Macro Recruiting Intensity from Micro Data*

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Abstract

We merge QCEW and JOLTS microdata to study the recruiting intensity of firms in the cross-section and over time. Vast establishment-level heterogeneity in vacancy filling rates is entirely explained by differences in gross hiring rates. Through the lens of standard theory, we aggregate firm-level decisions into an measure of aggregate recruiting intensity (ARI). Procyclicality of ARI is primarily due to cutting recruiting effort in slack labor markets. Given this we provide an ARI index easily computable from publicly available macroeconomic data. Declining ARI in the Great Recession accounted for much of the increase in unemployment, but little of its persistence.

Keywords: Aggregate Matching Efficiency, Firm Heterogeneity, Recruiting Intensity, Unemployment, Vacancies.

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1 Introduction

Aggregate match efficiency is a useful concept in macroeconomics. Its fluctuations expand and contract the hiring possibility frontier of the economy in an analogous manner to the way changes in total factor productivity shift its production possibility frontier. As such, movements in match efficiency are crucial to understanding the volatility of the job finding rate, the chief determinant of unemployment (Shimer, 2012).

The Great Recession offers a striking example. While the job finding rate fell sharply, leading to sustained unemployment, its decline was much more severe than historically implied by the decrease in labor market tightness—the ratio of available jobs (vacancies) to idle workers (the unemployed). The measured productivity, or efficiency, of the matching process broke down significantly (Elsby, Michaels, and Ratner, 2015).

A deterioration in aggregate match efficiency may in principle derive from a number of sources. There may be a reduction in search intensity among the pool of job seekers, or a compositional shift in this pool toward workers with lower job finding rates. In addition, there may be a surge in misallocation across labor markets between the job requirements of open positions and the characteristics of job seekers. The respective role of workers' search effort and mismatch as shifters of the aggregate matching function have been well understood and investigated for almost three decades, as thoroughly discussed in the survey by Petrongolo and Pissarides (2001).[1]

Instead, and somewhat surprisingly, macroeconomists have not focused as much on the role played by firms' recruiting intensity (the counterpart of workers' search effort) in labor market fluctuations. The empirical analysis of Davis, Faberman, and Haltiwanger (2013) (henceforth DFH) has been a game changer in this literature. DFH exploited establishment-level JOLTS data to document a great deal of heterogeneity in recruiting intensity across firms and, in particular, a strong positive relationship between the vacancy yield (the success rate of a vacancy) and the hiring rate in the cross section.[2] Their work has spurred new interest on the topic, in

[1]Clearly, the Great Recession has revived both literatures. In the context of the U.S., Hornstein, Kudlyak, and Lange (2016), Hall and Schulhofer-Wohl (2018), and Mukoyama, Patterson, and Şahin (2018) have investigated the jobseekers' search intensity channel. Barlevy (2011), Şahin, Song, Topa, and Violante (2014), Herz and Van Rens (2019), and Kothari, Saporta-Eksten, and Yu (2013) have explored the role of the mismatch hypothesis.

[2]In particular, this key empirical finding represents a rejection of the classical theoretical result in chapter 5

terms of both measurement from microdata (see working papers by Mueller, Kettemann, and Zweimuller, 2018; Carrillo-Tudela, Kaas, and Gartner, 2018; Lochner, Merkl, Stuber, and Gurtzgen, 2019) and theoretical equilibrium modelling (Kaas and Kircher, 2015; Gavazza, Mongey, and Violante, 2018; Leduc and Liu, 2019). Our paper contributes to this line of research.

Aim. We use U.S. microdata on hires, employment, and vacancies, combined with minimal structure from a dynamic model of firm hiring in a frictional environment, in order to understand the economic forces behind the dynamics of aggregate recruiting intensity (ARI) over the cycle and to draw some lessons about labor market dynamics.

Data. Our paper systematically addresses heterogeneity in hiring behavior across firms. To take a broad view of this heterogeneity we link *Job Openings and Labor Turnover Survey* (JOLTS) microdata to *Quarterly Census of Employment and Wages* (QCEW) microdata at the U.S. Bureau of Labor Statistics (BLS). We can therefore, for the first time, incorporate heterogeneity in establishment age and per worker earnings into the analysis, along with size and industry (variables also used by DFH). As a companion to this paper, we are placing online a repository of cross-tabulations from our new linked JOLTS-QCEW microdata that will benefit other researchers interested in firm dynamics, job flows, and worker flows.

Method. We approach this question in four steps. First, we derive an expression for aggregate recruiting intensity from first principles. We decompose this measure of ARI into three factors: slackness, growth, composition. The first summarizes the general equilibrium response to labor market conditions that are common across firms, the second captures the economy-wide hiring rate, the third reflects heterogeneity within and across groups of firms. Second, we show how to construct each of these components from QCEW-JOLTS microdata. The data enters these measures directly and also indirectly through parameters that we estimate in a first stage. Third, we decompose the empirical time-series variance of ARI into its three theoretical components.

of Pissarides (2000) stating that if the recruiting cost per vacancy is isoelastic in effort (and independent of the vacancy rate), then the optimal search intensity is a constant and we are back to the model without effort choice. This 'neutrality' result was taken as a benchmark reference for a long time and was, perhaps, one of the reasons why macroeconomists appeared uninterested in studying recruiting intensity.

Finally, we use our decomposition results to motivate a simple empirical index that can be entirely computed using publicly available data.

Findings. Our analysis contains three main findings. First, the bulk of cross-sectional variation in the speed at which firms fill vacancies can be entirely explained by heterogeneity in firm-level hiring rates, even after controlling for firm age and establishment wage information, our two new variables imported from QCEW into JOLTS data. This stark regularity takes one step further the result uncovered by DFH that the hiring rate is a strong determinant of vacancy yields in the cross section. We conclude that the hiring rate is, quantitatively, a 'sufficient statistic' for the vacancy filling rate. This empirical regularity is important because (as we show in Proposition 1), jointly with optimality, it puts tight restrictions on the form of the firm-level recruiting cost function.

Second, we aggregate our micro-founded recruiting intensity decisions up to the macro level. Decomposing our aggregate measure of recruiting intensity reveals that its procyclicality is chiefly caused by firms optimally cutting back on recruiting effort when labor markets are slack. This dominant general equilibrium feedback motivates the construction of a proxy-index that explains the bulk of time-series variation in ARI and is easily computable from publicly available data. We show that a representative firm choosing aggregate vacancies and recruiting effort will in equilibrium yield a measure of recruiting intensity identical to our index. This index is conceptually different from the that proposed by DFH: their approach imputes an estimated cross-sectional elasticity to a macro elasticity and so abstracts from general equilibrium.

Third, in order to guide future research on the dynamics of unemployment around the Great Recession, we conduct a simple counterfactual experiment. We illustrate that the sharp fall in our empirical measure of the recruiting intensity of hiring firms can account for much of the decline in the job finding rate in the aftermath of the Great Recession, but little of its slow recovery. In other words, the high duration of unemployment which lingered well after the end of the recession appears to have other culprits.

Outline. The paper proceeds as follows. Section 2 presents the theoretical framework for our empirics. Section 3 describes JOLTS and QCEW microdata and our empirical approach. Section

4 presents our main results. Section 5 concludes. An online appendix contains additional figures and tables (Appendix A), mathematical derivations (Appendix B), and additional details on data construction and treatment (Appendix C).

2 Theory

We derive our empirical model of recruiting intensity from a dynamic decision problem of a firm hiring in a frictional labor market. Consider a firm i in period t that has n_{it} employees at its disposal, productivity z_{it} and fixed idiosyncratic match efficiency ϕ_i. Flow profits of the firm π_{it} consist of its value added net of operating costs $f(z_{it}, n_{it})$ minus wage payments w_{it}, and the costs associated with recruiting.

A firm recruits workers by spending resources on two inputs: vacancies v_{it} and recruiting intensity e_{it}. In order to be consistent with microdata, our notion of a vacancy in this paper hues to the tight definition of a vacancy used by the BLS. In the JOLTS a vacancy is an *"open position ready to be staffed in 30 days, for which the establishment is actively recruiting externally"*.[3] We allow costs per vacancy to depend on employment n_{it}, the number of open positions v_{it}, and on *recruiting intensity* e_{it}: $\mathcal{C}_i(e_{it}, v_{it}, n_{it})$. Recruiting intensity includes expenditures on all other variable inputs such as advertising, screening, recruiting events, etc.[4] More recruiting intensity increases the effectiveness of a vacancy, such that firm hires are a product of the firm's *effective vacancies* $v^*_{it} = \phi_i e_{it} v_{it}$ and the aggregate meeting rate of effective vacancies Q^*_t, which the firm takes as given and we specify later.[5]

Let s^t be the history of firm-level and aggregate shocks until date t, $\mathcal{M}_{it}\left(s^t\right)$ the subjective discount rate associated with history s^t, and $\delta_{it}\left(s^t\right)$ the rate of exogenous job destruction. The

[3] See Bureau of Labor Statistics, Handbook of Methods, Chapter 18 - *Job Openings and Labor Turnover Survey*, for detailed definition of responses. A copy of the short form filled in by hiring managers is available at https://www.bls.gov/jlt/jltc1.pdf

[4] The survey data collected in O'Leonard, Krider, and Erickson (2015) show that these expenditures are sizable and vary by type of firm.

[5] Note that this implies that the hiring technology is constant returns to scale in vacancies. We provide evidence of this later.

firm solves the following dynamic problem:

$$\max_{\{e_{it}(s^t),v_{it}(s^t)\}_{\forall t,\forall s^t|s_0}} \quad \sum_{t=0}^{\infty}\sum_{s^t|s_0} \mathcal{M}_{it}\left(s^t\right)\pi_{it}\left(s^t\right) \quad , \quad \text{subject to} \tag{1}$$

$$\begin{aligned}
\pi_{it} &= f\Big(z_{it}\left(s^t\right), n_{it}(s^t)\Big) - w_{it}\left(s^t\right) n_{it}(s^t) - \mathcal{C}_i\Big(e_{it}(s^t), v_{it}(s^t), n_{it}(s^t)\Big) v_{it}(s^t) \\
n_{it+1}(s^{t+1}) &= (1-\delta_{it+1}(s^{t+1}))n_{it}(s^t) + h_{it}(s^t) \\
h_{it}(s^t) &= Q_t^*(s^t)\,\phi_i\, e_{it}(s^t)\, v_{it}(s^t),
\end{aligned}$$

where the first equality is the definition of profits, the second is the law of motion for employment, and the third is the firm-level hiring technology.

Separability. Naturally, the problem separates into two stages: (1) controlling the dynamics of employment through hiring, (2) minimizing the recruiting costs associated with this hiring. Intuitively, since (i) the recruiting inputs are variable and (ii) costs are sunk after hiring a worker, the choice of inputs is irrelevant for future hiring decisions. Therefore, given a path for hires $h_{it}(s^t)$, the firm solves a static recruiting cost-minimization problem at each node s^t.

Recruiting problem. Dropping the history notation which is now redundant, the problem of a firm with employment n_{it} and target hires h_{it} is

$$\min_{e_{it},v_{it}} \; \mathcal{C}_i\Big(e_{it}, v_{it}, n_{it}\Big)v_{it} \qquad \text{s.t.} \qquad h_{it} = Q_t^*\,\phi_i\, e_{it}\, v_{it}.$$

In specifying the cost function we ensure that the model is consistent with the empirical observation that, in the microdata, the vacancy yield of firms (h_{it}/v_{it}) is approximately log-linear in the gross hiring rate of the firm (h_{it}/n_{it}). First documented by DFH in JOLTS microdata from 2002 to 2006, we update this relationship and show it to be robust through and after the Great Recession in Appendix A, Figure A3.

Proposition 1. ***If and only if*** *the per-vacancy cost function $\mathcal{C}_i$ is of the following form:*

$$\mathcal{C}_i\left(e_{it}, v_{it}, n_{it}\right) = x_i\, g_c\left(g_e(e_{it}) + g_v\left(\frac{v_{it}}{n_{it}}\right)\right), \tag{2}$$

*with isoelastic (constant elasticity) g_c, g_e and g_v, **then** optimality implies that the firm's job-filling rate $f_{it} = (h_{it}/v_{it})$ and vacancy rate (v_{it}/n_{it}) are log-linear in the hiring rate (h_{it}/n_{it}).*

Proof. *See Appendix B.*

In what follows, we consider the class of functions $\mathcal{C}_i$ that satisfy this property. We note that the requirement that the cost function depends on the vacancy *rate* has the intuitive interpretation that adding a given number of positions v in a small firm is more costly than in a larger firm (e.g., in terms of reorganization of production).[6]

Recruiting intensity. Let the two constant elasticities of g_e and g_v be given by γ_e and γ_v, respectively. In Appendix B we show that minimization under (2) subject to the hiring constraint yields the following policy:

$$\log e_{it} = Const. - \frac{\gamma_v}{\gamma_e + \gamma_v} \log Q_t^* - \frac{\gamma_v}{\gamma_e + \gamma_v} \log \phi_i + \frac{\gamma_v}{\gamma_e + \gamma_v} \log \left(\frac{h_{it}}{n_{it}} \right). \tag{3}$$

in which the constant includes the elasticity γ_c and other parameters. The firm's recruiting intensity depends positively on its hiring rate: more hiring requires more inputs. A higher rate at which effective vacancies produce hires due to market-wide productivity in matching Q_t^* or idiosyncratic productivity in matching ϕ_i, requires less inputs. In equilibrium Q_t^* encodes the mass of idle workers U_t, the intensity of worker search which below we denote A_t, the vacancies of competitors V_t and their recruiting intensity decisions. Note that when γ_v is large relative to γ_e increasing marginal costs of vacancies set in quickly, leading the firm to adjust more on the recruiting intensity margin in response to changes in h_{it} or Q_t^*.

Vacancy yield. Using the firm's hiring technology —the last constraint in (1)—we can express (3) in terms of the vacancy yield, which is observable in JOLTS microdata:

$$\log \left(\frac{h_{it}}{v_{it}} \right) = Const. + \frac{\gamma_e}{\gamma_e + \gamma_v} \log Q_t^* + \frac{\gamma_e}{\gamma_e + \gamma_v} \log \phi_i + \frac{\gamma_v}{\gamma_e + \gamma_v} \log \left(\frac{h_{it}}{n_{it}} \right). \tag{4}$$

[6] In the only two existing equilibrium macroeconomic models of recruiting intensity, Gavazza, Mongey, and Violante (2018) assume a cost function that is a special case of this class and Leduc and Liu (2019) assume a functional form for recruiting costs that is not included in this class. Proposition 1 should provide some guidance to future literature that models firms' hiring effort decisions.

In Appendix B Figures B1(a)-(b) provide a graphical characterization of the cost-minimizing recruiting choice in terms of unobserved intensity and observed vacancy yield.

Aggregation. We construct our empirical measure of ARI by aggregating establishment level recruiting decisions. We first specify an aggregate matching function consistent with firm level hiring:

$$H_t = V_t^{*\,\alpha} S_t^{*\,1-\alpha} \quad , \quad V_t^* = \int \phi_i e_{it} v_{it} : di \quad , \quad S_t^* = \sum_{k=1}^{K} a_{kt} \mathcal{S}_{kt}. \tag{5}$$

In this expression V_t^* is the mass of *effective vacancies*. The mass of *effective worker search effort* S_t^* is determined by the time-varying search intensity a_{kt} of the K different searcher types, with masses $\{\mathcal{S}_{kt}\}_{k=1}^K$. Using the convention $\mathcal{S}_1 = U$ and multiplying and dividing by U_t yields $S_t^{*\,1-\alpha} = A_t U_t^{1-\alpha}$, where A_t is *aggregate worker search intensity*:[7]

$$A_t = \left[\sum_{k=1}^{K} a_{kt} \frac{S_{kt}}{U_t} \right]^{1-\alpha}.$$

This delivers the matching function $H_t = A_t V_t^{*\,\alpha} U_t^{1-\alpha}$. This can be expressed in terms of JOLTS vacancies, unemployment and *aggregate recruiting intensity* Φ_t:

$$H_t = \Phi_t A_t V_t^{\alpha} U_t^{1-\alpha} \quad , \quad \Phi_t = \left(\frac{V_t^*}{V_t} \right)^{\alpha} = \left[\int \phi_i e_{it} \frac{v_{it}}{V_t} \, di \right]^{\alpha}. \tag{6}$$

Let $\theta_t = (V_t / U_t)$ denote *measured market tightness*. The matching function implies the aggregate meeting rate Q_t^* depends on $\{\Phi_t, A_t, \theta_t\}$:

$$Q^* \left(\Phi_t, A_t, \theta_t \right) = \frac{H_t}{V_t^*} = A_t \left(\frac{V_t^*}{U_t} \right)^{-(1-\alpha)} = \Phi_t^{-\frac{1-\alpha}{\alpha}} \underbrace{A_t \theta_t^{-(1-\alpha)}}_{:=Q(A_t, \theta_t)}. \tag{7}$$

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[7] Dividing and multiplying also by search effectiveness of the unemployed a_{1t} yields $A_t = a_{1t} \left[\sum_{k=1}^{K} \frac{a_{kt} S_{kt}}{a_{1t} U_t} \right]^{1-\alpha}$. The term in the square bracket reflects the composition of the pool of job seekers and can be estimated from type-k worker flow data. The term a_{1t} remains the only unobservable. In what follows, we show how to estimate A_t. Splitting A_t further into its components is a straightforward exercise, but beyond the scope of this paper.

Aggregate recruiting intensity. We measure aggregate recruiting intensity by substituting the microeconomic optimal policy (3) into the macroeconomic aggregate (6):

$$\Phi_t = \left[\int Q^* \left(\Phi_t, A_t, \theta_t\right)^{-\gamma} \phi_i^{1-\gamma} \left(\frac{h_{it}}{n_{it}}\right)^{\gamma} \frac{v_{it}}{V_t}\, di \right]^{\alpha} \quad , \quad \gamma := \frac{\gamma_v}{\gamma_e + \gamma_v}. \tag{8}$$

This equation describes a mapping $\Phi' = \varphi(\Phi, Q(A_t, \theta_t))$, for which general equilibrium ARI is the fixed point. A key implication is that recruiting intensity decisions across firms are *strategic complements*: $\varphi_\Phi > 0$. An increase in Φ tightens the labor market, decreasing Q^* with elasticity $\frac{1-\alpha}{\alpha}$ (see 7), which increases recruiting intensity with elasticity γ (see 3), which increases Φ' with elasticity α (see 6). On net, therefore, a one percent increase in Φ increases Φ' by $\gamma(1-\alpha)$ percent. Since $\gamma(1-\alpha) < 1$, this recursive system is stable, and features a multiplier of $1/(1-\gamma(1-\alpha))$.[8] As an example, the direct effect of Q_t on Φ_t is $\gamma\alpha$: the effect of Q_t on e_{it} times the effect of e_{it} on Φ_t. The general equilibrium multiplier blows this up to $\gamma\alpha/(1-\gamma(1-\alpha)) > \gamma\alpha$.

Theoretical decomposition of ARI. We obtain our main decomposition by consolidating (8). First, we substitute our expression for the meeting rate (7) and collect Φ_t terms. Second, we write the firm hiring rate in deviations from the aggregate hiring rate. Third, we extract from the integral terms that do not depend on i. We obtain the following expression for ARI which includes the general equilibrium multiplier:

$$\Phi_t = \underbrace{Q(A_t, \theta_t)^{-\frac{\gamma\alpha}{1-\gamma(1-\alpha)}}}_{Slack_t} \underbrace{\left(\frac{H_t}{N_t}\right)^{\frac{\gamma\alpha}{1-\gamma(1-\alpha)}}}_{Growth_t} \underbrace{\left[\int \phi_i^{1-\gamma} \left(\frac{h_{it}/n_{it}}{H_t/N_t}\right)^{\gamma} \frac{v_{it}}{V_t}\, di \right]^{\frac{\alpha}{1-\gamma(1-\alpha)}}}_{Comp_t} . \tag{9}$$

The first term is the *slackness component*. The labor market slackens in response to increasing worker search effort or a compositional shift toward higher search intensity types, both encoded in residual match efficiency A_t. It also slackens due to changes in the ratio of vacancies to unemployed workers in the economy, which is encoded in *measured market tightness* $\theta_t = (V_t/U_t)$. When the labor market slackens, a firm's desired hires can be attained with less costly inputs:

[8] Figure B1(c) in Appendix B characterizes how this strategic complementarity effects the general equilibrium response to an increase in Q_t^*.

recruiting intensity and vacancies. The elasticity at which firms cut-back on e_{it} relative to v_{it} is γ. Therefore, the closer is γ to one (i.e., the smaller γ_e is relative to γ_v) the stronger is the response of Φ_t to changes in labor market tightness.

The second term is the *growth component*. When a firm grows it requires more recruiting intensity to realize hires. The common hiring rate of firms in the economy therefore effects aggregate recruiting intensity. Symmetric exponents on the two components stem from the hiring technology:

$$h_{it} = Q_t^* \, \phi_i \, e_{it} \, v_{it} \qquad \Longrightarrow \qquad e_{it} \left(\frac{v_{it}}{n_{it}}\right) = \left(\frac{1}{Q_t^*}\right) \left(\frac{1}{\phi_i}\right) \left(\frac{h_{it}}{n_{it}}\right).$$

The response of e_{it} is the same in magnitude, but opposite in sign, in response to an increase in input productivity (Q_t^*), or a increase in input demand (h_{it}/n_{it}).

The final term is the *composition factor* which reflects the contribution of firm heterogeneity. This term increases when the vacancy share distribution shifts toward (i) firms that are highly efficient in recruiting, i.e. that have high ϕ_i's, and (ii) firms that hire a lot relative to the aggregate. By construction, if hiring firms are identical then Φ_t exactly equals $(Slack_t \times Growth_t)$.

Summary. Our approach in what follows is to construct the decomposition (9) entirely from microdata.[9] Even though we observe H_t, N_t and θ_t from aggregate data and $\{h_{it}, n_{it}, v_{it}\}$ from JOLTS microdata, we cannot fully construct Φ_t from only (9) because we do not observe A_t. However, we can solve for both Φ_t and A_t by noting that the matching function itself provides an additional equation in observables and the same two unknowns:

$$H_t = \Phi_t A_t V_t^{\alpha} U_t^{1-\alpha}. \tag{10}$$

We therefore proceed in two steps: (i) estimate ϕ_i and γ, which along with a choice of α and microdata $\{h_{it}, n_{it}, v_{it}\}$, allows us to construct $Comp_t$, (ii) combine $Comp_t$ with aggregate data $\{H_t, N_t, V_t, U_t\}$ and use equations (9) and (10) to solve for Φ_t and A_t.

[9] This exercise is therefore distinct from the simulations in Gavazza, Mongey, and Violante (2018), where ARI was inferred within the model and what was studied was an impulse response function of ARI to a financial shock.

3 Data, identification, and estimation

Data. Our primary data sources are the restricted use BLS microdata underlying JOLTS and the QCEW. JOLTS data are monthly *establishment level* responses of hiring managers with respect to employment on the twelfth of the month, hires over the calendar month, and open positions (vacancies) at the end of the month.[10] Apart from a permanent sample of firms that have remained in the JOLTS since inception, most establishments are present in the survey for 12 months, giving a short panel dimension. Our sample runs from 2002 to 2018. We drop 2001 due to reliability of JOLTS data in the year in which the initial panels of the survey were being rolled in.

QCEW data are obtained through the UI system and provide month-end payroll and employment observations for the universe of establishments.[11] From the QCEW we compute establishment *wage* as payroll divided by employment. We obtain establishment *age* using a BLS produced measure of entry into QCEW sample. The data are merged using BLS identifiers. To the best of our knowledge, few previous papers have used the JOLTS microdata, and this is the first to combine them with the QCEW to construct age and average wage for JOLTS establishments.[12]

As a preamble to our estimation, Figure 1 shows that across industries, ages, sizes and wages there is vast heterogeneity in terms of participation to the labor market—the gross rate of vacancy and hiring rates (panels A, B, C, D)—and experiences in terms of the number of hires relative to open vacancies (panels E, F, G, H). As emphasized in DFH, this kind of evidence rejects the standard random matching model where all firms face the same vacancy filling rates. Our model interprets these differences as systematically different recruiting intensities.

[10] Since only some or one of a firm's establishments may be surveyed in a given month, one cannot construct firm level measures for multi-establishment firms.

[11] We check monthly employment in the QCEW against the establishment reported employment in the JOLTS and find them to have a correlation coefficient close to one.

[12] Examples of previous articles to use the JOLTS microdata are Faberman and Nagypal (2008), Davis, Faberman, Haltiwanger, and Rucker (2010), Davis, Faberman, and Haltiwanger (2012), Faberman (2014), DFH, Elsby, Michaels, and Ratner (2018).

Specification. Using data at the month t, establishment i level, we would ideally estimate the following specification, which is the empirical counterpart of (4):

$$\log\left(\frac{h_{it}}{v_{it}}\right) = \delta_t + \xi_i + \beta \log\left(\frac{h_{it}}{n_{it}}\right) + \varepsilon_{ijt}. \tag{11}$$

The time effect δ_t absorbs other unobserved aggregates beyond Q_t^*, so we do not use it to infer Q_t^* in our construction of (8). Instead we show how $Q(A_t, \theta_t)$ can be computed directly. We do use estimates of fixed effects ξ_i to infer recruiting efficiencies ϕ_i, and β to infer γ. With a choice of α, and microdata we can then construct all terms in (9).

Implementation. First, due to short panels of only twelve months at the firm level, we estimate ξ_i for groups of firms $j = 1, \ldots, J$. We consider different approaches to these groupings, allowing j to determine quintiles of either (i) age, (ii) employment, or (iii) wage, as well as (iv) the same 11 industry categories used by DFH. Second, *within* these groups j, we aggregate firms within narrow industries. This is done to ameliorate measurement error that might bias estimates of β downward. For example, once specification uses age quintiles for j and then within each age quintile we aggregate firms within $NAICS3$ industries to construct h_{ijt}, n_{ijt} and v_{ijt}.[13]

This delivers 15 approaches to estimating (11). Given quintiles of age, size, or wage, we aggregate within these groups at either the $NAICS1$, $NAICS2$, $NAICS3$ or $NAICS4$ level ($3 \times 4 = 12$). When we let j denote industries we are already aggregating at approximately the $NAICS1$ level, so we only consider $NAICS2$, $NAICS3$ or $NAICS4$ aggregation within our eleven industry groups ($12 + 3 = 15$).

Estimates. Figure 2A provides estimates of $\gamma = \hat{\beta}$ for these different specifications. From left to right, aggregating at finer industry levels within groups lowers the coefficient estimate, suggesting measurement error. From top to bottom, the estimate of γ is robust to the categorization of j. The overall inter-quartile range of estimates is only 0.07. By comparison, DFH group firms by net employment growth, aggregate all observations within these groups over

[13]When constructing h_{ijt}, v_{ijt} and n_{ijt} we aggregate within ijt using the same weights that the BLS applies to compute published aggregates. These account for systematic biases on non-response, as well as generating a representative sample.

six years, and obtain an estimate of 0.82 (cf: Figure IX). Our estimates are remarkably similar given that we aggregate at the far finer {month, NAICS4, employment quintile}-level. Figure A3 extends a key figure of DFH and shows (i) non-parameterically that imposing a log-linear relationship is without loss of generality, and (ii) that the relationship is stable in and out of the Great Recession.[14]

Discussion. Figure 2B sheds light on the robustness of these results across different categorizations of firms. For a given categorization—size, age, wage, industry—we split firms into 15 quantiles. Within each group we pool employment, hires and vacancies to compute the average hiring rate and vacancy yield.[15] Remarkably, across group differences in vacancy-yields are revealed entirely through differences in hiring rates. If there was something special about the efficiency of young firms (or small, high-wage, etc.) in attaining higher vacancy yields, we would expect them to deviate from the systematic relationship between hiring rate and vacancy yield displayed in the data.[16]

4 Results

Given our estimates of γ and ϕ_j and microdata $\{h_{ijt}, n_{ijt}, v_{ijt}\}$, we can compute our measure of aggregate recruiting intensity Φ_t from (8), and decompose it using (9). The only additional object we require is the matching function elasticity of meetings to effective market tightness. We set $\alpha = 0.50$, a value common in the literature.

[14]Figures A1 and A2 extend the 'hockey' stick figures of DFH, which considered data from 2001 to 2006, to the 2002 to 2018 sample used throughout this paper.

[15]Note that computing total quantile hires $H_q = \sum_{it \in q} h_{it}$, and total employment $N_q = \sum_{it \in q} n_{it}$, and then computing the hiring rate as H_q / N_q, is equivalent to computing the employment weighted hiring rate within quantile q.

[16]In Appendix A, Figure A4 we provide similar plots for vacancy rates, as well as the daily vacancy flow rates and daily job filling rate implied by the model of daily hiring used in DFH. The same results are obtained in these cases, the main determinant of *across group* differences in recruiting behavior are driven by *across group* differences in hiring rates.

4.1 Variance decomposition

Table 1 and Figure 3 describe the decomposition (9). We take logs of (9), first difference to remove the constant, smooth the series using the X13-ARIMA-SEATS filter, then compute time-series variances of each term.[17] Regardless of how we group establishments to compute ϕ_j or coarseness of aggregation within groups, by far the dominant component is $Slack_t$, on average accounting for nearly 60 percent of the time-series variance of Φ_t.[18] The $Growth_t$ and $Comp_t$ terms, combined, account for less than 10 percent. Unsurprisingly the covariance term is positive and large, and driven mostly by the covariance between the slackness and growth factors.

To further understand the small role of heterogeneity, we split the composition term between and within groups:

$$\underbrace{\left[\int \phi_j^{1-\gamma}\left(\frac{h_{it}/n_{it}}{H_t/N_t}\right)^{\gamma}\frac{v_{ijt}}{V_t}\right]^{\frac{\alpha}{1-\gamma(1-\alpha)}}}_{Comp_t} = \tag{12}$$

$$\underbrace{\left[\sum_{j=1}^{J}\phi_j^{1-\gamma}\left(\frac{h_{jt}/n_{jt}}{H_t/N_t}\right)^{\gamma}\frac{v_{jt}}{V_t}\right]^{\frac{\alpha}{1-\gamma(1-\alpha)}}}_{Between_t}\underbrace{\left[\sum_{j=1}^{J}\left[\int_{i\in j}\left(\frac{h_{ijt}/n_{ijt}}{h_{jt}/n_{jt}}\right)^{\gamma}\frac{v_{ijt}}{v_{jt}}\right]\left\{\frac{\phi_j^{1-\gamma}(h_{jt}/n_{jt})^{\gamma}\frac{v_{jt}}{V_t}}{\sum_{j=1}^{J}\phi_j^{1-\gamma}(h_{jt}/n_{jt})^{\gamma}\frac{v_{jt}}{V_t}}\right\}di\right]^{\frac{\alpha}{1-\gamma(1-\alpha)}}}_{Within_t}$$

The final columns of Table 1 show that in general the within group-j term dominates. That is, $Comp_t$ is not driven by the cyclical reallocation of vacancy-shares across high or low ϕ_j groups.

Figure 3 presents these results graphically. For the case of j denoting quintiles of employment, and i giving $NAICS4$ (line 11 in Table 1) Panel A shows the slackness component closely following Φ_t. A steep drop in the growth factor also contributes. In this case, almost 100 percent

[17] X13-ARIMA-SEATS is processed in the *R* package *'seasonal'* and chooses the appropriate transformation of the raw series. The X13-ARIMA model assumes the first difference of nonseasonal and seasonal components follow $MA(1)$ processes. This approach was chosen to most closely match the relationship between published (i) non-seasonally-adjusted and (ii) seasonally adjusted BLS data for aggregate hires, unemployment, employment and vacancies.

[18] This macro finding has a micro counterpart. There is a tradition in labor economics of designing small-scale ad-hoc surveys to investigate recruitment methods of firms. Some papers in the literature document that firms respond to aggregate conditions. A recent example is Forsythe and Weinstein (2018) which finds that when campus recruiters expect the labor market to be slack, they cut recruiting intensity through on-campus career fairs, job postings and advertising. A classic article in this literature is Malm (1954). On page 519, the author writes: *During a tightening of the labor market [...] employers react to the increasing difficulty of finding job applicants by using more intensive (usually more expensive, both in terms of time and in cash outlay) recruiting methods.*

of the composition term is driven by within-size-quantile, across-NAICS4 variation in recruiting intensity (panel B).[19]

4.2 An easily computable index of aggregate recruiting intensity

We use the above results to produce an easy to measure, microfounded, *index* of aggregate recruiting intensity. Our microdata exercise has taught us that we can capture the true empirical measure of Φ_t with only $Slack_t$ and $Growth_t$. Abstracting from the composition factor in (9), we obtain

$$\Phi_t^{Index} = \underbrace{Q\left(A_t, \theta_t\right)^{-\frac{\gamma\alpha}{1-\gamma(1-\alpha)}}}_{Slack_t} \underbrace{\left(\frac{H_t}{N_t}\right)^{\frac{\gamma\alpha}{1-\gamma(1-\alpha)}}}_{Growth_t}$$

Since it contains A_t, this expression cannot be computed on publicly available data. However, we can use the aggregate vacancy yield from the matching function to substitute out $Q\left(A_t, \theta_t\right)$:

$$\frac{H_t}{V_t} = \Phi_t^{Index} Q\left(A_t, \theta_t\right).$$

Combined, it is clear that H_t drops out and we are left with a convenient expression that depends only on the *vacancy rate*:

$$\Phi_t^{Index} = \left(\frac{V_t}{N_t}\right)^{\frac{\gamma\alpha}{1-\gamma}}. \tag{13}$$

Figure 3C plots Φ_t^{Index}, alongside our empirical measure Φ_t. The index closely tracks Φ_t, and on average across specifications Φ_t^{Index} accounts for 98 percent of the time-series variance of Φ_t.

Comparison. We compare our index to that computed by DFH. Their index is computed as $\Phi_t^{DFH} = \left(H_t/N_t\right)^{0.82}$. The foundation for their index is as follows. As discussed earlier, from JOLTS microdata they estimate equation (4) and obtain a micro-elasticity of the job filling rate to the gross hiring rate of 0.82. They then impute the macro elasticity from this micro-elasticity. Our measure differs. We find that the main contributing factor to the variation of job filling rates

[19] Panel D plots the implied residual match efficiency A_t. Our estimates suggest that this residual is countercyclical, but less volatile than ARI. Countercyclical workers' job search effort (Mukoyama, Patterson, and Şahin, 2018) could drive its behavior.

is the response of firm recruiting choices to aggregate market tightness, which their transition from cross-sectional to time-series does not capture.

Representative firm. To further ground our index, we show that a representative firm delivers Φ_t^{Index} as the exact measure of aggregate recruiting intensity in equilibrium.

Consider an economy populated by a unit measure of identical firms. Given initial employment n_t, each firm chooses its hires for the period h_t, along with the level of vacancies v_t and recruiting intensity e_t to minimize total hiring costs. Firms are competitive in that they take the meeting rate for effective vacancies Q_t^* as given and, for any given pair (h_t, n_t), solve:

$$\min_{e_t, v_t} \; \mathcal{C}\left(e_t, v_t, n_t\right) v_t \quad \text{s.t.} \quad h_t = Q_t^* e_t v_t.$$

Under the assumptions on $\mathcal{C}$ in Proposition 1, and the definition $\gamma := \gamma_v / \left(\gamma_e + \gamma_v\right)$, the first order conditions of this problem deliver the same policies for recruiting intensity we derived in our model with heterogeneous firms:

$$e_t = Const. \times \left(Q_t^*\right)^{-\gamma} \left(\frac{h_t}{n_t}\right)^{\gamma}. \tag{14}$$

In equilibrium, $x_t = X_t$ for all variables. Since $V_t^* = \int_0^1 e_t v_t di = E_t V_t$, then $E_t = \left(V_t^* / V_t\right) = \Phi_t^{1/\alpha}$. As before, the matching function implies $Q_t^* = \Phi_t^{-(1-\alpha)/\alpha} Q(A_t, \theta_t)$. In equilibrium, these properties and the first order condition (14) imply:

$$\Phi_t = Q_t^{*-\gamma\alpha} \left(\frac{H_t}{N_t}\right)^{\gamma\alpha} = Q(A_t, \theta_t)^{-\frac{\gamma\alpha}{1-\gamma(1-\alpha)}} \left(\frac{H_t}{N_t}\right)^{\frac{\gamma\alpha}{1-\gamma(1-\alpha)}}.$$

This expression contains the exact slackness and growth components of our general model. This formulation may be used by future researchers to represent firm recruiting choices in arbitrarily rich DSGE environments with frictional labor markets.

4.3 Counterfactual

As a final exercise we ask the following question: *Over the Great Recession, how would the job finding rate F_t and unemployment U_t have evolved if aggregate recruiting intensity Φ_t fell, but vacancies V_t and residual match efficiency A_t remained unchanged?* To answer this question we consider the following dynamic system:

$$\begin{aligned} H_t &= \Phi_t A_t U_t^{\alpha} V_t^{1-\alpha} \qquad , \qquad F_t := \frac{H_t}{U_t} \\ U_{t+1} &= (1 - F_t)\, U_t + S_t. \end{aligned}$$

With our series for Φ_t, and data on $\{H_t, U_t, V_t\}$ we construct residual match efficiency A_t from the matching function, and a consistent series for separations S_t from unemployment dynamics. We then set counterfactual $\widetilde{A}_t = A_{2008:1}$ and $\widetilde{V}_t = V_{2008:1}$ for all t so that the only time-varying input into hiring is Φ_t. We construct our counterfactual by starting from $\widetilde{U}_{2008:1}$, and using $\left\{\widetilde{A}_t, \widetilde{V}_t, \Phi_t, S_t\right\}$ along with the above equations to construct counterfactual $\left\{\widetilde{F}_t, \widetilde{U}_t\right\}_{t=2008:1}^{2018:12}$ (for more details see the footnote of Figure 4).[20]

Figure 4 shows that the decline in the recruiting intensity of hiring firms alone accounts for a large part of the decline in the job finding rate, and for about half the increase in unemployment at the onset of the recession. However, as vacancies recover quickly and the labor market starts tightening again, recruiting intensity rebounds, and thus counterfactual unemployment is again near its pre-recession level by 2012, while still being 60 percent above its pre-recession level in the data. We conclude that the decline in ARI is important in explaining unemployment dynamics at the onset of the recession, but not its slow recovery.[21]

[20] Similar counterfactuals have been performed in the literature, but they focus on the role of aggregate match efficiency and, as such, they confound all the many forces that determine its dynamics. Our estimation allows us to isolate the role of ARI.

[21] Further proof on the role of ARI is offered by the dynamics of the aggregate vacancy yield $H_t/V_t = \Phi_t A_t \theta_t^{-(1-\alpha)}$. The fall in ARI is key to depress the vacancy yield in the Great Recession. In its absence, the vacancy yield would display a fourfold increase relative to the data. This finding represents a challenge for models of the last recession which claim to succeed in explaining unemployment dynamics with constant aggregate match efficiency (e.g. Christiano, Eichenbaum, and Trabandt, 2015).

5 Conclusion

We conclude by highlighting two natural directions for further research.

First, motivated by empirical evidence (O'Leonard, Krider, and Erickson, 2015; Forsythe and Weinstein, 2018), we emphasized expenditures on recruiting activities as the key instrument firms use to modulate their search effort. Other margins, such as varying compensation packages and screening standards, may be important too. There is currently no representative microdata for the U.S. that allows to disentangle these different mechanisms, but progress is being made for other countries, such as Austria and Germany (Mueller, Kettemann, and Zweimuller, 2018; Carrillo-Tudela, Kaas, and Gartner, 2018). This promising line of research that digs deeper into the black box of firm-level recruiting decisions could lead, eventually, to a comprehensive model of firm recruiting which can be embedded into the canonical frameworks used by macroeconomists to study labor market dynamics.

Second, firms' recruiting intensity is only one of the factors that moves aggregate match efficiency and, at the end of the day, that is what matters for the volatility of the unemployment rate. The literature linking micro to aggregate recruiting intensity, effectively initiated by Davis, Faberman, and Haltiwanger (2013), is still in its infancy. A more established literature has studied two other sources of match efficiency dynamics over the business cycle: variation in worker's search effort and variation in misallocation ('mismatch') between vacant jobs and job seekers across sectors (occupations, industries, regions) of the economy. Research on these three factors has been, so far, disjoint. A unified framework to coherently estimate these various forces and theoretically understand how they interact with each other—in producing amplification and complementarities—would be another welcome advancement in the literature (see Crump, Eusepi, Giannoni, and Şahin (2019) and Leduc and Liu (2019) for first steps in this direction).

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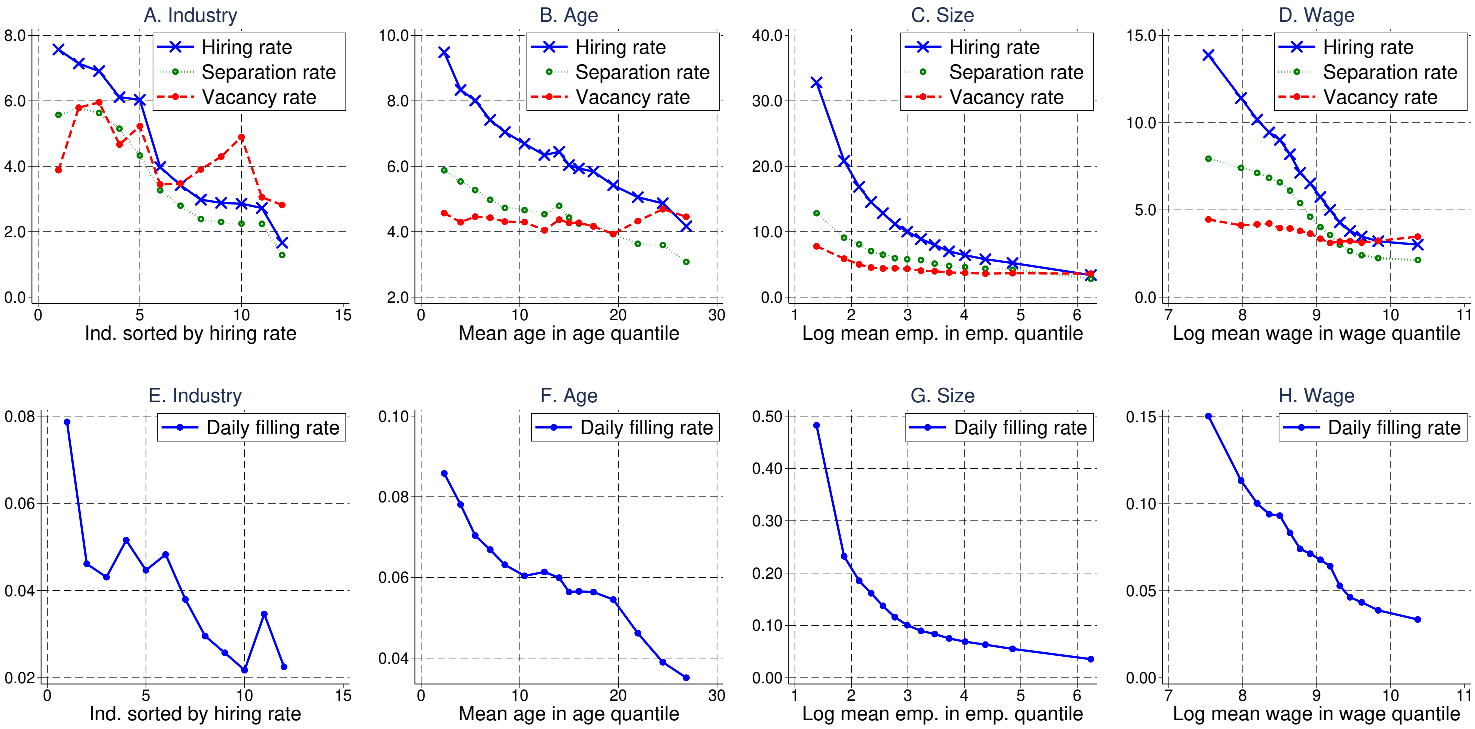


Figure 1: Heterogeneity in recruiting

Notes: Consider a point in panel A, B, or C. We follow DFH. Establishment-month observations are first categorized by, for example, 15 quantiles of firm age. When constructing quantiles we pool all data from 2002-2018. Within an age quantile, we then pool across time and compute total hires, vacancies, employment, separations. We use these to construct the hiring rate, separation rate and vacancy rate. For Panel A, establishments are categorized by the industries by NAICS into the groups defined in Table C1, we then sort industries by hiring rate to construct the x-axis. Panels D, E and F plot the *daily filling rate* computed from the daily recruiting model of DFH, details and closed forms are found in Appendix B.

A. Estimated elasticities $\hat{\beta}$

Categories j	NAICS			
	1	2	3	4
Industry	-	0.76	0.77	0.73
Age	0.84	0.77	0.76	0.73
Size	0.83	0.76	0.65	0.64
Wage	0.73	0.70	0.74	0.70

B. Hiring rates and vacancy yields

Figure 2: Recruiting intensity in the cross-section

Notes: Panel A gives point estimates of the coefficient on the hiring rate from regression (11). In all cases the coefficient is statistically significant at the one percent level. The estimation uses JOLTS microdata from 2002:1 to 2018:12. Rows give the manner in which establishments are grouped in order to estimate ϕ_j terms. Columns give the industry level at which hires, vacancies and employment are aggregated within these groups. Panel B plots the log of the employment weighted hiring rate against the vacancy weighted vacancy yield (note that this is equivalent to total hires divided by total employment, and total hires divided by total vacancies, respectively, i.e. $H_g/V_g = \sum_{i \in g} (v_{ig}/V_g)(h_{ig}/v_{ig})$). These are computed within 15 unweighted quantiles of establishment age, size, wage (measured as total payroll per worker), and the 12 industry groups defined in Table C1. Quintiles are marked, and industries are sorted from highest (=1) to lowest (=12) by hiring rate. The main take-away from the markings is that low numbers—young, small, low wage—gravitate to the North-East, and high numbers—old, large, high wage—gravitate to the South-West. Figure A4 replicates this figure with alternative variables on the vertical axis: (A) daily vacancy flow, (B) daily filling rate (both computed from the DFH daily hiring model), (C) vacancy rate.

j	NAICS	1. Aggregate recruiting intensity				2. Composition		
		Slack	Growth	Comp.	Cov.	Between	Within	Cov.
Industry	2	0.57	0.028	0.020	0.38	0.13	0.47	0.40
	3	0.57	0.025	0.026	0.38	0.09	0.57	0.34
	4	0.54	0.033	0.050	0.38	0.08	0.68	0.24
Age	1	0.67	0.015	0.058	0.26	0.05	0.64	0.31
	2	0.61	0.028	0.045	0.32	0.05	0.67	0.28
	3	0.61	0.030	0.042	0.32	0.03	0.78	0.19
	4	0.55	0.035	0.138	0.28	0.05	0.68	0.27
Size	1	0.72	0.018	0.017	0.24	0.02	0.84	0.14
	2	0.63	0.031	0.028	0.31	0.03	0.85	0.12
	3	0.52	0.051	0.045	0.38	0.02	0.84	0.14
	4	0.50	0.054	0.081	0.36	0.02	0.88	0.10
Wage	1	0.44	0.033	0.074	0.45	0.12	0.47	0.41
	2	0.47	0.042	0.050	0.44	0.11	0.58	0.31
	3	0.54	0.037	0.046	0.38	0.06	0.75	0.19
	4	0.55	0.047	0.078	0.32	0.04	0.98	-0.02
Average		0.57	0.034	0.051	0.35	0.07	0.69	0.24

Table 1: Decomposing aggregate recruiting intensity

Notes: This table presents the time-series variance decomposition of equation (9) (**1. Aggregate recruiting intensity**) and (12) (**2. Composition**). The decomposition in each case is computed as follows. First, logs of the equation are taken. Second, the time-series variance of each term is computed. Third, the entry in the table gives the fraction of the time-series variance of the left-hand side variable attributable to the different right-hand side variables. The contribution due to covariance terms are grouped together under *Cov.*. The different rows represent the alternative groupings used to estimate (11). For example for $j =$"Age" and $NAICS = 3$, the categorical variable used to construct the ϕ_j match efficiency terms are quintiles of establishment age. Within these quintiles firms are split into 3-digit NAICS subsectors. Within these sub-groups we then aggregate establishment-month hires, employment, and vacancies to compute $\{h_{ijt}, n_{ijt}, v_{ijt}\}$ which are used as inputs into the regression and for the computation of the terms in the variance decompositions.

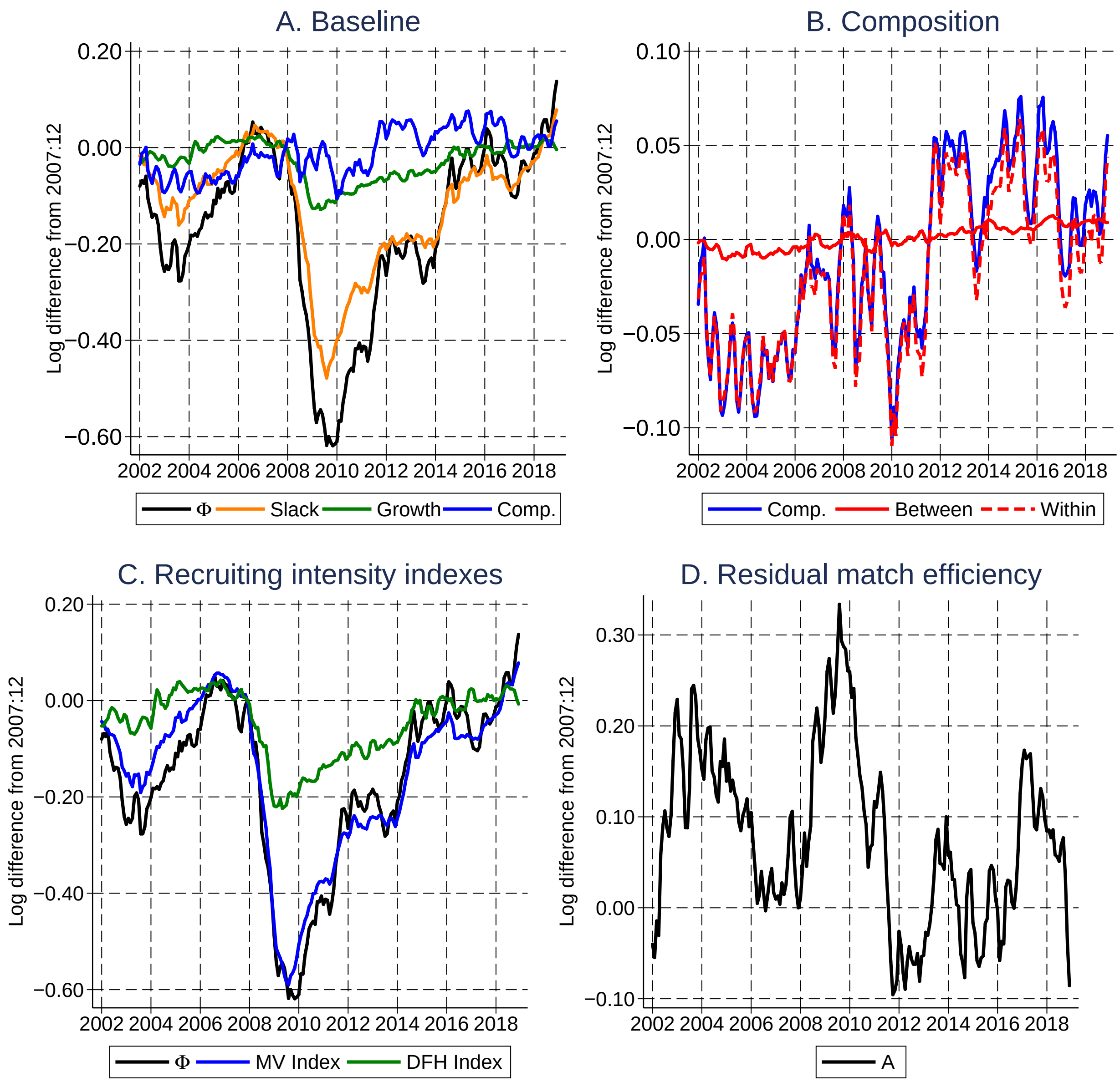


Figure 3: Decomposing aggregate recruiting intensity

Notes: Panels A and B present an example of the components of equations (9) and (12). In this case we have grouped firms by quintiles of employment for estimating ϕ_j, and within these quintiles aggregated hires, vacancies and unemployment within 4 digit industries. Panel C plots ARI (Φ_t), alongside our index Φ_t^{Index}, and that constructed by DFH. Panel D plots residual match efficiency A_t, implied the matching function under Φ_t and aggregate data on H_t, V_t and U_t. In all cases time-series are first deseasonalised using X13-ARIMA-SEATS. For presentation in this figure only we also apply a three month centered moving average to each series.

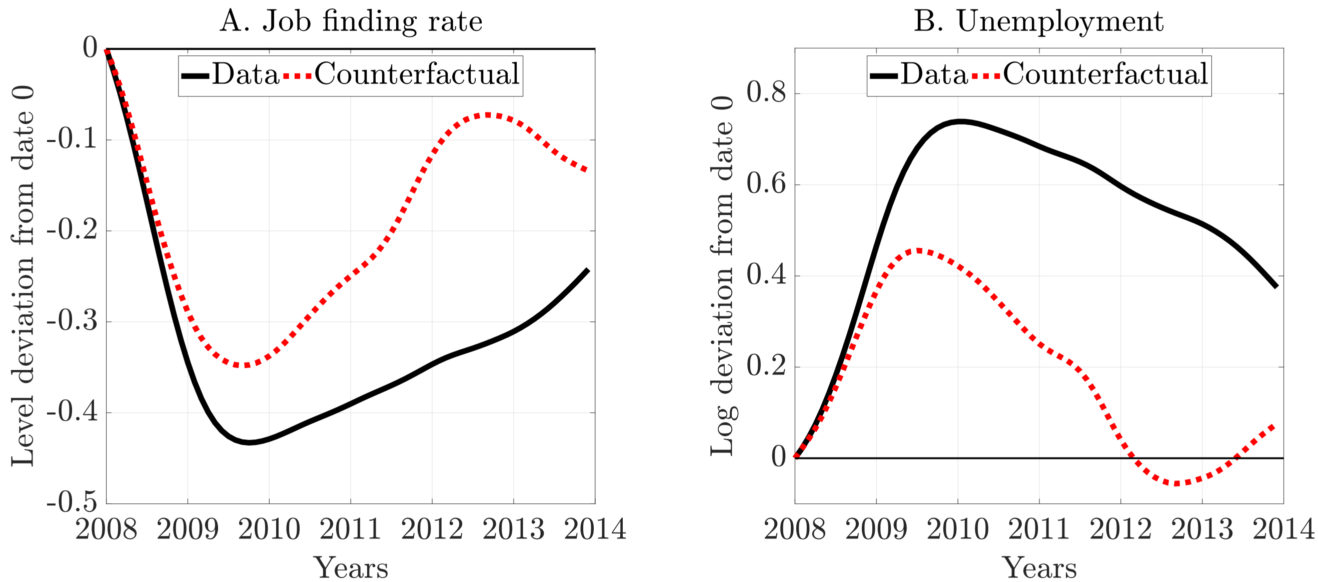


Figure 4: Counterfactual job finding rate and unemployment due only to the decline in Φ_t

Notes: The counterfactual series in this figure are constructed as follows. First take the aggregate matching function $H_t = \Phi_t A_t U_t^{\alpha} V_t^{1-\alpha}$. The job finding rate is $f(A_t, \Phi_t, U_t, V_t) = H_t/U_t$. We combine this with the empirical law of motion $U_{t+1} = (1 - f(A_t, \Phi_t, U_t, V_t))\, U_t + S_t$. Given data on $\{H_t, \Phi_t, U_t, V_t\}$ we use the matching function to construct A_t, and the law of motion for unemployment to construct S_t. We then freeze non-recruiting intensity inputs, setting $A_t = A_0$, $V_t = V_0$. We then use $\{A_0, V_0, \Phi_t, S_t\}$ to construct a counterfactual path for unemployment $\widetilde{U}_t$ starting at U_0 as in the data. That is, $\widetilde{U}_1 = (1 - f(A_0, \Phi_0, U_0, V_0))\, U_0 + S_0$, and then $\widetilde{U}_2 = (1 - f(A_0, \Phi_1, \widetilde{U}_1, V_0))\widetilde{U}_1 + S_1$. Panel A plots $\widetilde{f}_t = f(A_0, \Phi_t, \widetilde{U}_t, V_0)$. Panel B plots $\widetilde{U}_t$. The red lines therefore measure the drop in the job finding rate and the consequent rise in unemployment due only to the decrease in aggregate recruiting intensity Φ_t, holding all other determinants of the job finding rate fixed, i.e. residual match efficiency A_0 and aggregate vacancies V_0. Note that, by construction, by feeding in also the observed series for V_t and our estimated series for A_t, we would match exactly the data for both job finding rate and unemployment.

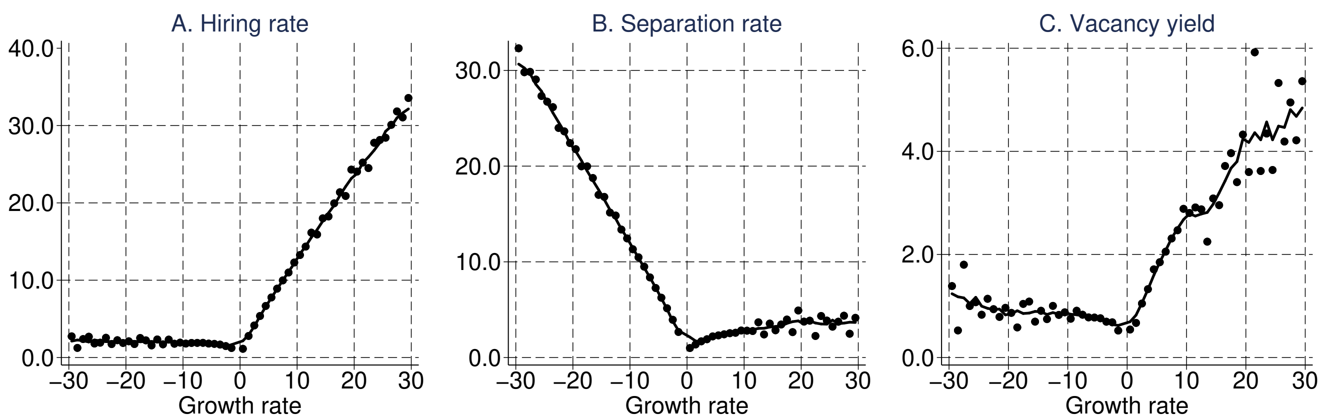
Appendix For Online Publication

This Appendix is organized as follows. Section A provides additional figures and tables. Section B provides details on math. Section C provides additional data on variable construction.

A Additional figures and tables

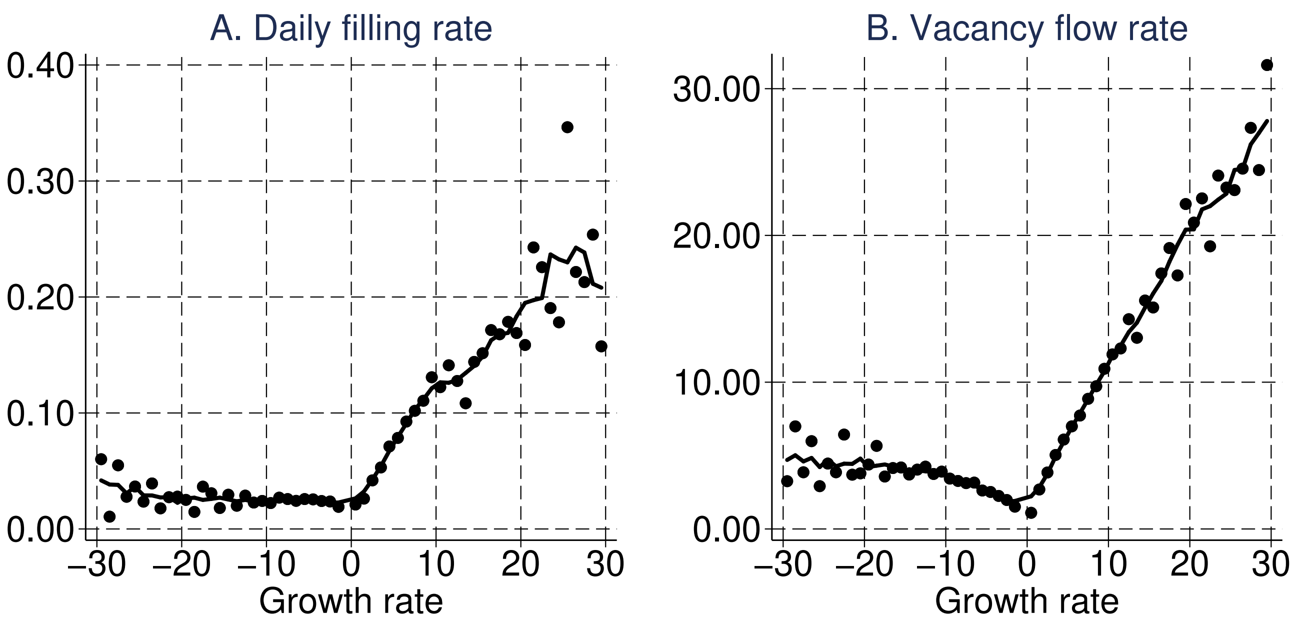
This appendix section contains additional figures and tables referenced in the main text.

Figure A1: Hockey stick plots - Hiring rate, separation rate, vacancy yield



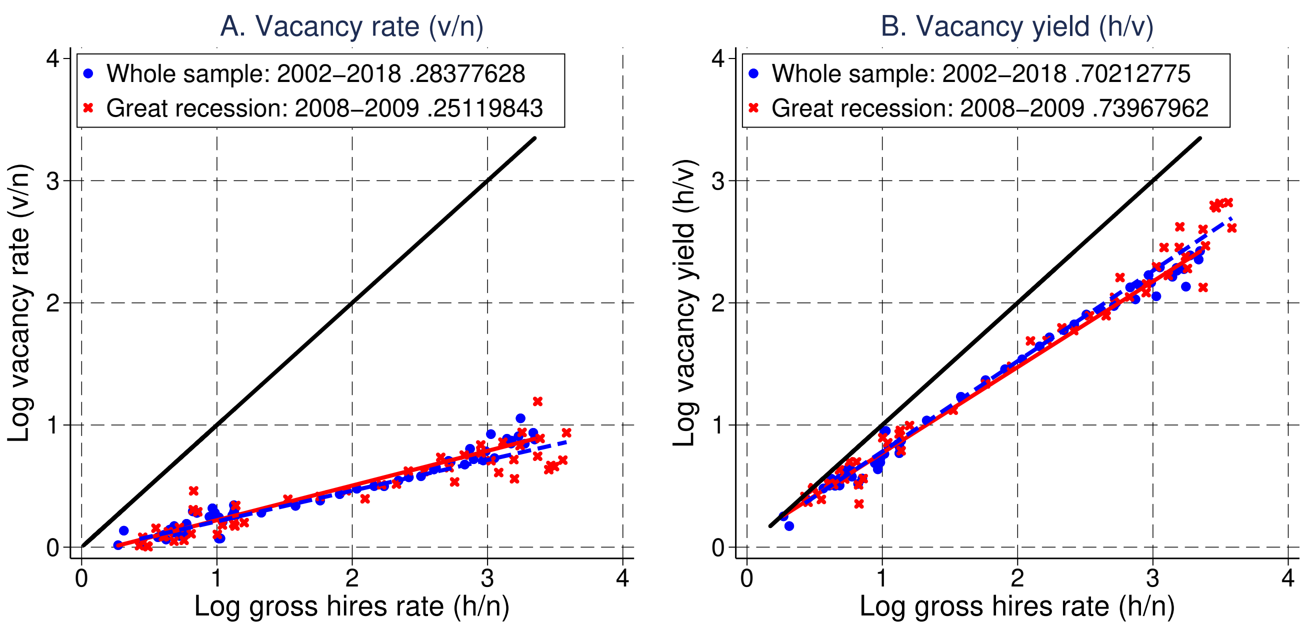
Notes Establishment-month observations in JOLTS microdata 2002-2018 are pooled in bins, where bins are determined by net monthly growth rate, and have a width of 1 percent. Growth rates computed as in DFH. Within bins b, total hires h_b, separations s_b, employment n_b, vacancies v_b are computed. From these, the gross hiring rate h_b/n_b (panel A), separation rate s_b/n_b (panel B), and vacancy yield h_b/v_b (panel C) are computed Bins with positive gross hiring rates are kept.

Figure A2: Hockey stick plots - Filling and vacancy flow



Notes: See note to Figure A1. Daily filling rate and vacancy flow rates are computed using our simplifications of the algebra of DFH daily hiring model. See Appendix B for details.

Figure A3: Vacancy rate and vacancy yield by gross hiring rate - JOLTS, 2002-2018



Notes Establishment-month observations in JOLTS microdata 2002-2018 (blue circles), or 2008-2009 (red crosses) are pooled in bins, where bins are determined by net monthly growth rate, and have a width of 1 percent. Growth rates computed as in DFH. Within bins b, total hires h_b, total vacancies v_b, total employment n_b are computed. From these, the gross hiring rate h_b/n_b, vacancy yield h_b/v_b and vacancy rate $v_b/(v_b+n_b)$ are computed Bins with positive gross hiring rates are kept. Points plotted are logs of these variables, differenced about the bin representing a one percent net growth rate.

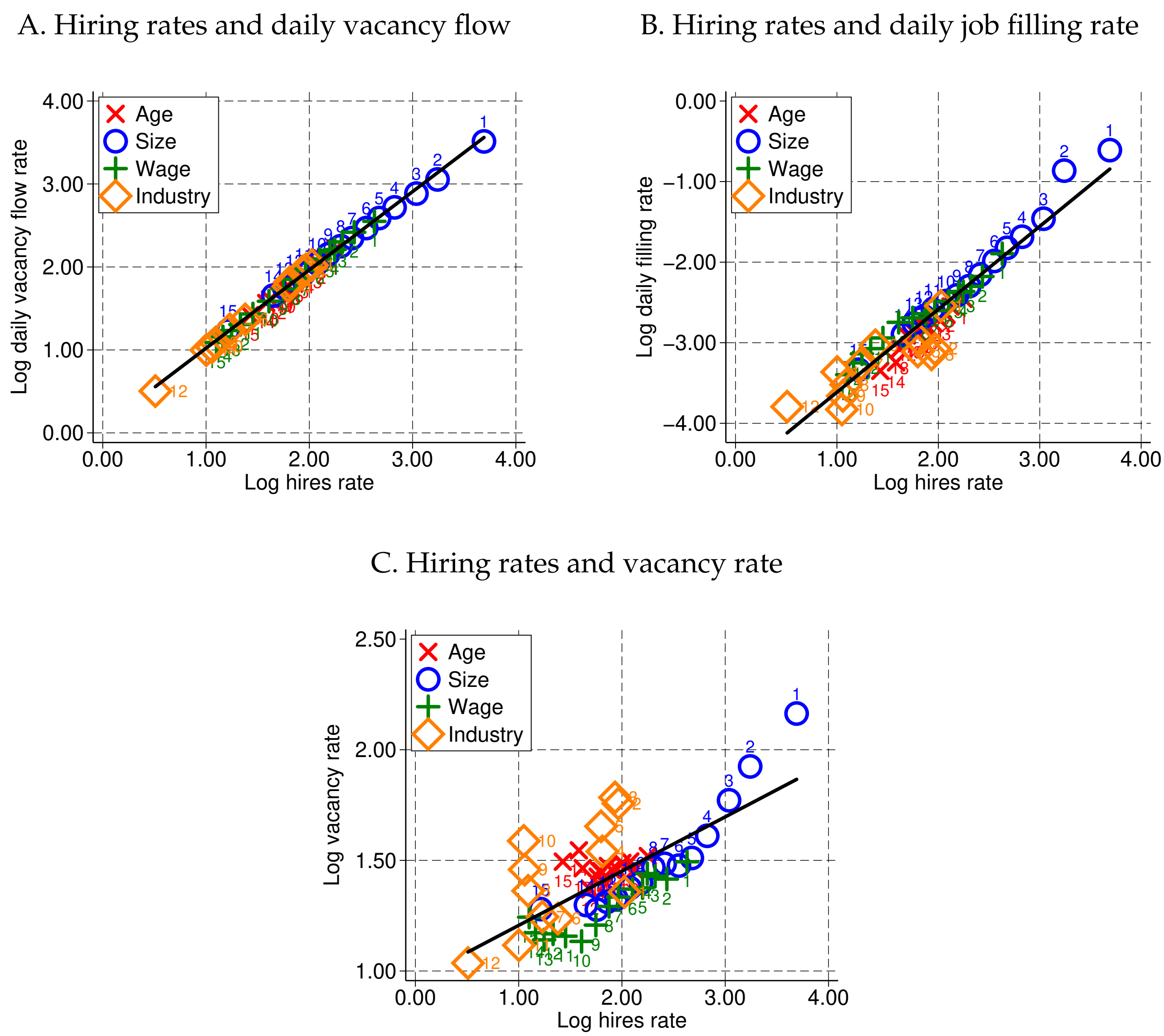


Figure A4: Recruiting intensity in the cross-section - Additional figures

Notes: These figures plots the log of the employment weighted hiring rate against (A) daily vacancy flow, (B) daily filling rate (both computed from the DFH daily hiring model), (C) vacancy rate. These are computed within 15 unweighted quantiles of establishment age, size, wage (measured as total payroll per worker), and the 12 industry groups defined in Table C1. Quintiles are marked, and industries are sorted from highest (=1) to lowest (=12) by hiring rate. The main take-away from the markings is that low numbers—young, small, low wage—gravitate to the North-East, and high numbers—old, large, high wage—gravitate to the South-West. Figure A4 replicates this figure with alternative variables on the vertical axis:

B Mathematical details

This section contains (1) the proof of Proposition 1, (2) a graphical representation of firms' optimal hiring choices and their aggregation, and (3) the derivation of the daily filling rate and vacancy flow rate used in the text.

B.1 Proof of Proposition 1

We begin by working explicitly with a cost function in the form of $\mathcal{C}_i(e_{it}, v_{it}, n_{it}) = x_i C(e_{it}, v_{it}/n_{it})$, and in the necessity part of the proof show that this is the only way in which v and n can enter. Let $\widetilde{v} = (v/n)$ denote the vacancy rate, and $\widetilde{h} = (h/n)$ denote the hiring rate. The hiring problem can be written as follows:

$$\min_{e_{it}, v_{it}} x_i C\left(e_{it}, \frac{v_{it}}{n_{it}}\right) v_{it} \qquad \text{s.t.} \qquad h_{it} = Q_t^* \phi_i e_{it} v_{it}$$

which, removing it subscripts for convenience, and setting $\phi_i = 1$ without loss of generality, we write as:

$$\min_{e,\widetilde{v}} xC\left(e, \widetilde{v}\right) \widetilde{v} n \qquad \text{s.t.} \qquad \widetilde{h} = Q^* e \widetilde{v} \tag{B1}$$

Sufficiency. We first show the following. If C is an isoelastic function $m(\cdot)$ of two, additive, isoelastic functions $g(e)$ and $f(\widetilde{v})$, then the solution to (B1) delivers a vacancy yield $h/v = \widetilde{h}/\widetilde{v}$ and vacancy rate $\widetilde{v}$ that are log-linear in the hiring rate $\widetilde{h}$.

The first order conditions of the problem imply the following optimality condition, which along with the hiring constraint can be solved for $e\left(Q^*, \widetilde{h}\right)$ and $\widetilde{v}\left(Q^*, \widetilde{h}\right)$:

$$C_e\left(e, \widetilde{v}\right) e = C_v\left(e, \widetilde{v}\right) \widetilde{v} + C\left(e, \widetilde{v}\right). \tag{B2}$$

Note that since x scales the cost function, it does not appear in the optimality condition. Despite affecting the firms' dynamic decision that controls $\widetilde{h}$, x does not affect the recruiting input decision. If $C(e, \widetilde{v})$ has the form just described:

$$C(e, \widetilde{v}) = m\Big(g(e) + f\left(\widetilde{v}\right)\Big),$$

then the optimality condition (B2) can be written:

$$g\left(e\right)\left[\left(\frac{m'(g(e)+f(\widetilde{v}))(g(e)+f(\widetilde{v}))}{m(g(e)+f(\widetilde{v}))}\right)\left(\frac{g'(e)e}{g(e)}\right)-1\right]=f\left(\widetilde{v}\right)\left[\left(\frac{m'(g(e)+f(\widetilde{v}))(g(e)+f(\widetilde{v}))}{m(g(e)+f(\widetilde{v}))}\right)\frac{f'(\widetilde{v})\widetilde{v}}{f(\widetilde{v})}+1\right]$$

Since m, g and f are constant elasticity, this reduces to

$$g(e)\left[\gamma_m\gamma_e-1\right]=f(\widetilde{v})\left[\gamma_m\gamma_v+1\right]. \tag{B3}$$

Given that g and f are isoelastic, the solution to (B3) is of the form $\widetilde{v}=\Omega e^{\omega}$. Substituting this into the hiring technology $\widetilde{h}=Q^*e\widetilde{v}$ gives

$$\widetilde{h}=\Omega Q^* e^{1+\omega} \quad\Longrightarrow\quad e=\Omega^{-\frac{1}{1+\omega}}Q^{*-\frac{1}{1+\omega}}\widetilde{h}^{\frac{1}{1+\omega}}. \quad\overset{\widetilde{h}=Q^*e\widetilde{v}}{\Longrightarrow}\quad \frac{\widetilde{h}}{\widetilde{v}}=\Omega^{-\frac{1}{1+\omega}}Q^{\frac{\omega}{1+\omega}}\widetilde{h}^{\frac{1}{1+\omega}}.$$

Since $\widetilde{h}=Q^*e\widetilde{v}$ then it is immediate that $\widetilde{v}$ is also isoelastic in $\widetilde{h}$. Since γ_m only appears in the constant Ω, it can be normalized to one (i.e. $m(x)=x$) as we do in the paper without any impact on the key properties of the recruiting policies.

Necessity. We want to show the following. Suppose that under optimality the vacancy yield and vacancy rate are isoelastic in the hiring rate. Then the cost function takes the following form, where g and f are isoelastic: $C\left(e,v,n\right)=\left[g\left(e\right)+f\left(\frac{v}{n}\right)\right]$. Given our previous result that constant elasticity m only affects policy function constants we ignore it here. We proceed in five steps.

Step 1. We begin by simplifying the statement that we wish to prove. First, we show that if the supposition is true, then $\widetilde{v}$ and recruiting intensity must be isoelastic with respect to each other, i.e. have a constant elasticity relationship, as in $\widetilde{v}=\Psi e^{\psi}$. By the supposition $(\widetilde{h}/\widetilde{v})$ is log-linear in $\widetilde{h}$. From the hiring constraint $(\widetilde{h}/\widetilde{v})=Q^*e$. Therefore e is log-linear in $\widetilde{h}$: $e=\Omega\widetilde{h}^{\omega}$, which implies that $\widetilde{h}$ is an isoelastic function of e. Substituting this isoelastic function of e into the hiring constraint for $\widetilde{h}$ gives

$$\Omega^{-\frac{1}{\omega}}e^{\frac{1}{\omega}}=Q^*e\widetilde{v}.$$

The relationship between e and $\widetilde{v}$ is therefore constant elasticity: $\widetilde{v}=\Psi e^{\psi}$ for some Ψ and ψ.

Second, the supposition requires that the first order conditions hold. These give the optimality condition (B2).

Combining these two points allows us to simplify the statement that we wish to prove:

Suppose the optimality condition $C_e(e,\widetilde{v})\,e = C_v(e,\widetilde{v})\,\widetilde{v} + C(e,\widetilde{v})$ *implies that* $\widetilde{v} = \Psi e^{\psi}$, *for some* Ψ, ψ. *Then* $C(e,\widetilde{v}) = m(g(e) + f(\widetilde{v}))$, *with isoelastic* $m(x)$, $g(e)$ *and* $f(\widetilde{v})$.

We construct the proof by contradiction. Under the assumption that the cost function is not isoleastic, obtaining an optimal relation between e and $\tilde{v}$ that features constant elasticity leads to a contradiction.

Step 2. We establish a particular implication in the case that $C(e,\widetilde{v})$ is **not** additively separable. Taking (B2), and rearranging:

$$e = \left[\frac{C_v(e,\widetilde{v})}{C_e(e,\widetilde{v})}\widetilde{v}\right] + \left[\frac{C(e,\widetilde{v})}{C_e(e,\widetilde{v})}\right]. \tag{B4}$$

In order for the supposition to hold, this must imply that $e = \Omega\tilde{v}^{\omega}$. If C is **not** additively separable, then this requires that $e^{\frac{\omega-1}{\omega}}$ can be factored out of both terms on the right side of (B4), leaving only terms involving $\widetilde{v}$:

$$\frac{C_v(e,\widetilde{v})\,\widetilde{v}}{C_e(e,\widetilde{v})} = \Gamma_1(\widetilde{v})\,e^{\frac{\omega-1}{\omega}} \qquad , \qquad \frac{C(e,\widetilde{v})}{C_e(e,\widetilde{v})} = \Gamma_2(\widetilde{v})\,e^{\frac{\omega-1}{\omega}}.$$

Moreover, to obtain $e = \Omega\widetilde{v}^{\omega}$ we require that $\Gamma_1(\widetilde{v}) = \Gamma_1\widetilde{v}^{\gamma}$ and $\Gamma_2(\widetilde{v}) = \Gamma_2\widetilde{v}^{\gamma}$, so that we can add the terms on the right side of (B4). Imposing this condition and then dividing the above two expressions gives

$$\frac{C_v(e,\widetilde{v})\,\widetilde{v}}{C(e,\widetilde{v})} = \frac{\Gamma_1}{\Gamma_2}.$$

For this condition to hold, then it must be the case that $C(e,\widetilde{v}) = \Theta g(e) v^{\theta}$. We prove this last step at the end of the proof in **Lemma 1**.

Step 3. We show that if $C(e,\widetilde{v}) = \Theta g(e)v^{\theta}$, then there is no way for the supposition to hold. Under this functional form the optimality condition (B2) becomes:

$$\begin{aligned} C_e\left(e,\widetilde{v}\right)e &= C_v\left(e,\widetilde{v}\right)\widetilde{v} + C\left(e,\widetilde{v}\right), \\ \left[\Theta g'(e)\widetilde{v}^{\theta}\right]e &= \left[\theta\Theta g(e)\widetilde{v}^{\theta-1}\right]v + \Theta g(e)v^{\theta}. \end{aligned}$$

Since $\widetilde{v}^{\theta}$ can be factored out of both sides, the optimality condition implies that e is independent of $\widetilde{v}$ which violates the supposition.

Step 4. From steps 2 and 3 above we have established by contradiction that C must be additively separable for the supposition to hold. Now we show that if C is separable, then g and e must be isoelastic for the supposition to hold. If $C(e,\widetilde{v}) = m(g(e) + f(v))$, then the optimality condition can be written

$$\frac{m'(g(e)+f(\widetilde{v}))(g(e)+f(\widetilde{v}))}{m(g(e)+f(\widetilde{v}))}g_e\left(e\right)e - g\left(e\right) = \frac{m'(g(e)+f(\widetilde{v}))(g(e)+f(\widetilde{v}))}{m(g(e)+f(\widetilde{v}))}f_v\left(v\right)v - f\left(v\right).$$

The supposition requires that the addition of functions on both left and right sides are isoelastic in e and $\widetilde{v}$. This requires that m, g and f are themselves isoelastic.[22]

Step 5. Finally, note that the dependence of $C(e,v,n)$ on $\widetilde{v}$ and not v and n separately can be shown. In terms of sufficiency we have already covered this. In terms of necessity, if (v,n) entered not as $\widetilde{v} = (v/n)$, then the first order conditions would produce an extra term involving n's which would violate the requirement imposed by the data of an isoelastic relationship between $\widetilde{v}$ and e.

Lemma 1. *If a function $f(x,y)$ has the property that*

$$\frac{f_x(x,y)x}{f(x,y)} = c\,,$$

[22]It is immediate that the terms involving m must both be constants, and hence m is isoelastic. The terms are the same and if they involve both or either of $\widetilde{v}$ and $\widetilde{e}$ will not result in an isoelastic relationship between e and $\widetilde{v}$. To observe that f and g are isoelastic consider the following. We require that $F_x(x)x - F(x) = ax^b$. The left side can be written $F(x)\left[F_x(x)x/F(x) - 1\right]$. Therefore we require the term in the bracket to be a constant. This will only be the case if $F(x)$ is a constant elasticity function. We then require that the term outside the bracket is isoelastic. Therefore $F(x)$ must be isoelastic.

where c is a constant, then $f(x,y) = h(y)x^c$ for some function $h(y)$.

Proof. *Rearrange the above expression:*

$$\frac{f_x(x,y)}{f(x,y)} = \frac{c}{x}.$$

Integrating both sides and, without loss of generality, writing the constants of integration $\log h_1(y)$, and $\log h_2(y)$:

$$\log h_1(y) + \log f(x,y) \quad = \quad \log h_2(y) + c \log x.$$

Exponentiating delivers our the functional form we wished to establish:

$$f(x,y) \quad = \quad \underbrace{\frac{h_2(y)}{h_1(y)}}_{:=h(y)} x^c.$$

Policies. We now derive the policy functions in the text. Without loss of generality we let $C(e, \widetilde{v}) = c_m \left(c_e e^{\gamma_e} + c_v \widetilde{v}^{\gamma_v}\right)^{\gamma_m}$. Recalling equation (B3), the first order conditions implied

$$g(e)\left[\gamma_m \gamma_e - 1\right] = f(\widetilde{v})\left[\gamma_m \gamma_v + 1\right] \qquad \rightarrow \qquad \widetilde{v}(e) = \underbrace{\left[\frac{c_e}{c_v}\frac{\gamma_m \gamma_e - 1}{\gamma_m \gamma_v + 1}\right]^{\frac{1}{\gamma_v}}}_{:=\kappa} e^{\frac{\gamma_e}{\gamma_v}}$$

which is of the form $\widetilde{v}(e) = \Psi e^{\psi}$ as required. Proceeding as above, (i) substituting in for $\widetilde{v}$ in the hiring function $\widetilde{h}_{it} = Q^* e_{it} \widetilde{v}(e_{it})$, (ii) solving for e_{it} as a function of $\widetilde{h}_{it}$ and Q_t^*, (iii) multiplying by Q_t^* to convert e_{it} into the vacancy yield, (iv) taking logs:

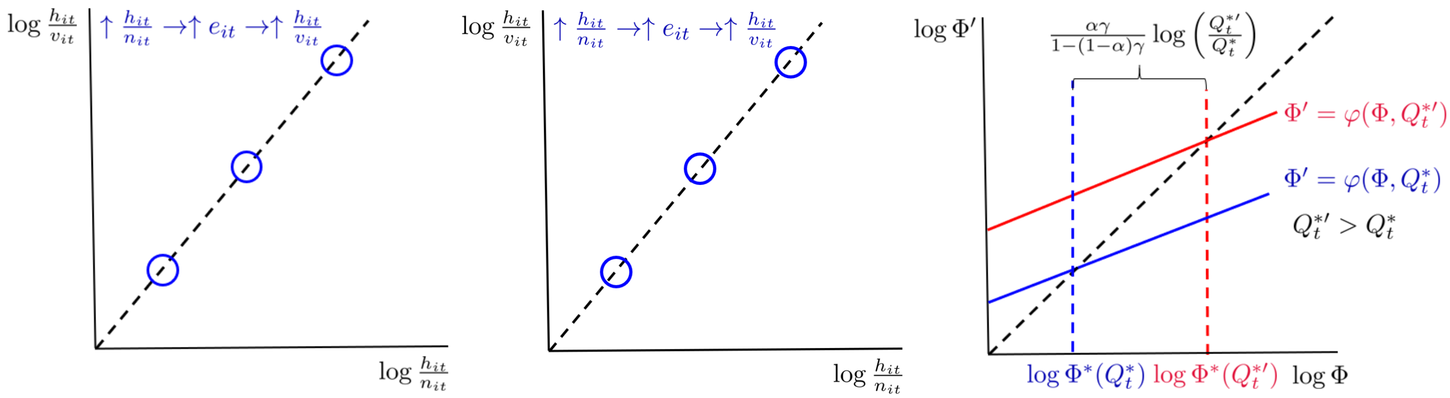
$$\log\left(\frac{h_{it}}{v_{it}}\right) \quad = \quad -\frac{1}{\gamma_e + \gamma_v}\log\kappa + \frac{\gamma_e}{\gamma_e + \gamma_v}\log Q_t^* + \frac{\gamma_e}{\gamma_e + \gamma_v}\log\phi_i + \frac{\gamma_v}{\gamma_e + \gamma_v}\log\left(\frac{h_{it}}{n_{it}}\right).$$

The vacancy rate can then be obtained from $\widetilde{v}(e)$:

$$\log\left(\frac{v_{it}}{n_{it}}\right) \quad = \quad \frac{1}{\gamma_e + \gamma_v}\log\kappa - \frac{\gamma_e}{\gamma_e + \gamma_v}\log Q_t^* - \frac{\gamma_e}{\gamma_e + \gamma_v}\log\phi_i + \frac{\gamma_e}{\gamma_e + \gamma_v}\log\left(\frac{h_{it}}{n_{it}}\right).$$

One can observe immediately that summing the two equations delivers $\log(h_{it}/n_{it})$, which verifies that the hiring constraint holds.

B.2 Graphical depiction of optimal policies and G.E. multiplier



(a) Unobserved recruiting (b) Observed outcomes (c) General equilibrium

Figure B1: Recruiting input decision

Notes: Panels (a) and (b) describe the unobserved recruiting choice and observed recruiting outcomes of a firm. Panel (a) plots isoquants of the hiring production technology in logs (blue), and the isocosts also in log (red). Keeping $Q_t^* \phi_i$ fixed, an increase in production $\uparrow (h_{it}/n_{it})$ requires an increase in the level of inputs: e_{it} and v_{it}/n_{it}. The parameter γ captures the elasticity of substitution in the average vacancy cost function $\mathcal{C}$ and so determines the slope of the expansion path in logs. Panel (b) shows the implications for the relationship between vacancy yield and hiring rate. On the x-axis, the hiring rate, which is our comparative static variable, is increasing. On the y-axis, the log vacancy yield—which is equal to $\log e_{it} + \log Q_t^* + \log \phi_i$—increases linearly (with slope 1) as $\log e_{it}$ increases linearly. Panel (c) describes the general equilibrium of the model. Given Φ_t on the x-axis, the angled lines plot the equilibrium response $\Phi' = \varphi(\Phi, Q^*)$. Since the slope of φ is $\gamma(1-\alpha)$ which is less than one, an increase in $Q_t^{*\prime} > Q_t^*$ shifts this function up, leading to a greater than one-for-one increase in $\Phi_t' > \Phi_t$.

B.3 Daily hiring model of DFH

Here we present the model and computations that underlie the estimates of the (i) daily job filling rate, (ii) daily vacancy flow rate referenced in the text and figures. We progress the results of their paper to arrive at a simple set of equations that can be solved numerically.

Define the following variables. Hires at firm i on day s of month t are h_{ist}. Vacancies at the end of the day are v_{ist}. Let f_{it} be the *daily job filling rate*, such that $h_{ist} = f_{it} v_{is-1t}$, assumed to be constant over the month t. Let θ_{it} be the *daily vacancy in-flow rate* and δ_{it} be the daily exogenous vacancy out-flow rate such that

$$v_{ist} = (1 - f_{it})(1 - \delta_{it}) v_{is-1t} + \theta_{it}.$$

Let there be τ days in a month. We observe the following in the JOLTS microdata: (i) *monthly hires* $h_{it} = \sum_{s=1}^{\tau} h_{ist}$, (ii) beginning of month vacancies $v_{it-1} = v_{i0t}$, (iii) end of month vacancies $v_{it} = v_{i\tau t-1}$.

Our aim is to use these data and the above equations to estimate $f_{it}, \theta_{it}, \delta_{it}$. Iterating on the vacancy equation, vacancies at any day s can be written in terms of $f_{it}, \theta_{it}, \delta_{it}$ and v_{it-1}:

$$v_{is-1t} = [1 - f_{it} - \delta_{it} + \delta_{it} f_{it}]^{s-1} v_{it-1} + \theta_{it} \sum_{j=1}^{s-1} [1 - f_{it} - \delta_{it} + \delta_{it} f_{it}]^{j-1}.$$

Using $h_{it} = \sum_{s=1}^{\tau} h_{ist} = \sum_{s=1}^{\tau} f_{it} v_{is-1t}$ and this expression:

$$h_{it} = f_{it} v_{it-1} \sum_{s=1}^{\tau} [1 - f_{it} - \delta_{it} + \delta_{it} f_{it}]^{s-1} + f_{it} \theta_{it} \sum_{s=1}^{\tau} (\tau - s) [1 - f_{it} - \delta_{it} + \delta_{it} f_{it}]^{s-1}. \quad \text{(B5)}$$

Evaluating the vacancy equation at the end of the month, we also have

$$v_{it} = [(1 - f_{it})(1 - \delta_{it})]^{\tau} v_{it-1} + \theta_{it} \sum_{j=1}^{\tau} [(1 - f_{it})(1 - \delta_{it})]^{j-1}. \quad \text{(B6)}$$

Equations (B5) and (B6) are two equations in three unknowns $\{f_{it}, \theta_{it}, \delta_{it}\}$. As in DFH we simplify this by assuming that δ_{it} is equal to the daily layoff rate ξ_{it}. The daily layoff rate is computed by taking month layoffs s_{it} divided by employment n_{it} and then dividing by τ: $\xi_{it} = (s_{it}/\tau n_{it})$. Setting $\delta_{it} = \xi_{it}$ makes (B5) and (B6) two equations in two unknowns $\{f_{it}, \theta_{it}\}$.

We can make some progress beyond DFH by applying results in algebra for finite sums. Let

$x_{it} = 1 - f_{it} - \delta_{it} + \delta_{it} f_{it}$. Plugging this in:

$$\begin{aligned} v_{it} &= x_{it}^{\tau} v_{it-1} + \theta_{it} \sum_{j=1}^{\tau} x_{it}^{j-1}, \\ h_{it} &= f_{it} \left[\sum_{s=1}^{\tau} x_{it}^{s-1} \right] v_{it-1} + f_{it} \theta_{it} \left[\sum_{s=1}^{\tau} (\tau - s) \, x_{it}^{s-1} \right]. \end{aligned}$$

Manipulating these obtains two expressions that can be computed sequentially given x_{it}:

$$\theta_{it} = \frac{v_{it} - x_{it}^{\tau} v_{it-1}}{g_0(x_{it})} \tag{B7}$$

$$f_{it} = \frac{h_{it}}{g_0(x_{it}) v_{it-1} + \theta_{it} g_1 (x_{it})} \tag{B8}$$

where the functions g_0 and g_1 are given by

$$g_0(x) = \frac{1 - x^{\tau}}{1 - x} \quad , \quad g_1(x) = \frac{\tau - g_0(x)}{1 - x}.$$

This implies a simple algorithm:

1. Guess $f_{it}^{(0)}$ and use this to compute $x_{it}^{(0)} = (1 - \delta_{it})(1 - f_{it}^{(0)})$.
2. Use equation (B7) to compute $\theta_{it}^{(0)}$, then equation (B8) to compute $f_{it}^{(1)}$.

- Iterate until $\left| f_{it}^{(k+1)} - f_{it}^{(k)} \right| < \varepsilon$.

In practice this converges after a very few iterations. In the figures and text instead of plotting θ_{it} directly, we transform θ_{it} into a monthly rate as a fraction of employment: $\theta_{it} \tau / n_{it}$.

C Empirical details

This section contains additional details about the data used in our estimation.

C.1 Trends in data

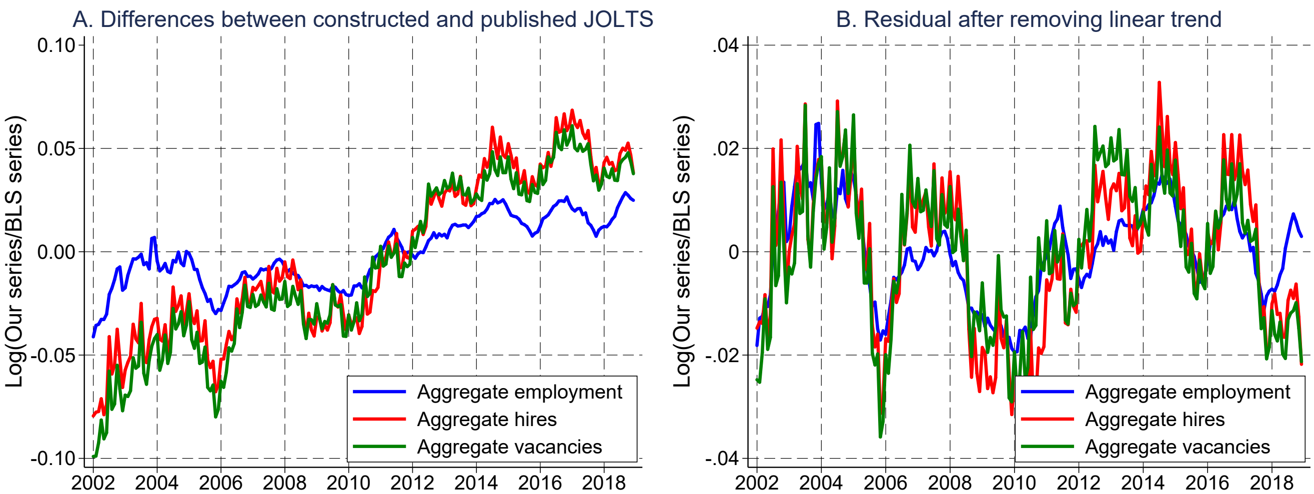


Figure C1: Trends in our data relative to published JOLTS aggregates

Figure C1A compares our construction of aggregate hires, employment and vacancies to officially published BLS data. For a given series X_t we first adjust our series for mean differences from published series in logs. Figure C1A then plots the ratio of the log of our adjusted series to the published series. As can be observed for all three series there is a trend in the bias, with our series being slightly less than the published data in the early part of the sample, and slightly larger in the latter part. This may be due to differences in compilation of published data or imputation in either data set. To account for these differences we take a linear trend out of both our data and the published data—both in logs—saving the residuals from the regression using our data. We then put the trend of the published data back into our residualized data. Figure C1C, plots the log difference between our final data and published data. There is now no longer any trend in bias between the two series, and differences are small, everywhere less than 3 percent in magnitude. There is some cyclicality but this is small. Importantly as our main measures in the paper consist of various ratios of H_t, N_t and V_t, we find that the difference

NAICS categories	Industry categories from DFH
21	Mining, Quarrying, and Oil and Gas Extraction
23	Construction
31,32,33	Manufacturing
22, 42, 48, 49	Utilities; Wholesale Trade; Transportation and Warehousing
44, 45	Retail Trade
51	Information
52, 53	Finance and Insurance; Real Estate and Rental and Leasing
54, 55, 56	Professional Services, Management, Administrative Services
62	Health Care and Social Assistance
71, 72	Arts, Entertainment, and Recreation; Accommodation and Food Services
81	Accommodation and Food Services
>90	Government

Table C1: Categorization of industries used in analysis

relative to published series move in step across the three variables. Finally, and separately, we take a linear time trend out of each of these series.

C.2 Microdata details

- All data are at the *establishment* level
- Age is defined as the number of years since the establishment first reported having more than one employee.
- QCEW data are reported quarterly but contain monthly payroll and employment at the establishment. These were checked for consistency against the JOLTS.
- Industry categorizations are given in Table C1. We drop Agriculture (11) and Educational Services (61) due to data collection issues that we were informed of by BLS staff.
- Participation in external researcher programs using employment and wage microdata are at the discretion of the states, which run the unemployment insurance programs report data used in the QCEW. Accessibility varies from project to project. Our project was granted access to data from 37 states: AL, AR, AZ, CA, CT, DE, GA, HI, IA, IN, KS, MD, ME MN, MO, MT, NJ, NM, NV, OH, OK, SC, SD, TN, TX, UT, VA, WA, WI, and WV. These represent over 70 percent of the population. The 5 largest states not included are FL, MI, NC, NY, and PA. Throughout we restrict our sample to the states made available

to us. This avoids changing samples when only using JOLTS data, versus when also using establishment age or wage, for which we require the QCEW.

- Wages w_{it} are computed as total payroll divided by total employment in a given month t at establishment i. Nominal wages are deflated to 2016 values using the CPI. These real wages are then detrended using annual fixed effects, and deseasonalized using month fixed effects.
- All aggregation is performed using weights provided by the BLS that adjust for systematic bias in survey non-response rates, and generate a representative sample.
- For further details on data definitions and statistical methods see the *BLS Handbook of Methods - Chapter 18 - Job Openings and Labor Turnover Survey*.