et}$. Taking logs, differentiating, and substituting into (9) yields

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

The advantage of this expression over (9) is that the measures of θ and f produced by our empirical model in Section 4 are adjusted for time aggregation. Proceeding as before to set the first and last terms on the right side to zero and rearranging, we obtain

$$\frac{d \log(f_{et})}{d \log(H_{et})} = [(\gamma - 1) / \gamma] \left[\frac{d \log(\theta_{et})}{d \log(H_{et})} \right].$$

Estimating the vacancy flow elasticity in a cross-sectional regression yields 0.979.²¹

Plugging in this value for the vacancy flow elasticity and 0.722 for the fill-rate elasticity implies $\gamma = 3.81$, which is even larger than the value we obtained directly from (9).

²⁰ The standard error of the elasticity estimate is 0.011. See the appendix for the scatter plot.

²¹ The standard error of the elasticity estimate is 0.01. See the appendix for the scatter plot.

Micro-level scale economies this powerful strike us as highly implausible. Hence, we see this analysis as providing compelling evidence that employers rely heavily on other recruiting instruments, in addition to vacancies, to vary hires. Perhaps the hiring technology also exhibits increasing returns to vacancies at the establishment level, but the matter requires more research. In this regard, it is worth remarking that the negative relationship between employer size and job-filling rates in Table 3 cuts against the view that scale economies dominate the cross-sectional variation in job-filling rates.

5.D. Aggregate Implications

We now use the generalized hiring function (8) 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 in (8) then yields a generalized matching function defined over unemployment, vacancies and recruiting intensity per vacancy:

$$H_t = \sum_e H_{et} = \mu \left(\frac{v'_t}{u_t} \right)^{-\alpha} \sum_e v_{et} \tilde{q}(x_{et}) = \mu \left(\frac{v'_t}{u_t} \right)^{-\alpha} v'_t = \mu v_t^{1-\alpha} u_t^\alpha \bar{q}_t^{1-\alpha}, \quad (10)$$

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

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 (10) reduces to the standard matching function (1). 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 (10) yields $\Delta \log H = \alpha \Delta \log u + (1 - \alpha) \Delta \log v + (1 - \alpha) \Delta \log \bar{q}$.

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 0.72. Given a value for α of about one-half, this working hypothesis yields the tentative conclusion that \bar{q}_t accounts for about 35% of movements in the aggregate hires rate.

We check this conclusion in two ways. First, if \bar{q}_t moves with aggregate hires, it implies a particular form of misspecification in the standard matching function (1). We find clear evidence for the implied form of misspecification. Second, we use (10) to generate an alternative \bar{q}_t series based solely on aggregate outcomes, comparing it to the “micro-based” \bar{q}_t series described above. The two series are very highly correlated. We now describe these two checks in detail and present the results.

According to the standard matching function (1), the aggregate vacancy yield obeys a simple relationship to inverse market tightness given by $(H / v) = \mu (u / v)^\alpha$. In contrast, the generalized matching function (10) yields $(H / v) = \mu (u / v)^\alpha \bar{q}_t^{1-\alpha}$. Thus, if employers cut back on recruiting intensity per vacancy in weak labor markets, (10) implies a decline in the vacancy yield relative to $\mu (u / v)^\alpha$. We evaluate this implication in Figure 11 for $\alpha = .5$ and μ chosen so that both curves have the same mean. The vacancy yield falls well short of the benchmark implied by (1) 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.

Our second check uses a more systematic approach. We plug aggregate data on hires, vacancies and unemployment into (10) to back out a “macro-based” \bar{q}_t series, and compare it to the micro-based \bar{q}_t series. Figure 12 carries out this comparison for $\alpha = .5$. 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 (10) 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. 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.

We have verified that the pattern in Figure 12 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.

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.

Pissarides analyzes a search equilibrium model with a free entry condition for new jobs, variable recruiting intensity, and a generalized matching function similar to (10).²² 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.²³ 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

²² 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.

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

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 11 and 12 that 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 widely used building block 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.²⁴ 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.

²⁴ 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.

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 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 an offer wage 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. 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 35% 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. 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. Recall from Table 2 that 42 percent of hires occur at establishments that start the month with zero vacancies. In some preliminary analysis, we find that the time aggregation phenomenon captured by the model explains only half of the observed hiring by employers with no recorded vacancies. This finding has at least three potential interpretations: JOLTS respondents systematically under report vacancies relative to hiring, unobserved heterogeneity leads the model to under predict hires by employers with no recorded vacancies, and many hires are not mediated through vacancies. We plan to evaluate these interpretations in future work.

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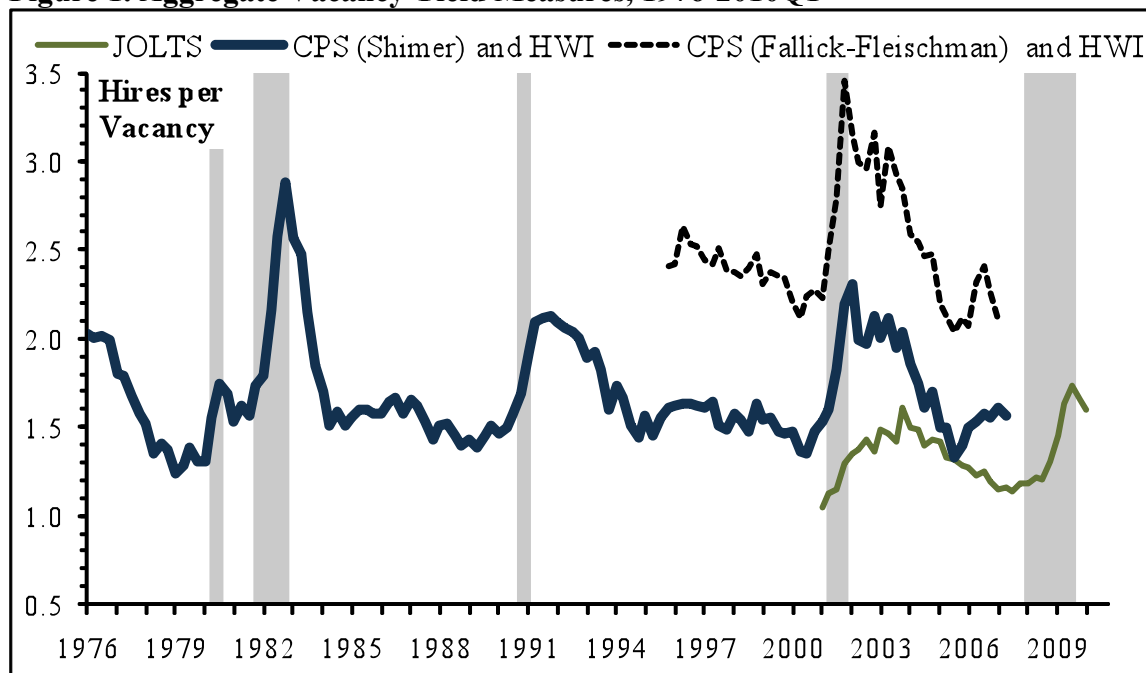
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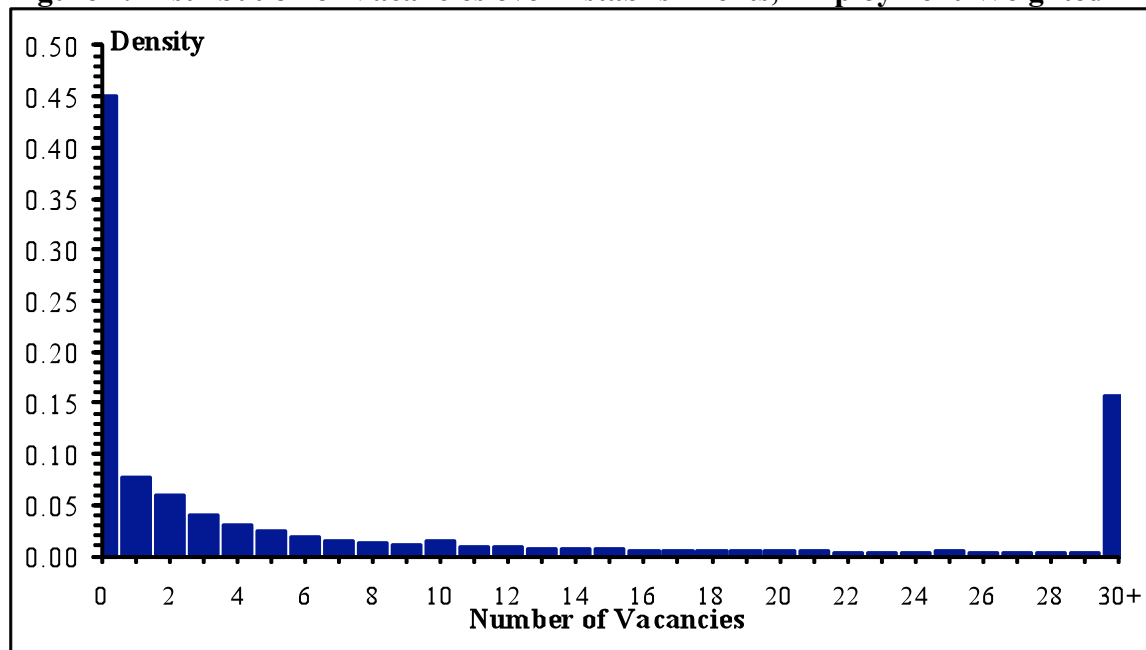
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Figure 1. Aggregate Vacancy Yield Measures, 1976-2010Q1



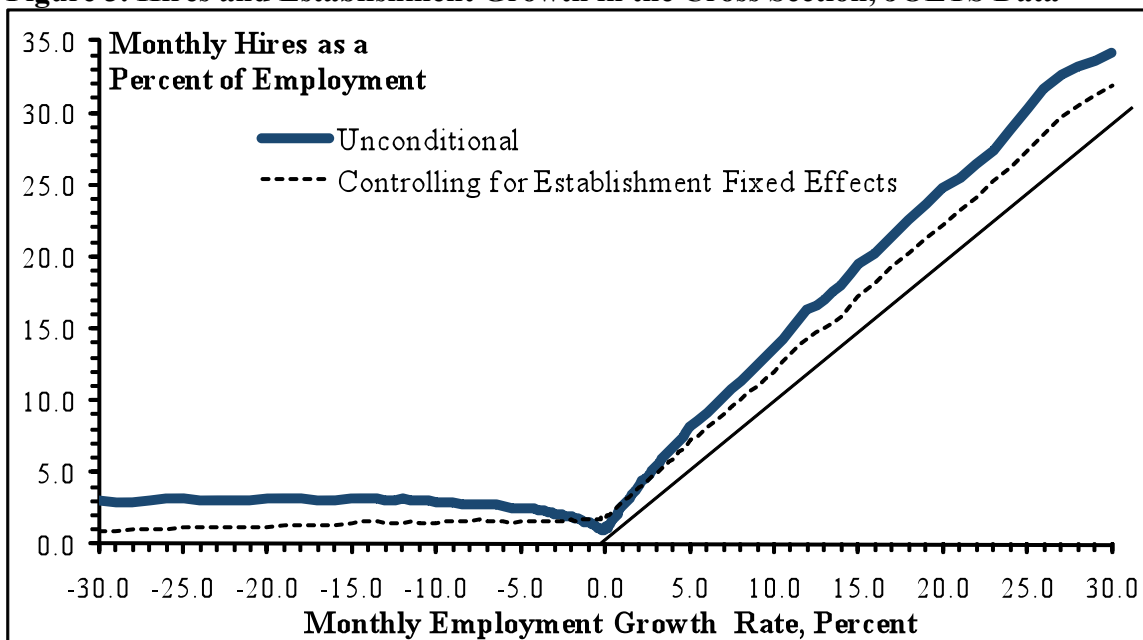
Notes: CPS Hires from Shimer (2007a) for 1976-2007q2 and from Fallick and Fleischman (2004, updated) for 1994-2007q2. Help Wanted Index from the Conference Board from 1976-2007q2. JOLTS data from 2001-2009q3 from the BLS. CPS (Shimer) and HWI series are detrended using an HP filter with smoothing parameter of $\lambda = 10^5$. See text for the vacancy yield calculations. Shaded regions depict NBER-dated recessions.

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



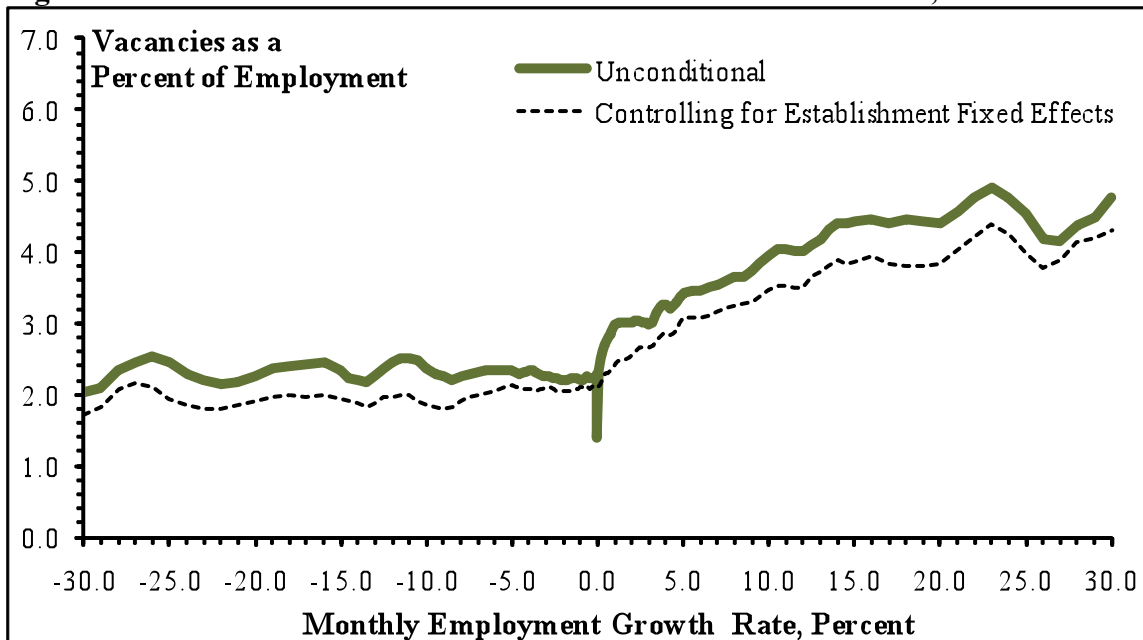
Note: JOLTS distributions calculated from approximately 577,000 monthly establishment-level observations from January 2001 to December 2006.

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



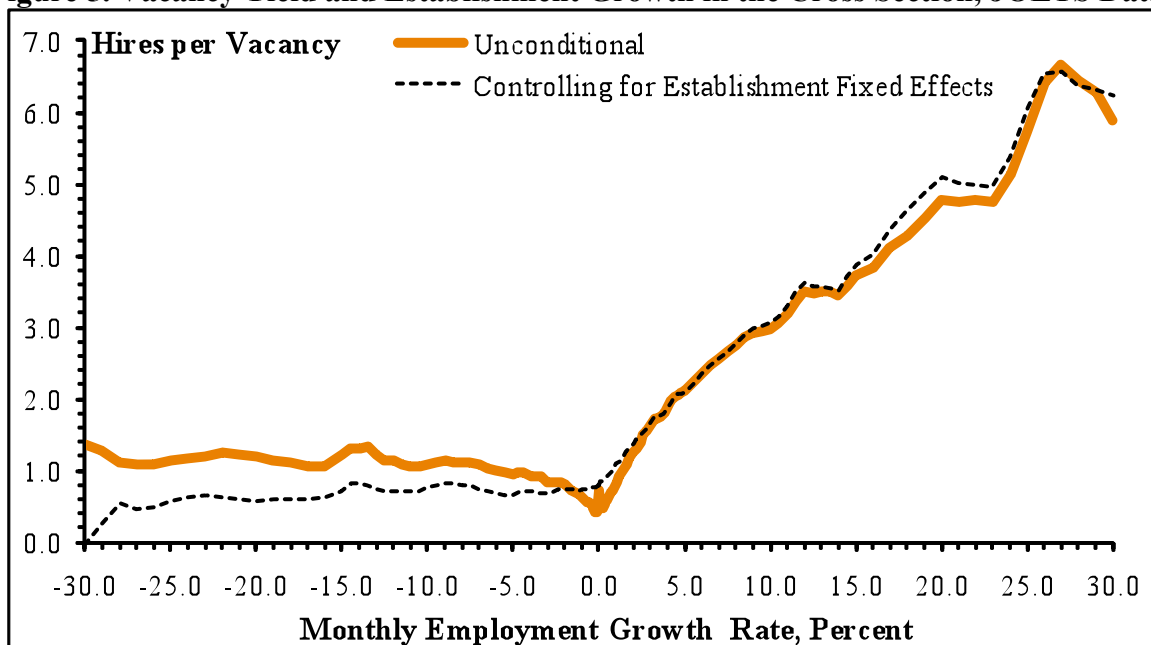
Note: The figure shows the cross-sectional relationship of the hires rate to the establishment growth rate, as fitted by nonparametric regression to approximately 577,000 monthly observations. See text for details. The straight thin line emanates from the origin at 45 degrees.

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



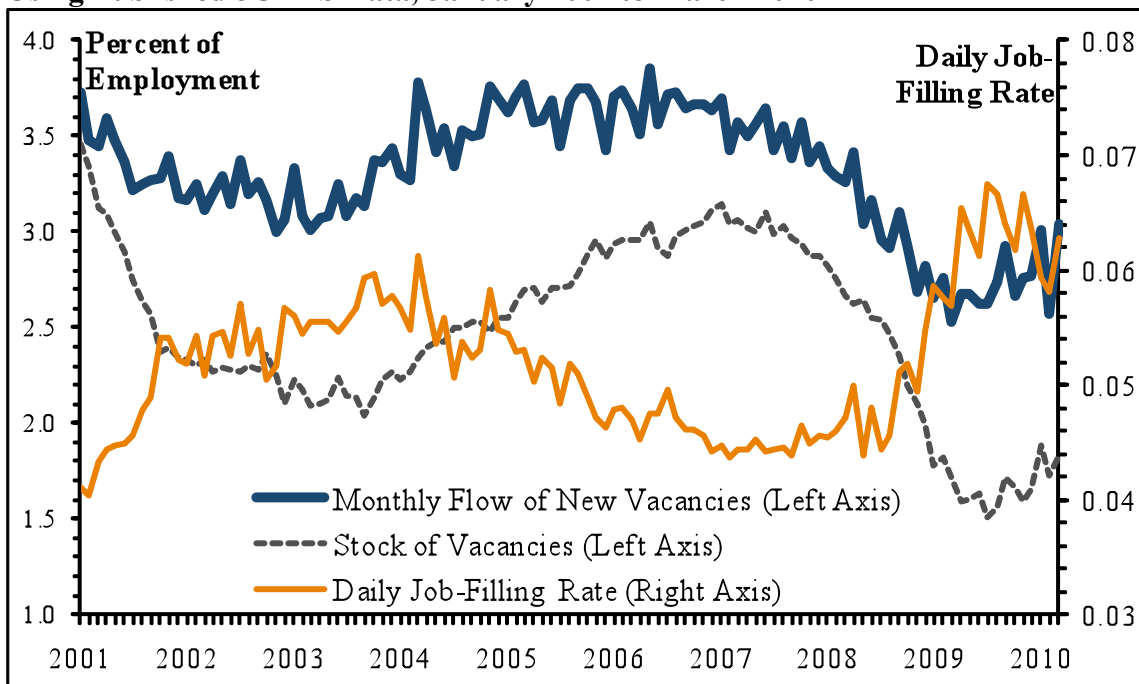
Note: The figure shows the cross-sectional relationship of the vacancy rate to the establishment growth rate, as fitted by nonparametric regression to approximately 577,000 monthly observations. See text for details.

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



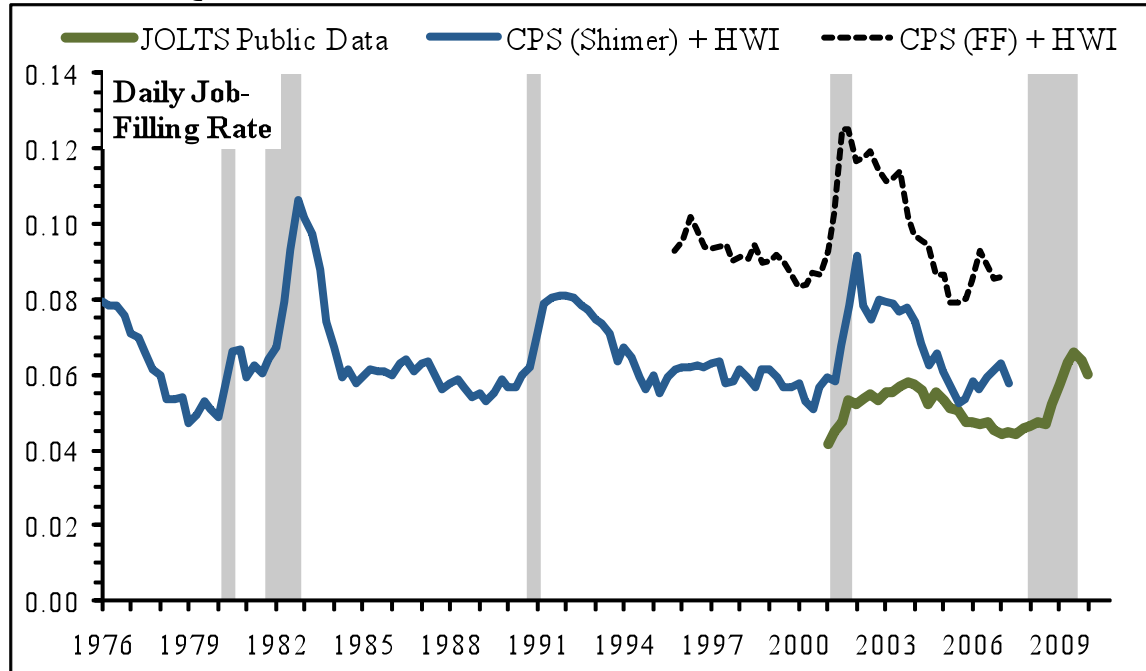
Note: The figure shows the cross-sectional relationship of the vacancy yield, as fit by nonparametric regression to approximately 577,000 monthly establishment-level observations. The vacancy yield is calculated as the number of hires during month t per vacancy reported at the end of month $t-1$. See text for additional details.

Figure 6. New Vacancy Flows and Daily Job-Filling Rate, Model-Based Estimates Using Published JOLTS Data, January 2001 to March 2010



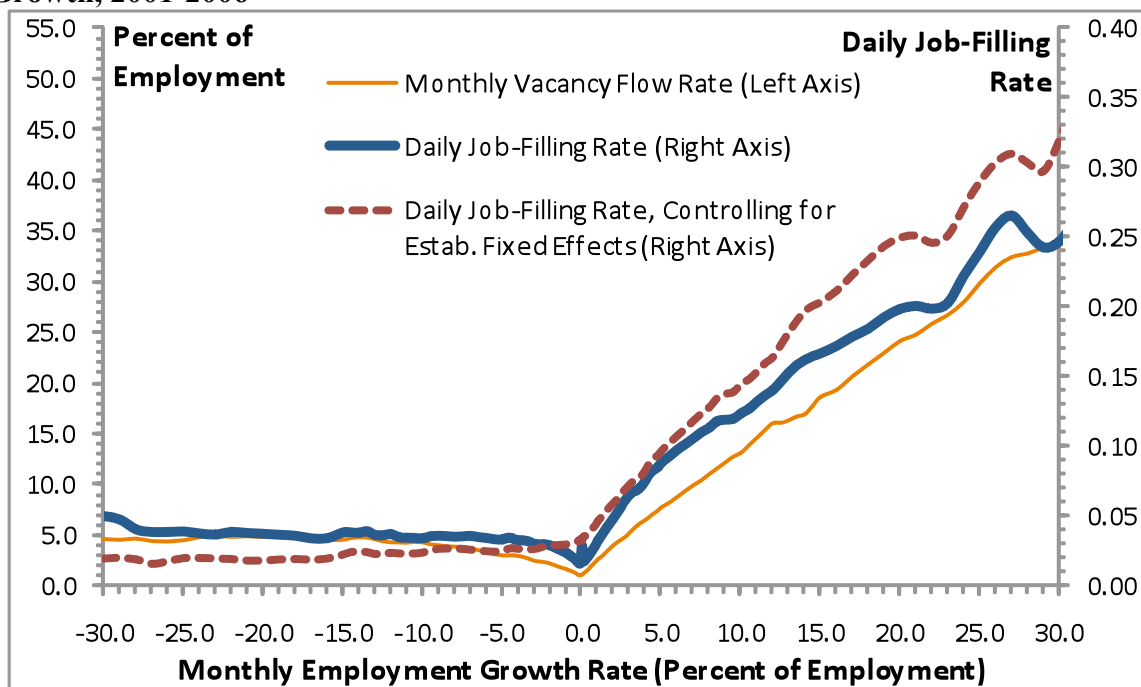
Notes: The stock of vacancies as a percent of employment is calculated directly from JOLTS data. The monthly flow of new vacancies and daily job-filling rate are model-based estimates using JOLTS data and the moment conditions (4) and (5).

Figure 7. Model-Based Estimates of the Daily Job Filling Rate, Various Data Sources, 1976 to 2010Q1



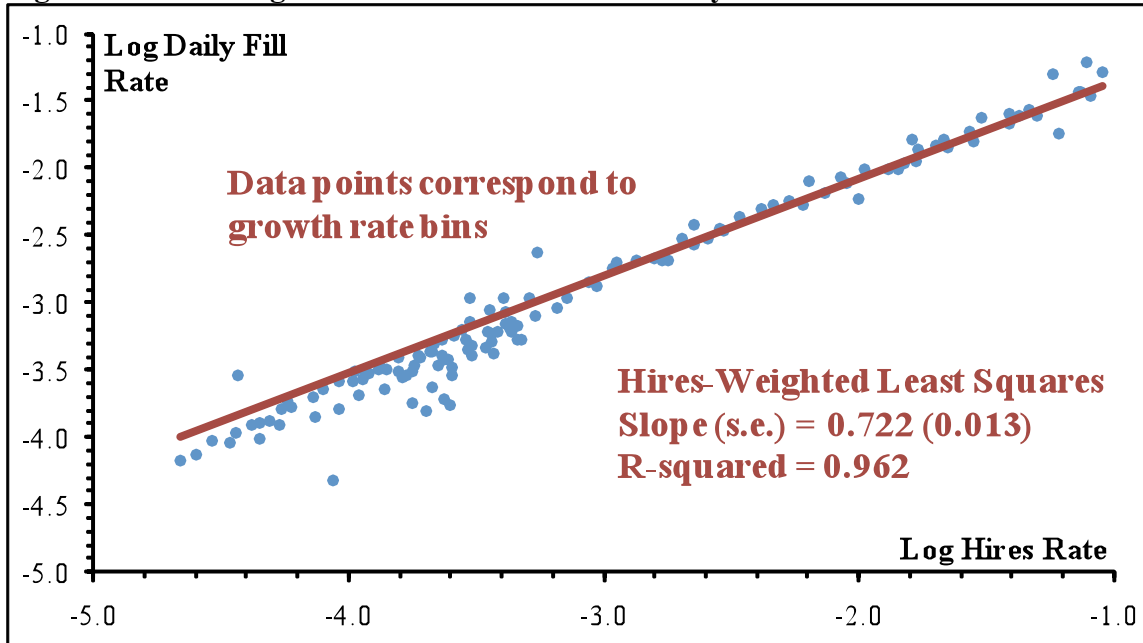
Notes: Figure shows the monthly flow of new vacancies and the daily job-filling rate, as estimated from the indicated data sources using the moment-matching method based on (4) and (5).

Figure 8. Fill Rates, Vacancy Flows and Layoffs as Functions of Establishment Growth, 2001-2006



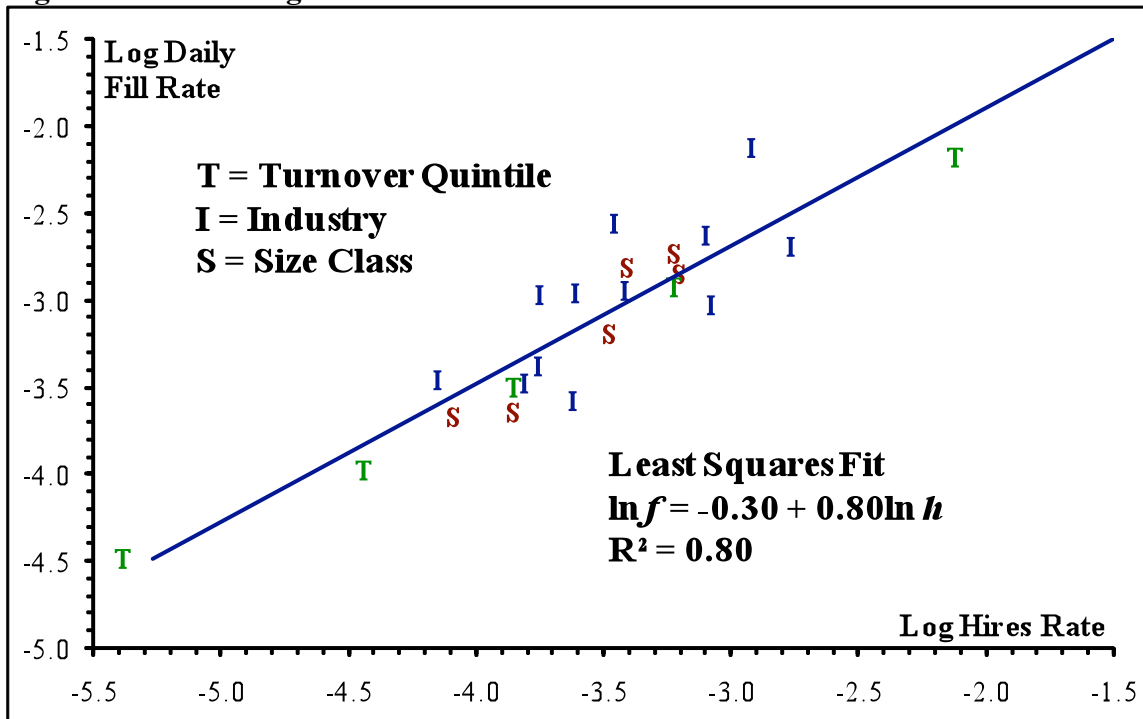
Notes: See text for description of curves.

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



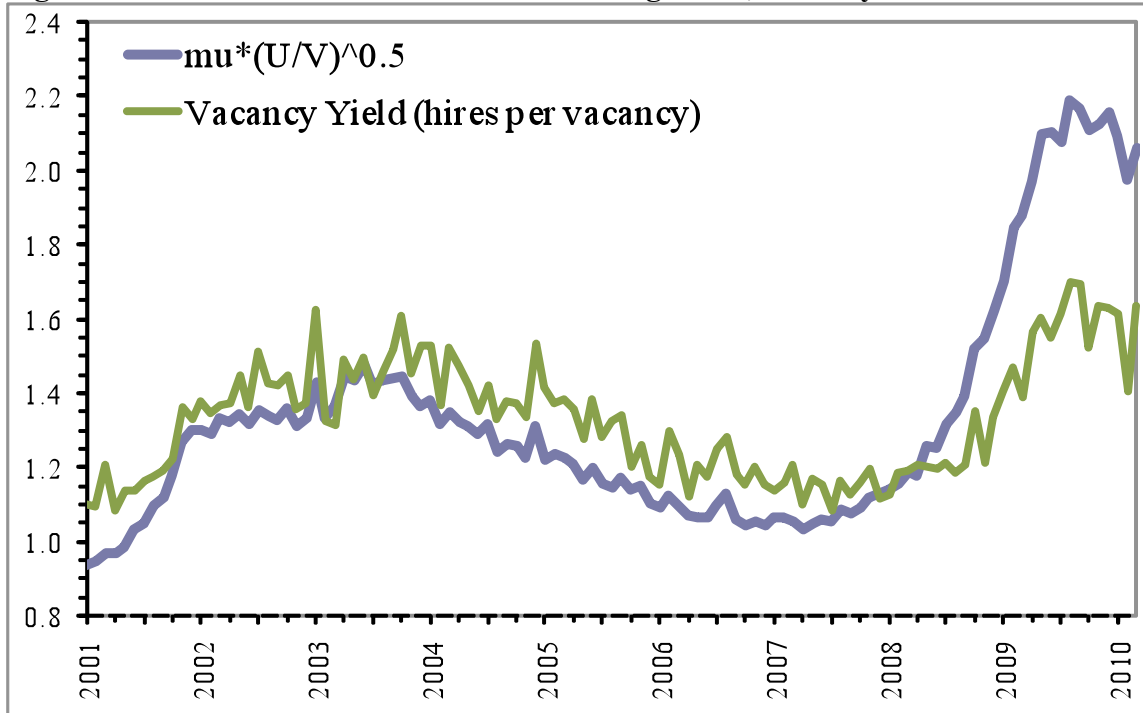
Notes: Figure plots relationship between the estimated daily job-filling rate and the hiring rate across 195 growth rate bins, along with the trendline from the hires-weighted least squares regression of the (log) fill rate on the (log) hires rate.

Figure 10. Job-Filling Rates and Gross Hires Rates in the Cross Section



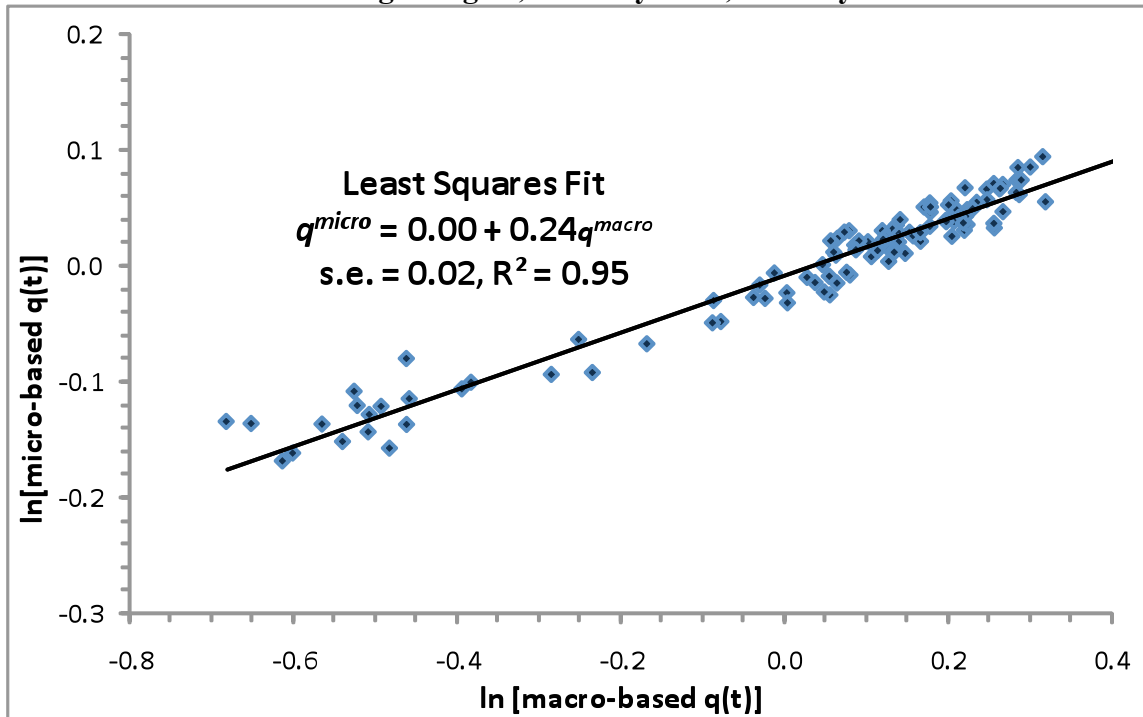
Notes: Figure plots relationship between the estimated daily job-filling rate and the hiring rate across worker turnover, industry, and establishment size class categories, along with the trendline from the least squares regression of the (log) fill rate on the (log) hires rate.

Figure 11. Two Measures of Inverse Market Tightness, January 2001 to March 2010



Notes: Published JOLTS data for nonfarm hires and vacancies, and CPS data for civilian unemployment.

Figure 12. The Relationship between Two Measures for the Effects of Employer Actions on Other Recruiting Margins, Monthly Data, January 2001 to March 2010



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
<i>Nonfarm Employment</i>	3.4	3.2	2.5	1.3	---
<i>Major Industry</i>					
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
<i>Establishment Size Class</i>					
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
<i>Worker Turnover Category</i>					
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 by Industry, Size, and Turnover

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

See notes to Table 1.

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

	Daily Job-Filling Rate, f_t	Monthly Vacancy Flow Rate, $\tau \cdot \theta_t$, As Percent of Employment	Mean Vacancy Duration in Days, $1/f_t$
<i>Nonfarm Employment</i>	0.050	3.4	20.0
<u><i>Major Industry</i></u>			
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
<u><i>Establishment Size Class</i></u>			
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
<u><i>Worker Turnover Category</i></u>			
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. Cross-Sectional Variance Decomposition Results for the Gross Hires Rate

Classification	Variance of $\log(H)$	Percentage of $\log(H)$ Variance Accounted for by Vacancies		
		<i>Using Equation (7)</i>	<i>Using Exact Expression</i>	<i>Using SS Approximation</i>
<i>Industry</i>	0.17	47.0	51.7	53.3
<i>Size Class</i>	0.13	13.9	16.7	15.0
<i>Turnover</i>	1.52	29.8	34.9	6.9
<i>Growth Bin</i>	0.95	37.9	50.7	9.5

Notes: The table entries report unweighted variance decomposition results for the log of the gross hires rates based on equation (7), the log version of equation (6) (“Exact”), and the expression for hires based on the steady-state approximation to (2) and (3). Employment-weighted variance decompositions are similar.

Appendix A: Deriving a Closed-Form Expression for the Hires Solution

Recall the solution for hires given by equation (5) 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

$$\begin{aligned} \sum_{s=1}^{\tau} x_t^{s-1} &= \frac{1 - x^{\tau}}{1 - x} \equiv B \text{ and} \\ \sum_{s=1}^{\tau} (\tau - s) x_t^{s-1} &= \frac{\tau(1 - x) - (1 - x^{\tau})}{(1 - x)^2} = \tau B \left[\frac{1}{1 - x^{\tau}} - \frac{(1/\tau)}{1 - x} \right] \end{aligned}$$

where we use the fact that

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

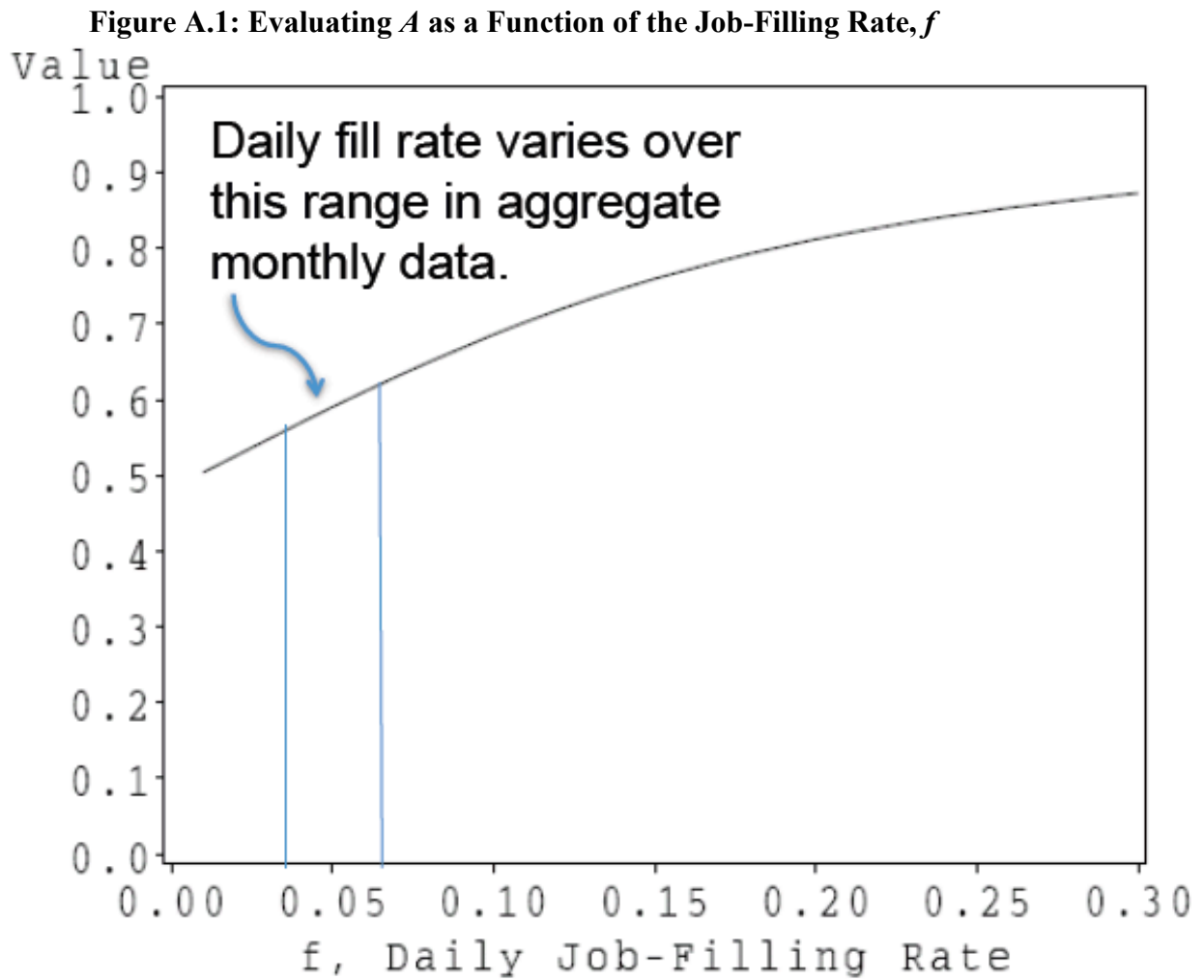
Therefore, and suppressing time subscripts, we can rewrite the solution for hires as

$$\begin{aligned} (6) \quad H &= Bf \left\{ v_{-1} + \left[\frac{1}{1 - x^{\tau}} - \frac{1/\tau}{1 - x} \right] \tau \theta \right\} \\ &\equiv Bf \left\{ v_{-1} + A(\tau \theta) \right\}. \end{aligned}$$

The term in braces is the sum of old vacancies and A times the flow of new vacancies, where A converges to unity as $\tau \rightarrow \infty$.

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 mean values for f and δ yields $\bar{A} = .5916$, which we use for the variance decompositions in Table 4.



Appendix B: Additional Empirical Results

Aggregate Hires and Vacancies

Figure B.1 draws on JOLTS, CPS, and HWI sources to plot aggregate hires and vacancies, expressed as percentages of employment. The HWI and the JOLTS-based measures show strong pro-cyclical patterns for hires and vacancies.²⁵ In contrast, the CPS-based measures show little cyclicalities 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). Figure 1 in the main text shows corresponding time series for the aggregate vacancy yield.

The Cross-Sectional Distribution of Vacancy Rates

Figure B.2 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.

²⁵ The economy was in recession from March to November 2001 according to NBER dating, but employment continued to contract until the middle of 2003.

Figure B.1. Hires and Vacancy Rates Over Time, 1976 to 2010Q1

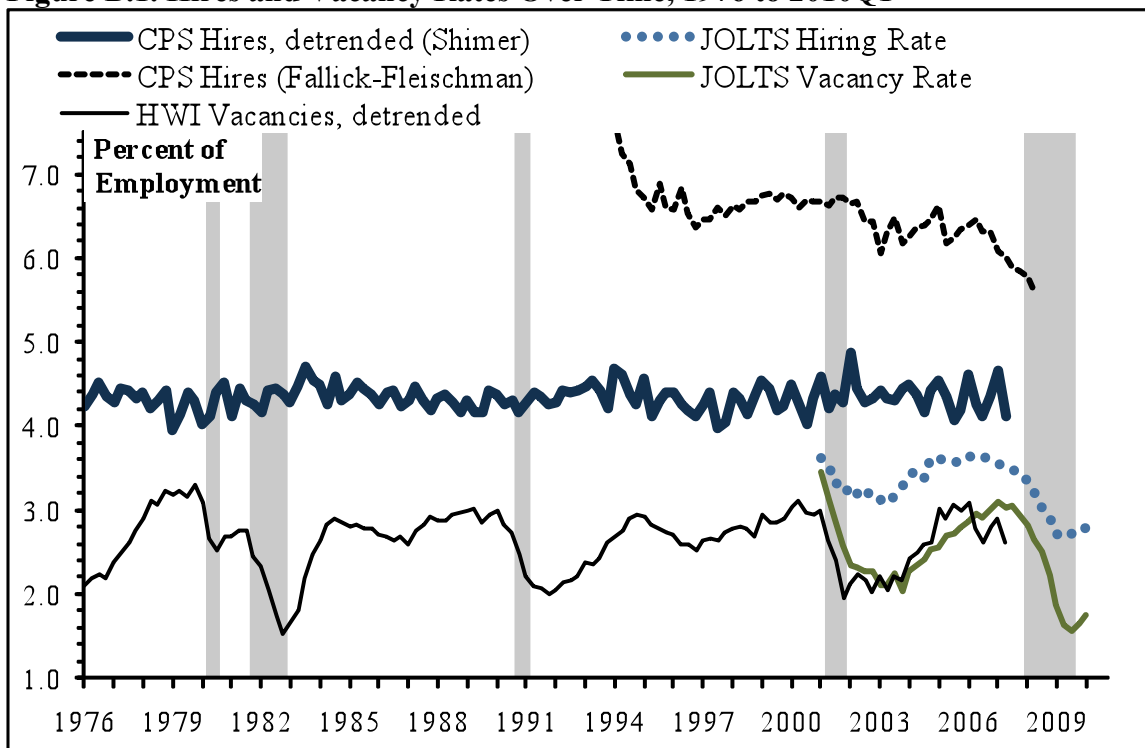
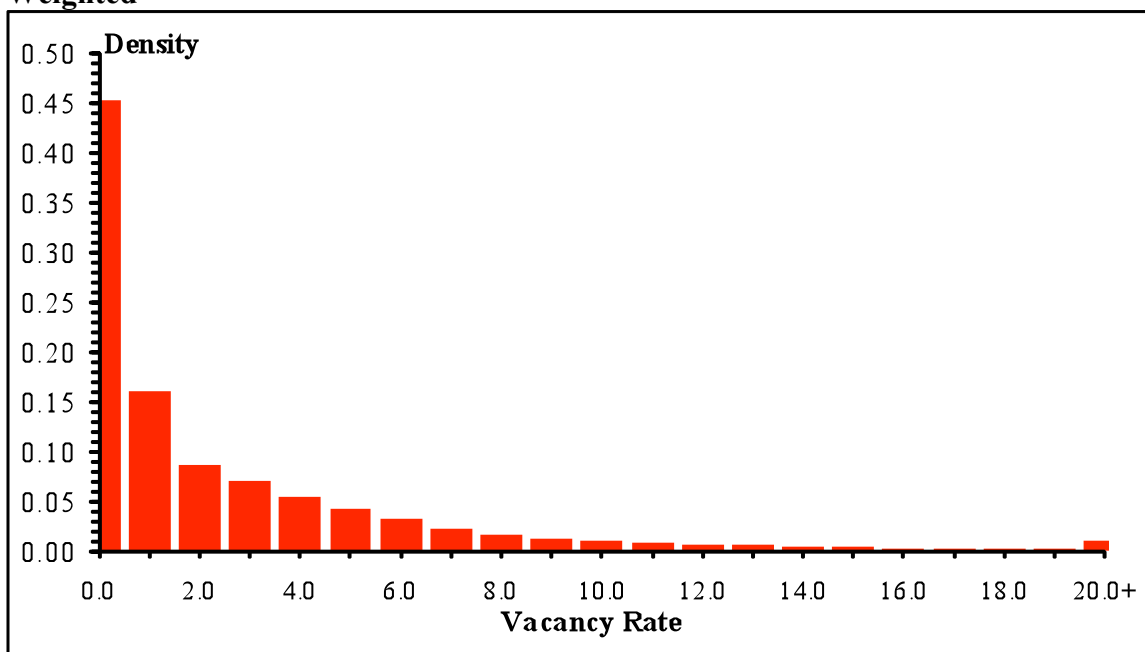


Figure B.2. The Distribution of Vacancy Rates across Establishments, Employment-Weighted



Quantifying the “Luck Effect” in the Simulation Exercises

Section 4.E in the main text describes a simulation exercise that quantifies the “luck effect” in the relationship between realized job-filling rates and realized employer growth rates. The main text also summarizes the results of the simulation exercise. Figures B.3 and B.4 report the full results. They show the job-filling rate as a function of realized growth rates in the simulation output and compare it to the job-filling rate estimated from the JOLTS micro data (Figure 8). For both simulated and actual data, we estimate the job-filling rate for each growth bin using the moment-matching method based on (4) and (5). Figure B.3 allocates the flow of new vacancies in proportion to an establishment’s employment, and Figure B.4 allocates in proportion to an establishment’s stock of vacancies at the end of the previous month.

As seen in the figures, the luck effect is present in the relationship between the job-filling rate and the employer growth rate, but it is much too small to account for the observed relationship in the JOLTS data.

Vacancy Stock and Vacancy Flow Elasticity with Respect to Hires

In Section 5.C, we use an estimate for the empirical elasticity of the vacancy rate with respect to the hires rate across growth rate bins. We obtain this estimate from the hires-weighted regression of the log vacancy rate on the log hires rate across growth rate bins. Figure B.5 reports the regression results and displays the corresponding scatter plot. We obtain the empirical elasticity of the vacancy flow rate with respect to hires in the same way. Figure B.6 reports the regression results and the corresponding scatter plot.

Figure B.3: Quantifying the “Luck Effect” Using Simulated Data: Vacancy Flow Allocation in Proportion to an Establishment’s Employment

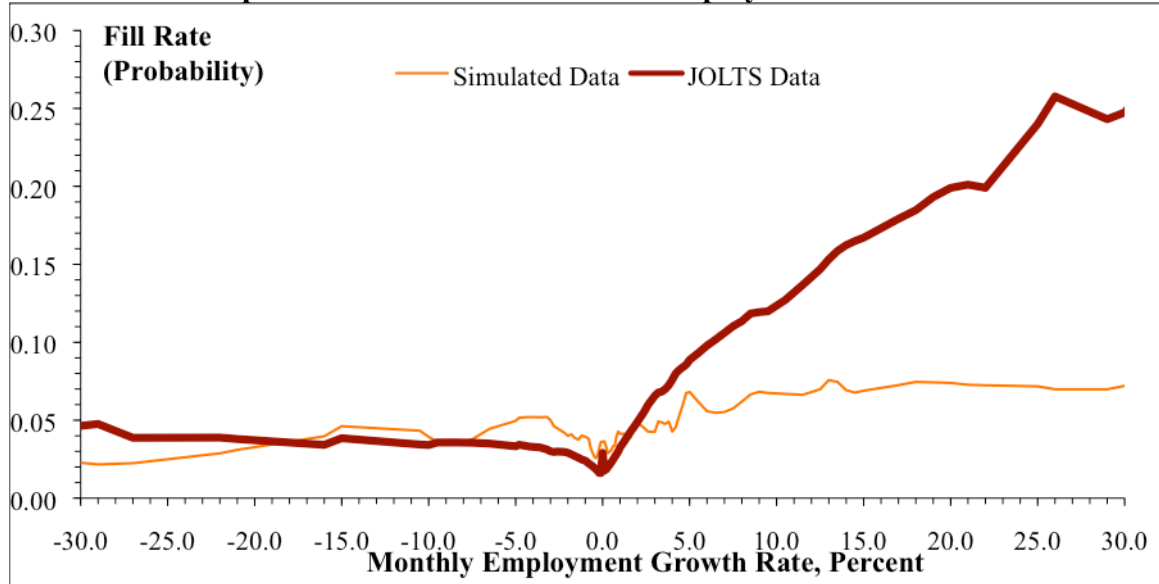


Figure B.4: Quantifying the “Luck Effect” Using Simulated Data: Vacancy Flow Allocation in Proportion to an Establishment’s Initial Vacancy Stock

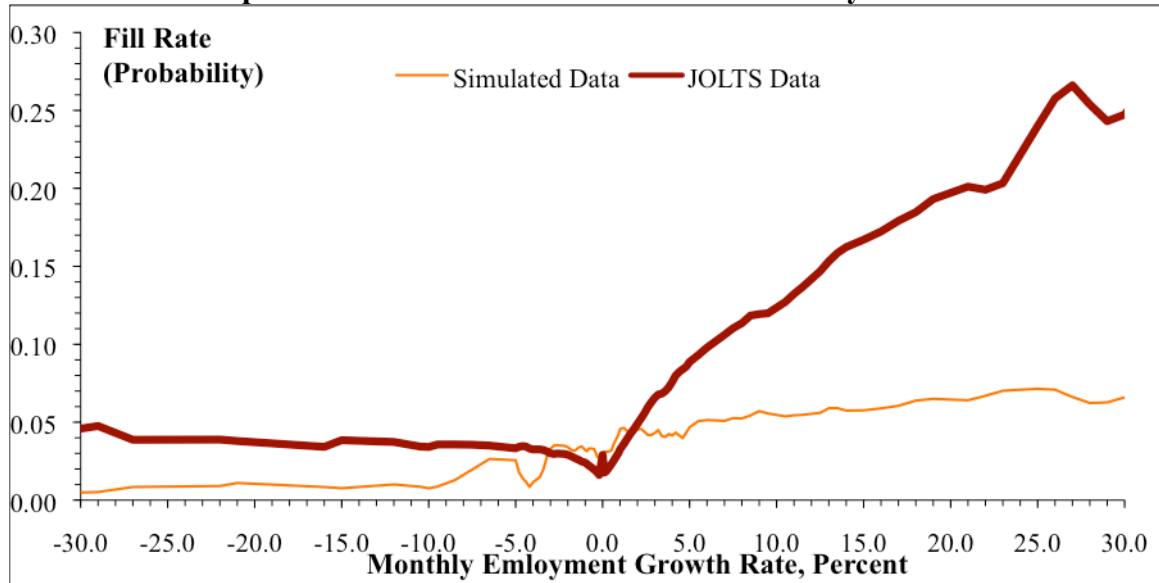


Figure B.5: Scatter Plot of the Log Vacancy Rate against the Log Hires Rate across Growth Rate Bins and Hires-Weighted Least Squares Regression Results

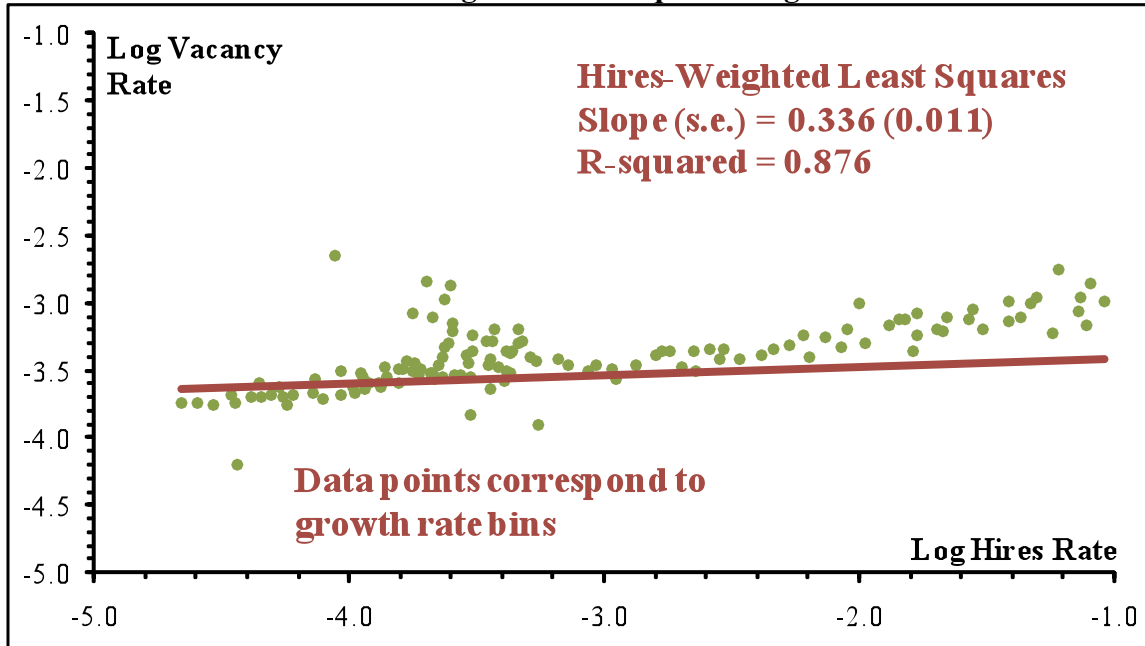


Figure B.6: Scatter Plot of the Log Vacancy Flow Rate against the Log Hires Rate across Growth Rate Bins and Hires-Weighted Least Squares Regression Results

