NBER WORKING PAPER SERIES

MACRO RECRUITING INTENSITY FROM MICRO DATA

Simon Mongey
Giovanni L. Violante

Working Paper 26231
http://www.nber.org/papers/w26231

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
September 2019, Revised October 2024

We thank Jaroslav Borovi ka, Steve Davis, DavidWiczer, and many seminar participants for useful comments. We are especially grateful to the staff of the Bureau of Labor Statistics for their support throughout the project, and to Hyejin Park for outstanding research assistance. The views expressed herein are those of the authors and not necessarily those of the Bureau of Labor Statistics, the Federal Reserve System, the Federal Reserve Bank of Minneapolis, or of the National Bureau of Economic Research.

At least one co-author has disclosed additional relationships of potential relevance for this research. Further information is available online at http://www.nber.org/papers/w26231

Macro Recruiting Intensity from Micro Data
Simon Mongey and Giovanni L. Violante
NBER Working Paper No. 26231
September 2019, Revised October 2024
JEL No. E24, E32

ABSTRACT

We merge QCEW and JOLTS microdata to study the recruiting intensity of firms in the cross-section and over time. We show that vast establishment-level heterogeneity in vacancy filling rates is entirely explained by differences in gross hiring rates. We provide theory that supports these empirical facts and, through the lens of this theory, combine firm-level decisions and data into an empirical measure of Aggregate Recruiting Intensity (ARI). We show that procyclicality of ARI is primarily due to reductions of recruiting effort in slack labor markets. Jointly, these results inform a proxy ARI index that is easily computable from publicly available macroeconomic time series. Fluctuations in ARI account for around 40% of the volatility of overall aggregate match efficiency from 2002 to 2019.

Simon Mongey
Federal Reserve Bank of Minneapolis
90 Hennepin Avenue
Minneapolis, MN 55401
and NBER
simonmongey@gmail.com

Giovanni L. Violante
Department of Economics
Princeton University
Julis Romo Rabinowitz Building
Princeton, NJ 08540
and NBER
violante@princeton.edu

1 Introduction

Aggregate match efficiency is a useful concept in macroeconomics. Its fluctuations expand and contract the hiring possibility frontier of the economy much like 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, a key driver of unemployment dynamics (Shimer, 2012).

The Great Recession offered a striking example. At the onset of the recession, the job finding rate fell sharply, leading to sustained unemployment. However, its decline was much more severe than what would usually be implied by the decrease in labor market tightness—the ratio of available jobs (vacancies) to idle workers (the unemployed)—alone. On the other side of the market there was only a moderate increase in the rate at which firms' vacancies were filled, much less than would usually be implied by the decrease in labor market tightness. The reason for both is precisely that measured productivity, or efficiency, of the matching process broke down significantly over this period (Elsby, Michaels, and Ratner, 2015).

A deterioration in aggregate match efficiency could 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, macroeconomists have focused less 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 relation-

[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' composition and 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.

ship 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 terms of both measurement from microdata (see Mueller, Kettemann, and Zweimuller, 2018; Carrillo-Tudela, Kaas, and Gartner, 2023; Lochner, Merkl, Stuber, and Gurtzgen, 2019; Forsythe and Weinstein, 2021) and theoretical equilibrium modelling (Kaas and Kircher, 2015; Gavazza, Mongey, and Violante, 2018; Leduc and Liu, 2020). Our paper contributes to this line of research.

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 answer a number of questions. What economic forces drive differences in observed recruiting outcomes at the firm level? What explains the dynamics of aggregate recruiting intensity over the cycle? And what lessons can we draw regarding aggregate labor market dynamics?

To answer these questions our paper systematically addresses heterogeneity in hiring behavior across firms. To take a broad view of this heterogeneity we create a new dataset that links firm-level observations in two existing sources of firm-level microdata at the U.S. Bureau of Labor Statistics (BLS): the *Job Openings and Labor Turnover Survey* (JOLTS) and the *Quarterly Census of Employment and Wages* (QCEW). We can therefore, for the first time, incorporate heterogeneity in establishment age and per-worker earnings into the analysis, along with size and industry which are available in JOLTS. 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 reallocation, and worker flows.

To provide a framework for understanding the data we first specify a model of heterogeneous firms facing shocks to separations and productivity, nested in a general equilibrium random search environment. Each period firms first choose their desired rate of gross hires, and then choose a combination of two inputs to attain this: recruiting intensity and vacancies. The stronger is recruiting intensity, the faster firms' vacancies are filled (and the higher the vacancy yield). To link micro to macro we use the model to derive an expression for aggregate recruiting

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

intensity (ARI) from first principles.

We combine our model and micro data to decompose our measure of ARI into three factors: slackness, growth, composition. The first factor summarizes the general equilibrium response of recruiting effort 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. We show how to build each of these components from the ground up using our QCEW-JOLTS microdata. These data enter the measures directly as inputs, and indirectly through parameters that we estimate in a first stage. Having constructed these measures, we empirically decompose the time-series variance of ARI into its three theoretical components. Finally, we use our decomposition results to motivate a simple empirical index that can be entirely computed using publicly available data, and conduct counterfactual exercises.

Our analysis contains four main findings. First, at the micro level, the bulk of cross-sectional variation in the rate at which firms fill vacancies can be explained by heterogeneity in firm-level hiring rates, even after controlling for firm age, establishment wage, wage growth, quit rate, employment, employment growth and industry information, which are available from our merged QCEW-JOLTS data. This stark regularity significantly extends—through the addition of controls—the initial observation of DFH that in the *cross-section of establishment gross hiring rates*, firms with higher gross hiring rates tend to have higher vacancy yields.[3] We conclude that at the firm level the hiring rate is, quantitatively, a 'sufficient statistic' for the vacancy filling rate. This empirical regularity is important. We show in Proposition 1 that, joint with firm optimality, it puts tight restrictions on functional forms in a theory in which firms choose cost-minimizing combinations of recruiting inputs.

Second, we combine our microdata and theory to aggregate our micro-founded recruiting intensity decisions up to the macro level measure of ARI. We document that aggregate recruiting intensity is strongly procyclical and that its fluctuations account for roughly 40% of the volatility of overall aggregate match efficiency from 2002 to 2019. The residual component of match efficiency beyond ARI —which captures other mechanisms studied in the literature such as workers' job search effort, jobseekers' composition, and sectoral mismatch— is also procycli-

[3]See their Figure IX, which our Figure 1 extends from their 2001-2006 sample to 2001-2018.

cal.

Third, decomposing our aggregate measure of recruiting intensity reveals that its procyclicality is chiefly due to firms optimally cutting back on recruiting effort when labor markets are slack and plenty of job seekers are available. 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. Proposition 2 shows that a representative firm choosing aggregate vacancies and recruiting effort will, in equilibrium, yield a measure of recruiting intensity identical to our index. We show that this index is conceptually different from that proposed by DFH: their approach imputes the estimated value of the cross-sectional elasticity to a macro elasticity, and by doing so it abstracts from general equilibrium forces.

Finally, 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 immediate 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 empirical results. Section 5 shows the robustness of these results. Section 6 returns to the model to interpret our results through an index of ARI and conduct counterfactuals. Section 7 discusses (a) alternative theories linking vacancy yields and hiring rates, and (b) our findings in the context of overall cyclicality of match efficiency. Section 8 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. We first specify the partial equilibrium microeconomic environment, and then close the model in order to study the aggregate labor market.

2.1 Microeconomic environment

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 Bureau of Labor Statistics (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"*.[4] Recruiting intensity includes expenditures on all other variable inputs such as advertising, screening, recruiting events, etc.[5] We allow *costs per vacancy* to depend on employment n_{it}, the number of open positions v_{it}, and on recruiting intensity e_{it}: $\mathcal{C}_i(e_{it}, v_{it}, n_{it})$. More recruiting intensity increases the effectiveness of a vacancy, such that firm hires h_{it} 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.[6] For now we defer closing the model, which will require specifying Q^*_t consistently with the firm-level hiring technology, to the next section.

The firm's problem is as follows. Let $\mathbf{s}^t$ be the history of firm-level and aggregate shocks until date t, $\mathcal{M}_i\left(\mathbf{s}^t\right)$ the subjective discount rate associated with history $\mathbf{s}^t$, and $\delta_{it}\left(\mathbf{s}^t\right)$ the stochastic rate of exogenous separations. The firm chooses sequences of recruiting intensity $e_{it}(\mathbf{s}^t)$, vacancies $v_{it}(\mathbf{s}^t)$ and endogenous separations $s_{it}(\mathbf{s}^t)$ to solve the following dynamic

[4] 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

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

[6] Note that this relation $h_{it} = Q^* v^*_{it}$ implies that the hiring technology is constant returns to scale in vacancies. We provide evidence of this property later.

problem:

$$\max_{\{e_{it}(\mathrm{s}^t),v_{it}(\mathrm{s}^t),s_{it}(\mathrm{s}^t)\}_{\forall t,\forall \mathrm{s}^t|\mathrm{s}_0}} \quad \sum_{t=0}^{\infty}\sum_{\mathrm{s}^t|\mathrm{s}_0} \mathcal{M}_{it}\left(\mathrm{s}^t\right)\pi_{it}\left(\mathrm{s}^t\right) \quad , \quad \text{subject to} \tag{1}$$

$$\begin{aligned}
\pi_{it}(\mathrm{s}^t) &= f\Big(z_{it}\left(\mathrm{s}^t\right), n_{it}(\mathrm{s}^t)\Big) - w_{it}\left(\mathrm{s}^t\right) n_{it}(\mathrm{s}^t) - \mathcal{C}_i\Big(e_{it}(\mathrm{s}^t), v_{it}(\mathrm{s}^t), n_{it}(\mathrm{s}^t)\Big) v_{it}(\mathrm{s}^t) \\
n_{it+1}(s^{t+1}) &= \Big(1-\delta_{it+1}(s^{t+1})\Big) n_{it}(\mathrm{s}^t) + h_{it}(\mathrm{s}^t) - s_{it}(\mathrm{s}^t) \\
h_{it}(\mathrm{s}^t) &= Q_t^*(\mathrm{s}^t)\,\phi_i\,e_{it}(\mathrm{s}^t)\,v_{it}(\mathrm{s}^t) \quad , \quad v_{it}(\mathrm{s}^t) \geq 0 \quad , \quad s_{it}(\mathrm{s}^t) \geq 0.
\end{aligned}$$

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. Clearly, if the firm chooses positive endogenous separations $s_{it}(\mathrm{s}^t) > 0$, then recruiting inputs are optimally set to zero.

Separability. The problem separates into three stages: (1) decide whether to hire workers or separate with workers, (2) conditional on hiring, choose the optimal number of hires, which delivers the state-contingent policy $\{h_{it}(\mathrm{s}^t)\}_{t,\mathrm{s}^t}$, (3) choose inputs to minimize the recruiting costs associated with $h_{it}(\mathrm{s}^t)$. 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 $h_{it}(\mathrm{s}^t)$, the firm solves a static recruiting cost-minimization problem at each node s^t.[7]

Recruiting problem. Since the aggregate history only enters the recruiting problem through $Q_t^*(\mathrm{s}^t)$ and $h_{it}(\mathrm{s}^t)$, it is redundant once Q_t^* and h_{it} are taken as given by the firm at the recruiting stage. The problem of a firm with employment n_{it} and target hires h_{it} is therefore

$$\min_{e_{it},v_{it}} \; \mathcal{C}_i\Big(e_{it}, v_{it}, n_{it}\Big) v_{it} \qquad \text{s.t.} \qquad h_{it} = Q_t^*\,\phi_i\,e_{it}\,v_{it}. \tag{2}$$

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

[7] It is worth noting that there may exist cases in which we would not be able to attain this separability because current recruiting effort would affect future employment, even conditional on current hires. For example, suppose that firms vary their screening effort and low screening effort leads to hiring workers who are more likely to quit next period. In this case, in the law of motion for employment in (1) the exogenous separation rate δ_{it+1} would depend on e_{it}, i.e. e_{it} would affect n_{it+1} over and above its effect on h_{it}.

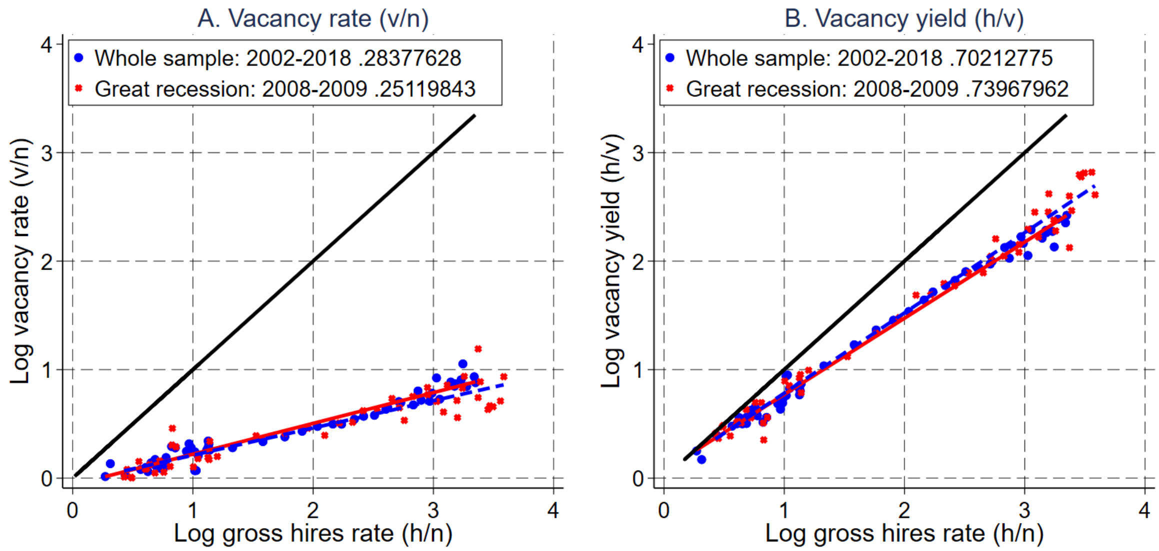


Figure 1: Vacancy rate and vacancy yield by gross hiring rate - JOLTS 2002-2018

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.

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 Figure 1. Our first theoretical contribution is to show that this relationship places tight and precise restrictions on C_i.

Proposition 1. ***If and only if*** *(i) the per-vacancy cost function C_i is of the following form:*

$$C_i\left(e_{it}, v_{it}, n_{it}\right) = x_i\, G_c\left(G_e(e_{it}) + G_v\left(\frac{v_{it}}{n_{it}}\right)\right)\,, \tag{3}$$

where the functions G_c, G_e and G_v are all isoelastic (constant elasticity), ***then*** *(ii) firm 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.*

The ***if*** component of Proposition 1 could be viewed as an exercise in structural reverse engineering: it reassuringly demonstrates that *there exists* a cost function that delivers the empirical relationship we observe in the data. The more substantive contribution of Proposition 1 is the ***only if*** component, which requires a more involved proof stating that the empirics places a very strong restriction on the theory. The ***only if*** part provides a family of functions for future work and, importantly, restricts the number of parameters in C.[8]

We make three points regarding cost functions implied by Proposition 1. First, individual level firm heterogeneity is restricted to entering through the multiplicative shifter x_i. Second, the requirement that the cost function depends on the vacancy *rate* tells us that in the data, firms find it more costly to add a given number of positions v in a small firm than in a larger firm (e.g., in terms of reorganization of production). Third, hiring inputs are *complements* in production: raising recruiting intensity makes each vacancy more productive. Through the cost function the data also reveals to us that they complements in costs. That is, any further microfoundation of behavior will require models in which increasing vacancies must increase the marginal cost of allocating more resources to recruiting intensity.

In order to adhere to the data, in what follows we consider only the class of functions $\mathcal{C}_i$ that satisfy this property. We let the three constant elasticities of the functions $G_c(\cdot)$, $G_e(\cdot)$ and $G_v(\cdot)$ be given by γ_c, γ_e and γ_v, respectively.

Optimal recruiting intensity. In Appendix B we show that minimization of (3) subject to the hiring constraint yields the following optimal policy for recruiting intensity which we express in logs

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

The constant includes the elasticity γ_c and other parameters.

To interpret the optimal policy it is useful to think of the firm's hiring technology in (2) as a production function that produces a hiring rate (h_{it}/n_{it}), with inputs of the vacancy rate (v_{it}/n_{it}) and recruiting intensity (e_{it}), and productivity term $(Q_t^* \phi_i)$. The firm's recruiting intensity depends positively on its hiring rate: more output requires more inputs. These inputs

[8] In the two equilibrium macroeconomic models of recruiting intensity that we are aware of, Gavazza, Mongey, and Violante (2018) assume a cost function that is a special case of this class, and Leduc and Liu (2020) 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.

are more productive when the rate at which effective vacancies produce hires due to market-wide productivity in matching (Q_t^*) or idiosyncratic productivity in matching (ϕ_i), are high, requiring less inputs. In equilibrium Q_t^* encodes the mass of idle workers and their average search intensity as well as the vacancies of competitors V_t and their recruiting intensity decisions. Below we show that recruiting choices of hiring firms are *strategic complements*.[9]

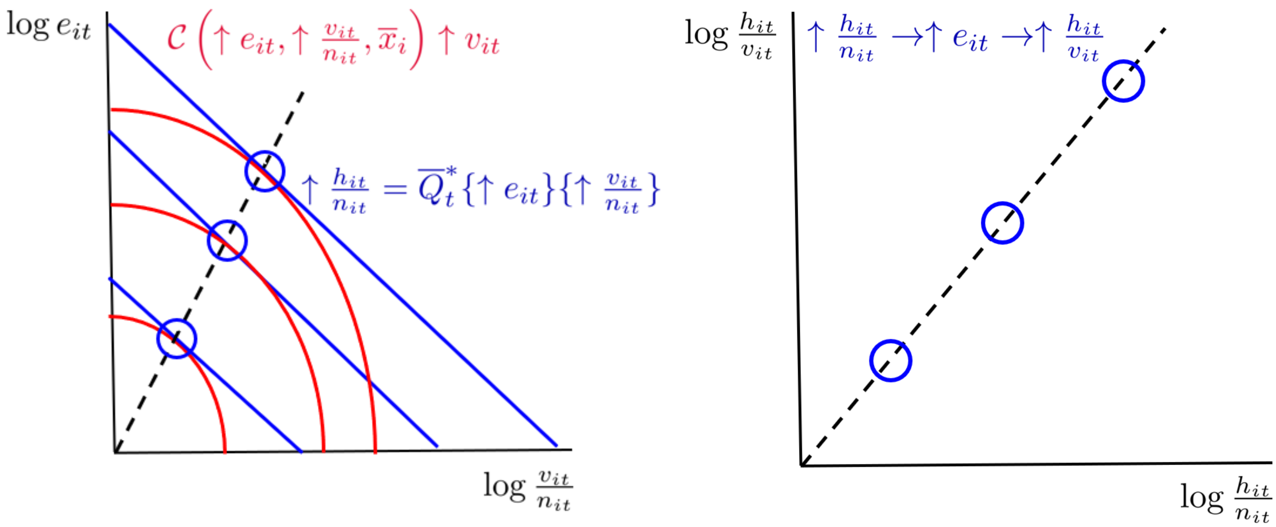
How is the shape of the policy function determined by the elasticities γ_v and γ_e? When γ_v is large relative to γ_e increasing marginal costs of vacancies set in quickly. This leads the firm to adjust more on the recruiting intensity margin in response to an increase in the demand for inputs due to an increase in output ($\uparrow h_{it}/n_{it}$). Similarly, when productivity falls ($\downarrow Q_t^* \phi_i$), the firm raises the recruiting intensity margin more the larger is γ_v relative to γ_e. The functional form for the hiring technology implies that optimal recruiting intensity responds symmetrically to either shift, which is reflected in equal but oppositely signed coefficients in (4).

Vacancy yield. Combining the firm's hiring technology and optimality condition (4) delivers the optimal vacancy yield which, unlike e_{it}, is observable in JOLTS microdata:

$$\log\left(\frac{h_{it}}{v_{it}}\right) = Const. + \frac{\gamma_e}{\gamma_e + \gamma_v} \log Q_t^* + \frac{\gamma_e}{\gamma_e + \gamma_v} \log \phi_i + \frac{\gamma_v}{\gamma_e + \gamma_v} \log\left(\frac{h_{it}}{n_{it}}\right). \quad (5)$$

Figure 2 provides a graphical characterization of the cost-minimizing recruiting choice in terms of unobserved intensity and observed vacancy yield, and how these respond to changes in the firm's desired hiring rate. Figure 2(a) shows how an increase in the hiring rate is equivalent to shifting out isoquants of the hiring technology in log vacancy-rate / recruiting intensity space. The firm then chooses the combination of hiring inputs that place it on its lowest isocost curve subject to the technology, where the composite parameter $\gamma = \gamma_v/(\gamma_e + \gamma_v)$ determines the gradient of the isocost curves. Under a cost function that satisfies Proposition 1, an increase in h_{it}/n_{it} leads to a log-linear expansion path of the vacancy-rate and recruiting intensity, with the slope of this path determined by γ. Figure 2(b) shows how this maps into the log-linear relationship between the hiring rate and vacancy yield that we observe in the microdata in Figure

[9]Clearly, Q_t^* might also encompass other factors determining the aggregate level of match efficiency in the economy which we do not model explicitly, such as the degree of sectoral mismatch between job-seekers and vacancies.



(a) Optimal recruiting choice as desired hiring rate increases

(b) Observable outcomes consistent with Figure 1

Figure 2: Microeconomic choice of recruiting intensity

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 logs (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 observable 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.

1. The key result is that the slope of the observed relationship in Panel B is informative of the marginal rate of substitution between inputs in Panel A, and hence γ_v and γ_e.

2.2 Macroeconomic environment

We construct our empirical measure of aggregate recruiting intensity (ARI) in two steps. First, we aggregate establishment level recruiting decisions into our measure of ARI. Second, since establishment level recruiting decisions depend on the meeting rate Q_t^*, which itself depends on ARI, we have to solve a general equilibrium fixed point. A contribution of the paper is to derive this fixed point in closed form and characterize the multiplier associated with changes in market tightness on ARI.

In order to aggregate establishment level recruiting decisions we specify an aggregate matching function that is consistent with the firm level hiring constraint $(h_{it} = Q_t^* \phi_i e_{it} v_{it})$:

$$H_t = V_t^{*\,\alpha} S_t^{*\,1-\alpha} \quad , \quad V_t^* = \int \phi_i e_{it} v_{it}\, di \quad , \quad S_t^* = \sum_{k=1}^{K} a_{kt} \mathcal{S}_{kt}, \tag{6}$$

This delivers consistency in that $H_t = \int h_{it} di = Q_t^* V_t^*$. 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, and their masses $\{\mathcal{S}_{kt}\}_{k=1}^K$. Let type $k = 1$ denote unemployed workers. We normalize the search intensity of the unemployed to 1 such that in (6) we have $a_{1t}\mathcal{S}_{1t} = U_t$ where U_t is the measure of unemployed workers. Multiplying and dividing the matching function by $U_t^{1-\alpha}$ we obtain $H_t = A_t V_t^{*\,\alpha} U_t^{1-\alpha}$, where A_t is *aggregate worker search intensity*:

$$A_t = \left[\sum_{k=1}^{K} a_{kt} \frac{\mathcal{S}_{kt}}{U_t} \right]^{1-\alpha}. \tag{7}$$

The term in the square bracket reflects the composition of the pool of job seekers.

The empirical matching function $H_t = A_t V_t^{*\,\alpha} U_t^{1-\alpha}$ contains unobserved effective vacancies, but can be expressed in terms of JOLTS vacancies, unemployment and *aggregate recruiting intensity* Φ_t, which we define:

$$H_t = \Phi_t A_t V_t^{\alpha} U_t^{1-\alpha} \quad , \quad \Phi_t = \left(\frac{V_t^*}{V_t} \right)^{\alpha} = \left[\int \phi_i e_{it} \frac{v_{it}}{V_t}\, di \right]^{\alpha}. \tag{8}$$

Note, however, that this is only a *partial equilibrium* definition. Changes in Φ_t alter the tightness of the labor market, and hence meeting rates Q_t^*, which affect choices of search intensity e_{it}. Hence Φ_t is in both the left and right sides of (8).

General equilibrium. To solve for Φ_t in general equilibrium, first let $\theta_t = (V_t/U_t)$ denote *measured market tightness*. The matching function implies that the aggregate meeting rate $Q_t^* = H_t/V_t^*$ depends on $\{\Phi_t, A_t, \theta_t\}$:

$$Q^*\left(\Phi_t, A_t, \theta_t\right) = A_t \left(\frac{V_t^*}{U_t} \right)^{-(1-\alpha)} = \left(\frac{V_t^*}{V_t} \right)^{-(1-\alpha)} A_t \left(\frac{V_t}{U_t} \right)^{-(1-\alpha)} = \Phi_t^{-\frac{1-\alpha}{\alpha}} \underbrace{A_t \theta_t^{-(1-\alpha)}}_{:=Q(A_t,\theta_t)}. \tag{9}$$

Here we define $Q(A_t, \theta_t) := Q^*(1, A_t, \theta_t)$, which we use extensively below. Given this definition $Q(A_t, \theta_t)$ is equal to the *measured meeting rate*, $Q(A_t, \theta_t) = H_t/V_t$.

We measure aggregate recruiting intensity in general equilibrium by substituting the microeconomic optimal policy (4) into the macroeconomic aggregate (8):

$$\Phi_t = \left[\int Q^* \left(\Phi_t, A_t, \theta_t \right)^{-\gamma} \phi_i^{1-\gamma} \left(\frac{h_{it}}{n_{it}} \right)^{\gamma} \frac{v_{it}}{V_t} \, di \right]^{\alpha} \quad , \quad \gamma := \frac{\gamma_v}{\gamma_e + \gamma_v} \in (0, 1). \tag{10}$$

Along with (9), this describes a mapping $\Phi' = \varphi(\Phi, Q)$, for which general equilibrium ARI is the fixed point.

Characterization. A key property of the mapping φ is that recruiting intensity decisions across firms are *strategic complements*. That is, $\varphi(\Phi, Q)$, is such that $\varphi_\Phi \in (0, 1)$, and hence the solution is also stable. Intuitively amplification occurs as follows. An increase in Φ tightens the labor market. From the macroeconomics of the frictional labor market, this decreases the meeting rate Q^* with elasticity $\frac{1-\alpha}{\alpha}$ (equation 9). From the microeconomics of firm behavior, firms respond to this decline in effective meeting rates by increasing recruiting intensity with elasticity γ (equation 4). When aggregated, this microeconomic response increases Φ' with elasticity α (equation 8). Combining these three forces, a one percent increase in Φ increases Φ' by $\gamma(1-\alpha) \in (0, 1)$ percent. Since $\gamma(1-\alpha) < 1$, this recursive system is stable, and features a multiplier of $1/(1-\gamma(1-\alpha))$. If γ is large, as we will find it is in the data, then these general equilibrium multiplier effects can also be large.

From this we can derive the general equilibrium multiplier associated with a change in the effective meeting rate Q_t^*. The *partial equilibrium direct effect* of an increase in Q_t^* on Φ_t is $-\gamma\alpha$. From the firm level policy, a change in Q_t^* affects e_{it} with elasticity $-\gamma$ (4), which is propagated via V_t^* to Φ_t with elasticity α (8). To get to the *general equilibrium indirect effect* we apply the multiplier on Φ_t and conclude that a one percent increase in Q_t^* decreases Φ_t by $-\gamma\alpha/(1-\gamma(1-\alpha)) < -\gamma\alpha$. Note that, for given α, the closer is γ to 1 the larger is the multiplier effect. Figure 3 illustrates this equilibrium mechanism for an increase in Q^* and the resulting decline in Φ. A higher value of γ would flatten the blue and red curves representing $\varphi(\Phi, Q)$, holding Q fixed. This would increase the multiplier effect.

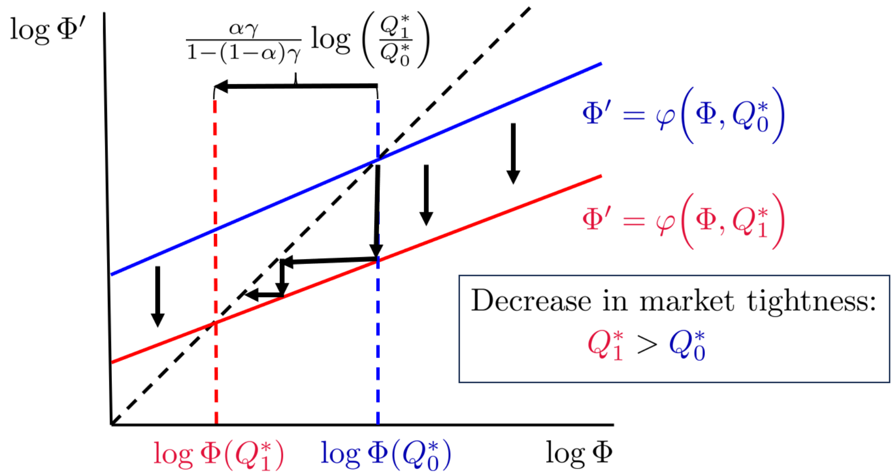


Figure 3: Macroeconomic propagation of recruiting intensity

Notes: This figure describes the general equilibrium of the model. Given Φ on the x-axis, the angled lines plot the equilibrium response $\Phi' = \varphi(\Phi, Q^*)$. An increase in $Q_1^* > Q_0^*$ shifts this function down, leading to a greater than one-for-one decrease in $\Phi' < \Phi$. The overall decline in Φ is determined by the increase in Q and the elasticity $-\gamma\alpha/(1-\gamma(1-\alpha))$, consistent with equation (11).

Theoretical decomposition of ARI. By consolidating (10) we obtain our the main relationship, which we will decompose empirically. First, we substitute our expression for the meeting rate (9) 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:

$$\Phi_t = \underbrace{Q\Big(A_t, \theta_t\Big)^{-\frac{\gamma\alpha}{1-\gamma(1-\alpha)}}}_{Slack_t} \underbrace{\left(\frac{H_t}{N_t}\right)^{\frac{\gamma\alpha}{1-\gamma(1-\alpha)}}}_{Growth_t} \underbrace{\left[\int \phi_i^{1-\gamma} \left(\frac{h_{it}/n_{it}}{H_t/N_t}\right)^{\gamma} \frac{v_{it}}{V_t}\, di\right]^{\frac{\alpha}{1-\gamma(1-\alpha)}}}_{Comp_t}. \tag{11}$$

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: 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, following 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 distribution of vacancies 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, absent heterogeneity, if hiring firms are identical then Φ_t exactly equals $(Slack_t \times Growth_t)$.

Implementation. Equation (11) can be used to answer our question: what drives aggregate recruiting intensity over the business cycle, and what are the roles of micro decisions and macro propagation. Our approach is to implement (11) empirically by constructing each term entirely from microdata.[10]

In doing so we must resolve the issue that A_t is not observed. 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 (11) because we do not observe A_t. Rather than try to construct A_t from worker search data and (7), which we do not seek to model here, we approach this in a model-consistent way by using a cross-equation restriction imposed by general equilibrium. Note that the matching function itself provides an additional equation in observables $\{H_t, V_t\}$ and the same two unknowns $\{\Phi_t, A_t\}$:

$$H_t = \Phi_t A_t V_t^{\alpha} U_t^{1-\alpha} \tag{12}$$

[10]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.

Our empirical implementation therefore proceeds in four steps. First, we estimate ϕ_i and γ using the firm's first order condition (5). Second, combining microdata on $\{h_{it}, n_{it}, v_{it}\}$, our estimates of ϕ_i and γ, and a choice of α we construct $Comp_t$. Third, combining macrodata on $\{H_t, N_t\}$, our estimate of γ and choice of α we construct $Growth_t$. Fourth, we use $Comp_t$ and $Growth_t$ along with aggregate data $\{H_t, N_t, V_t, U_t\}$ to simultaneously solve for Φ_t and A_t from equations (11) and (12).[11]

3 Measurement using microdata

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.[12] Apart from a permanent sample of firms that have remained in the JOLTS since inception, most establishments are present in the survey for 24 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 employment and total quarterly compensation observations for the universe of establishments.[13] From the QCEW we compute establishment *wage* as total payroll divided by average monthly employment.[14] We obtain establishment *age* using a BLS-produced entry date 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

[11]Specifically, equation (12) can be written as $(H_t/V_t) = \Phi_t Q_t$, and equation (11) can be written as $\Phi_t = Q_t^{-\mu}(H_t/N_t)^{\mu} Comp_t^{\mu/\gamma}$ where $\mu = \gamma\alpha/(1-\gamma(1-\alpha))$. These can be solved for Φ_t and Q_t. We then use $Q_t = A_t(V_t/U_t)^{-(1-\alpha)}$ to back out A_t. The data requirements for this inversion are the economywide hiring rate (H_t/N_t), vacancy yield (H_t/V_t) and market tightness (V_t/U_t), as well as $Comp_t$ which we construct from aggregating our microdata.

[12]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.

[13]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.

[14]We impute the same wage to the establishment in each month of the quarter. When we compute wage growth, we compute quarterly wage growth.

age and average wage for JOLTS establishments.[15]

Summary statistics. The decomposition (11) shows that, theoretically through $Comp_t$, heterogeneity can play an important role in shaping ARI. Figure 4 motivates careful measurement of $Comp_t$ by depicting the vast heterogeneity in hiring in the cross-section. There is systematic heterogeneity across industries, ages, sizes and wages in recruiting outcomes of firms. The vacancy rate and gross hiring rates (panels A, B, C, D) and the number of hires relative to open vacancies (panels E, F, G, H), all vary systematically.[16] This evidence rejects the canonical random matching model where all firms face the same vacancy filling rates. Our model interprets these differences as systematically different recruiting intensities, and aggregates them into the $Comp_t$ term.

Specification. Using data at the month t, establishment i level, we would ideally estimate the following specification, which is the empirical counterpart of (5):

$$\log\left(\frac{h_{it}}{v_{it}}\right) = \delta_t + \xi_i + \beta \log\left(\frac{h_{it}}{n_{it}}\right) + \varepsilon_{ijt}. \tag{13}$$

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 (10). Instead, as we have shown, we construct $Q(A_t, \theta_t)$ directly. However 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 on $\{h_{it}, n_{it}\}$ we can then construct all terms in $Comp_t$ in equation (11).

Implementation. First, due to short panels of only twelve months at the firm level, we group firms into J groups, and estimate a single ξ_j for each group. We seek to be robust to the particular grouping of firms used, so consider different approaches, allowing j to determine quintiles of a number of variables, for example, quintiles of establishment age. Second, due to zeros

[15]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).

[16]The *daily filling rate* in these last four panels is computed from the daily recruiting model of DFH. Details and closed forms are found in Appendix B. For statistics that require employment in the previous month, we follow DFH and create a backward consistent measurement taking into account gross hires and separations: $n_{it-1} = n_{it} - (h_{it} - s_{it})$.

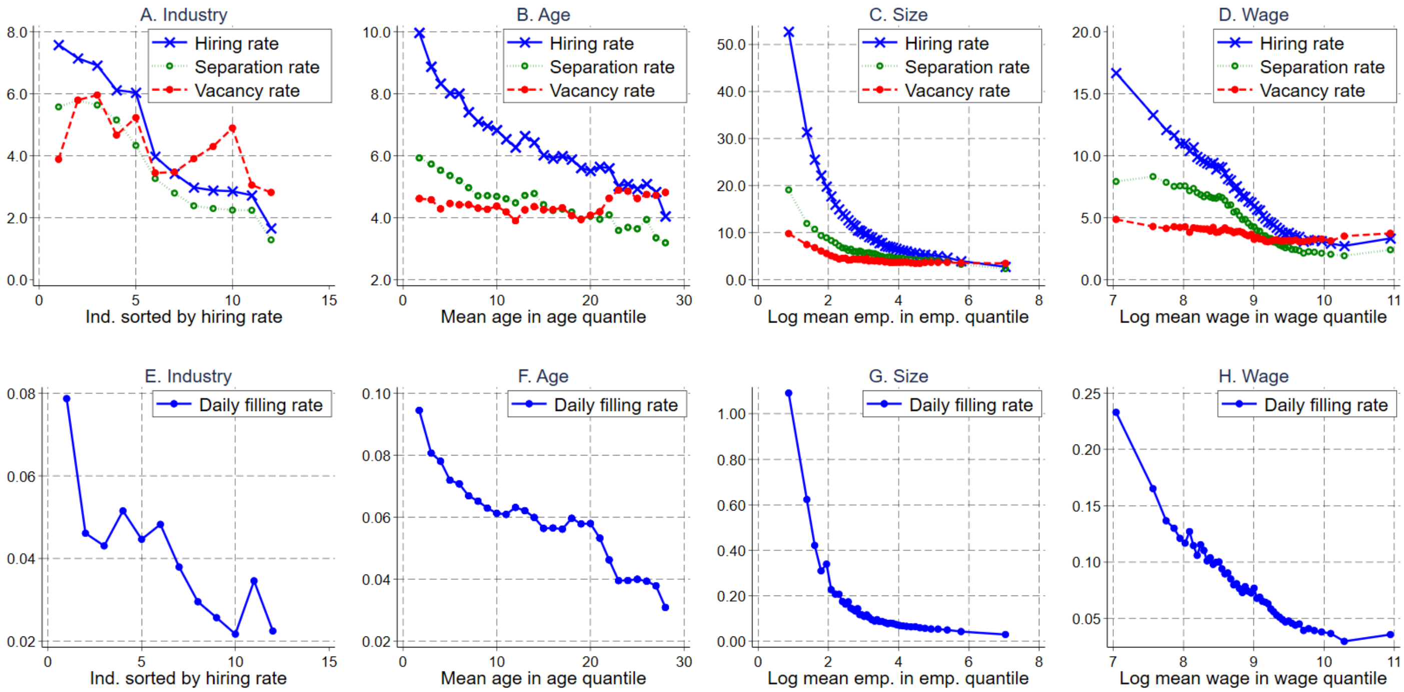


Figure 4: Summary statistics of heterogeneity in recruiting

Notes: Consider a point in panel C, for example. Establishment-month observations are first categorized by 50 quantiles of establishment size. When constructing quantiles we pool all data from 2002-2018. Within a size 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 into industries according to groupings of NAICS codes defined in Table C1, we then sort industries by hiring rate to construct the x-axis. In Panel B, they are categorized by their age, in years. In Panel C, they are categorized into size-groups measured as total employment. In panel D, they are categorized by average firm-wage computed as total payroll divided by employment. Panels E to H plot the daily filling rate computed from the daily recruiting model of DFH outlined in Appendix B.

in hires and vacancies at the monthly frequency for individual establishment, we aggregate within j to determine our i's.[17] We split out i within j by using fine industry codes. For example, one specification uses age quintiles for j and then within each age quintile we aggregate firms within $NAICS$ 4-digit industries to construct h_{ijt}, n_{ijt} and v_{ijt}. Thus, in this case, i indexes all firms of a specific 4-digit industry within an age quantile.[18]

[17] For example, for all firms that hire during the month $h_{it} > 0$ but some firms will hire with no vacancies v_{it-1}. As noted by DFH, around 40 percent of hires in month t ($h_{it} > 0$) occur in establishments with no vacancies at the end of month $t-1$ ($v_{it-1} = 0$). They pool data across time (2001-2006) within a growth rate bin in constructing their key Figure IX. Our approach is to pool at a far finer level: for example, within an {age-quantile}-{4 digit industry code}-{month} cell.

[18] 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 for non-response, as well as generating a representative sample.

The above strategy delivers numerous alternative approaches to estimating the following modification of (13):

$$\log\left(\frac{h_{ijt}}{v_{ijt}}\right) = \delta_t + \xi_j + \beta \log\left(\frac{h_{ijt}}{n_{ijt}}\right) + \varepsilon_{ijt}. \tag{14}$$

We consider many different variables whose quintiles are used to define the groups j. Our baseline results are given for j in {age, size, wage, 1-digit industry, separation rate, quit rate, turnover rate, employment growth rate}. Within these groups j, we then consider 4 different levels of aggregation which determine i, and aggregate within-(ijt) to obtain h_{ijt}, n_{ijt} and v_{ijt}. Our baseline results are given for i in NAICS-{1,2,3, or 4} digit industries. Hence, for example, when grouping firms by age, h_{ijt} may be total hires of all establishments in the lowest quintile of age (j) of establishments in a particular NAICS4 industry (i) in that month (t).[19]

Estimates. Table 1 provides estimates of $\widehat{\beta}$ which is our estimate of γ for 31 different specifications of (14). Our results are broadly robust to the different approaches for categorizing firms into groups based on heterogeneity in recruiting productivity ϕ_j and aggregation. Across the 31 cases, the mean estimate is 0.726, with an interquartile range of $[0.701, 0.761]$. These estimates are also precise, with a mean standard error of 0.007 and maximum standard error of 0.026. We do note that as we move from left to right—defining i by narrower levels of aggregation within groups j—the estimate tends to fall, suggestive of measurement error as the sample used to construct (ijt) measures gets smaller and becomes noisy due to zeros. By comparison, DFH group firms by 100 bins of net employment growth (i), aggregate all observations within these groups over 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, age quintile}-level.[20] We now show that these results are robust to a number of different treatments of the data.

3.1 Extensions

Narrower variation. Theory suggests that equation (14) should be estimated with separable time and group fixed effects. Despite this, we can verify that our estimates of β are consistent

[19] When j is 1-digit industries, we only consider NAICS-{2,3, or 4} digit aggregation leading to $12 + 3 = 15$ specifications in total.

[20] Note that we cannot disclose estimates of the ξ_j terms that are used to infer ϕ_j coefficients, or the h_{ijt}, v_{ijt}, n_{ijt} terms constructed for the estimation of (14).

Categories for j are quintiles of:	Level of aggregation for i			
	NAICS1	NAICS2	NAICS3	NAICS4
Industry	-	0.76 (0.008)	0.77 (0.007)	0.73 (0.004)
Age	0.84 (0.009)	0.77 (0.006)	0.76 (0.004)	0.73 (0.003)
Size	0.83 (0.010)	0.76 (0.009)	0.65 (0.005)	0.64 (0.004)
Wage	0.78 (0.009)	0.74 (0.006)	0.76 (0.004)	0.72 (0.003)
Separation rate	0.70 (0.011)	0.72 (0.007)	0.75 (0.004)	0.73 (0.003)
Quit rate	0.73 (0.012)	0.73 (0.008)	0.77 (0.004)	0.77 (0.003)
Turnover rate	0.51 (0.026)	0.63 (0.016)	0.68 (0.007)	0.69 (0.005)
Emp. growth rate	0.69 (0.010)	0.71 (0.008)	0.72 (0.005)	0.72 (0.003)

Table 1: Coefficient estimates

Notes: Point estimates of the coefficient on the hiring rate from regression (13), with standard errors in parentheses. 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.

with using narrower sources of variation. Appendix A provides estimates of β using only within-group-time, across-industry variation (i.e. using a (jt)-fixed effect, Table A1), and only within-group-industry, across-time variation (i.e. using a (ij)-fixed effect, Table A2). In both cases we find remarkably similar estimates to those in Table 1. In the former (latter) case the average estimate is 0.727 (0.739), with an average standard error of 0.007 (0.008). The first of these additional specifications makes clear identification of β in (14): ξ_{jt} pulls out the time series of group (e.g. age quintile-month) means, while β is identified using *within-group-month*, *across-industry* variation, where this variation is at as fine as a NAICS4 level.

In the following section we will use our estimates of the fixed effects to construct the composition term. Even in the case where we are estimating ϕ_{ij} fixed effects we have many observations per fixed effect. In our baseline specification, the average ϕ_j fixed effect has more than 200,000 observations behind it. Even when we estimate ϕ_{ij} fixed effects (Table A2), the average ϕ_{ij} fixed effect has close to 1,000 observations (Appendix Table A3) because we are pooling data across all months of the sample when estimating these fixed effects.

Wage growth. One might imagine that either wages or wage growth are systematically correlated with hiring rates and vacancy filling rates (either because high-wage firms attract more job seekers or because low-wage firms are those with low hiring standards), and that this variation may be responsible for the positive relationship between hiring rates and vacancy yields. When we control for these variables, however, the relationship remains the same. We residualize the log establishment wage (or wage growth) on NAICS3-month fixed effects and group firms by quantiles of these residuals. Hence we control for positions in the within-NAICS3-month wage (or wage growth) distribution. Table A4 shows that the estimates of β are unchanged. Table A5 shows that adding in $(jt)-$ fixed effects does little to change the estimates. The same holds if we group firms by the average value of their residual over the sample (lower panel of each table). Hence, *within* the group of firms that are paying the most in an industry, or whose wages are growing the most in an industry, those firms with higher hiring rates have higher vacancy yields.

One may be concerned that average wage is more about workforce composition within the establishment than about how much a firm pays similar workers, and hence the average wage is a poor measure of firm attractiveness or hiring standards. Using residual wages within 3 digit industries—where we may hope that composition of occupations is roughly constant—attempts to address this (see Table A4). A better approach would be to join the *Occupation Employment Statistics* (OES) microdata to our JOLTS/QCEW merged data. The OES has data on employment by occupation at the establishment level. Unfortunately, we were not able to add access to the OES to this project.

Quit rates. One may think that firms that have higher quit rates would have to generate more hires and do so by filling vacancies more quickly. That is, in an interacted specification higher quit rates firms may have a *higher* elasticity of hiring rate to vacancy yield. We run our entire analysis separately for establishments by the quintile of their quit rate. Due to disclosure issues we could only disclose results for these specifications where firm groups j are heterogeneous in their average wage level and, within group, these establishments are aggregated at the NAICS1 level (row 4, column 1 of Table 1). Figure A1 shows stable estimates across quit quintiles which slightly *decrease* at higher quit rates.

Across groups. Our fixed effects specifications compare establishments within a group of establishments (e.g. young firms in a particular month). We may also compare the groups of establishments themselves. Figure 5 compares means across different categorizations of firms. For a given categorization—size, age, wage, industry—we split firms into 15 quantiles. Within

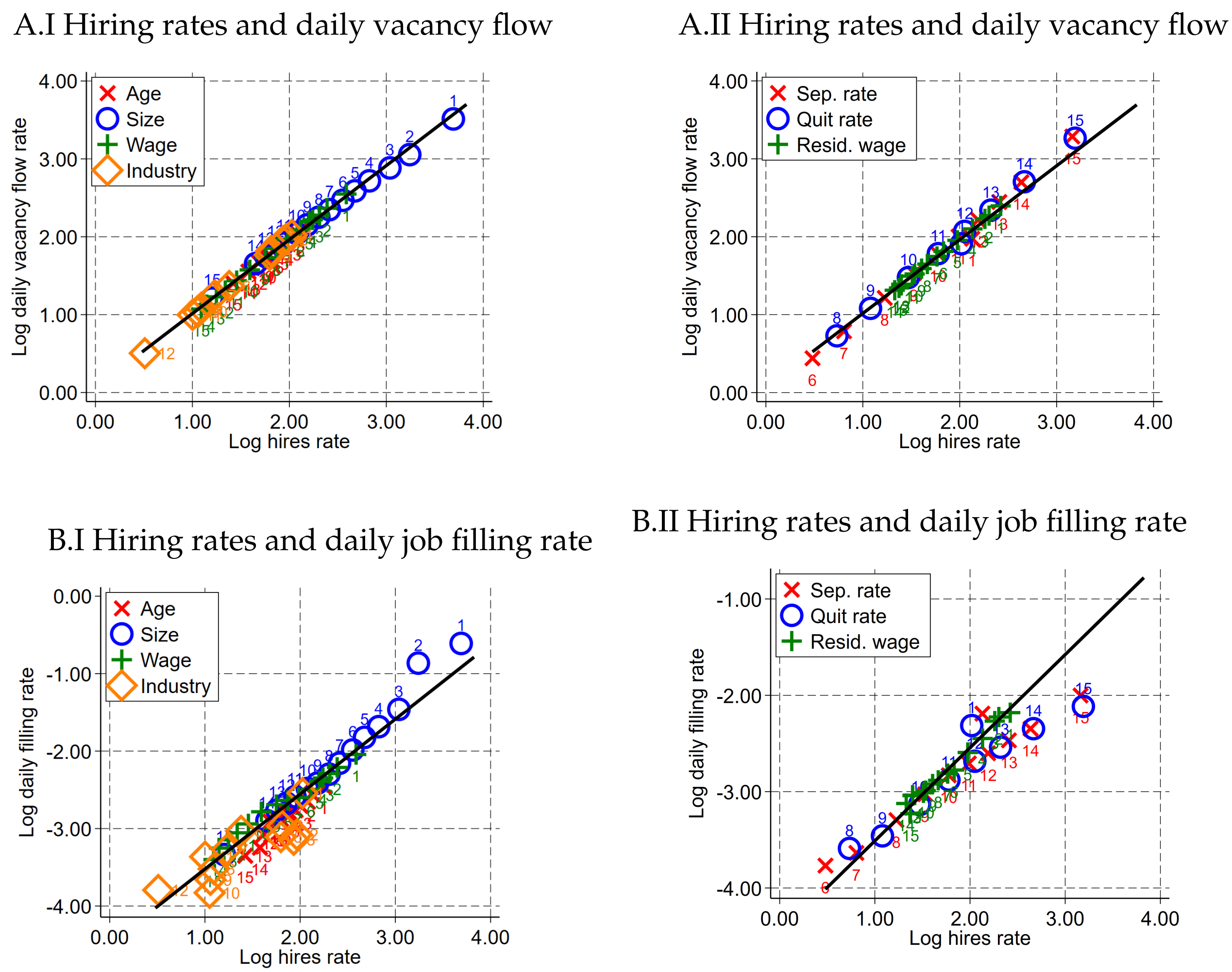


Figure 5: Recruiting intensity in the cross-section

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, and (D) vacancy yield (hires over vacancies). 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.

each group we pool employment, hires and vacancies to compute the average hiring rate and vacancy yield.[21] Remarkably, across-group differences in vacancy filling rates are revealed entirely through differences in hiring rates. If there was something special about the efficiency of young (or small, high-wage, etc.) firms in attaining higher vacancy yields, we would ex-

[21]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.

pect them to deviate from the systematic relationship between hiring rate and vacancy yield displayed in the data. In all cases the same pattern holds: differences *across* groups in the average vacancy yield and filling rate are determined by differences *across* groups in average hiring rates.

'Luck' Finally, one may be concerned that 'luck' drives these results. Given some measure of vacancies, some firms get lucky and hire many workers, which increases both their vacancy-yield and hiring-rate. These appear on the left and right side of (13), and would lead to a positive β while the underlying parameter γ is potentially zero. There are three reasons this is not a concern. First, in each regression firms are aggregated within narrow groups×industries, and hence these idiosyncratic events would wash out across the firms in each cell. Second, and in a similar spirit, luck can be ruled out by the systematic relationship shown *across groups* in Figure 5. This 'luck' would have to be perfectly correlated with establishment age, size, wage, and industry. Third, this possibility is also covered by DFH through Monte-Carlo exercises.[22] They conclude that *"the luck effect accounts for one-tenth of the observed positive relationship"*, which would moderate our estimates in Table 1 by $0.06 - 0.08$.

4 Aggregating to macro recruiting intensity

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 (10), and decompose it using (11). The only additional object we require is the matching function elasticity of meetings to effective market tightness. For the matching function elasticity, we set $\alpha = 0.25$. This is the mid-point of estimates in Barnichon and Figura (2015) (0.18-0.34). Shimer (2005) arrives at an estimate of $\alpha = 0.28$. Section 5 shows that our main results are robust to values of 0.15 and 0.50.

4.1 Variance decomposition

Table 2 decomposes the time-series variance of aggregate recruiting intensity using (11): $\Phi_t = Constant \times Slack_t \times Growth_t \times Comp_t$. We take logs of (11), deseasonalize each with X13-

[22]See their page 601 and Figure VIII.

ARIMA-SEATS filter, then difference from December, 2007, which removes constant terms. We then compute the time-series variance of each term. Table 2 expresses the fraction of the overall variance accounted for by each term. We have one set of results for each grouping of firms (j) and level of aggregation (i) considered in Table 1. Fixing a grouping and level of aggregation we have estimated a β and ξ_j fixed effects, which are used to construct γ and ϕ_j required in equation (11). Hence for any grouping we get a new set of aggregate time series for $Slack_t$, $Growth_t$, $Comp_t$, Φ_t, and A_t.

Our main result is that, regardless of how we group establishments to compute ϕ_j or coarseness of aggregation within groups, the dominant component is $Slack_t$, on average accounting for 50 percent of the time-series variance of Φ_t. The $Growth_t$ and $Comp_t$ terms, combined, account for less than 15 percent. Unsurprisingly the covariance term is positive and large, but this is driven mostly by the covariance between the slackness and growth factors rather than covariances associated with $Comp_t$. The fifth column presents the share of the variance attributable to $Comp_t$ via an alternative decomposition approach, commonly used in international trade.[23] By this measure, on average, less than 10 percent of the variance is due to the composition term.

Our second result, therefore, is the small role for heterogeneity. To further understand this finding we split the composition term $Comp_t$ between and within groups:

$$\underbrace{\left[\int \phi_j^{1-\gamma}\left(\frac{h_{ijt}/n_{ijt}}{H_t/N_t}\right)^{\gamma}\frac{v_{ijt}}{V_t}\right]^{\frac{\alpha}{1-\gamma(1-\alpha)}}}_{\text{Composition from (11): } Comp_t} = \tag{15}$$

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

where h_{jt}, v_{jt} and n_{jt} are aggregates at the group-j, month-t level. The final columns of Table 2 show that in general the within group-j term dominates. That is, $Comp_t$ is not driven by cyclical reallocation of vacancy-shares across high or low ϕ_j groups, which would be captured by $Between_t$. We conclude that a single sector model capturing aggregate $(Slack_t, Growth_t)$ and

[23] We take the approach and the following description from (Hottman, Redding, and Weinstein, 2016). In logs, then demeaned, regressing $Slack_t$, $Growth_t$ and $Comp_t$ one by one on aggregate recruiting intensity Φ_t yields three coefficients that sum to one, and allocates out the covariance equally across components.

Categories for j are quintiles of	Aggregation level for i	1. Aggregate recruiting intensity					2. Composition		
		Slack	Growth	Comp.	Cov.	β_{Comp}	Between	Within	Cov.
Industry	NAICS2	0.48	0.06	0.02	0.44	0.098	0.26	0.32	0.42
	NAICS3	0.47	0.06	0.03	0.44	0.109	0.19	0.44	0.37
	NAICS4	0.45	0.07	0.05	0.43	0.119	0.22	0.65	0.13
Age	NAICS1	0.59	0.04	0.06	0.31	0.079	0.12	0.48	0.40
	NAICS2	0.54	0.06	0.04	0.36	0.063	0.10	0.58	0.32
	NAICS3	0.52	0.07	0.04	0.37	0.070	0.06	0.72	0.22
	NAICS4	0.48	0.07	0.14	0.31	0.139	0.09	0.59	0.32
Size	NAICS1	0.61	0.04	0.02	0.33	0.038	0.06	0.73	0.21
	NAICS2	0.53	0.07	0.03	0.37	0.057	0.33	1.13	-0.46
	NAICS3	0.43	0.09	0.05	0.43	0.095	0.16	0.98	-0.14
	NAICS4	0.42	0.09	0.08	0.41	0.116	0.04	0.84	0.12
Wage	NAICS1	0.55	0.06	0.04	0.35	0.052	0.15	0.49	0.36
	NAICS2	0.52	0.08	0.05	0.35	0.059	0.18	0.53	0.29
	NAICS3	0.52	0.07	0.05	0.36	0.071	0.08	0.75	0.17
	NAICS4	0.49	0.08	0.08	0.35	0.098	0.05	0.83	0.12
Separation rate	NAICS1	0.45	0.08	0.06	0.41	0.111	0.34	0.26	0.40
	NAICS2	0.47	0.07	0.07	0.39	0.108	0.30	0.32	0.38
	NAICS3	0.51	0.07	0.07	0.35	0.081	0.26	0.45	0.29
	NAICS4	0.53	0.08	0.09	0.30	0.065	0.25	0.66	0.09
Quit rate	NAICS1	0.54	0.08	0.05	0.33	0.036	0.22	0.36	0.42
	NAICS2	0.55	0.08	0.06	0.31	0.037	0.21	0.49	0.30
	NAICS3	0.64	0.08	0.07	0.21	-0.008	0.27	0.74	-0.01
	NAICS4	0.72	0.09	0.13	0.06	-0.053	0.32	0.95	-0.27
Turnover rate	NAICS1	0.30	0.10	0.14	0.46	0.229	0.96	0.28	-0.24
	NAICS2	0.40	0.09	0.12	0.39	0.150	0.68	0.28	0.04
	NAICS3	0.47	0.09	0.11	0.33	0.106	0.56	0.29	0.15
	NAICS4	0.48	0.09	0.11	0.32	0.097	0.34	0.30	0.36
Emp. growth rate	NAICS1	0.49	0.09	0.03	0.39	0.055	0.20	0.52	0.28
	NAICS2	0.50	0.08	0.04	0.38	0.056	0.20	0.58	0.22
	NAICS3	0.47	0.08	0.04	0.41	0.085	0.04	0.80	0.16
	NAICS4	0.48	0.08	0.07	0.37	0.099	0.02	0.84	0.14
Average		0.50	0.075	0.066	0.36	0.08	0.23	0.59	0.18

Table 2: Decomposing aggregate recruiting intensity

Notes: This table presents the time-series variance decomposition of equation (11) (**1. Aggregate recruiting intensity**) and (15) (**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 (13). 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.

firm-level behavior $(Within_t)$ could approximate well the cyclical behavior of Φ_t.

Figure 6 presents these results graphically. In Section 6, Figure 10 we plot all series of Φ_t

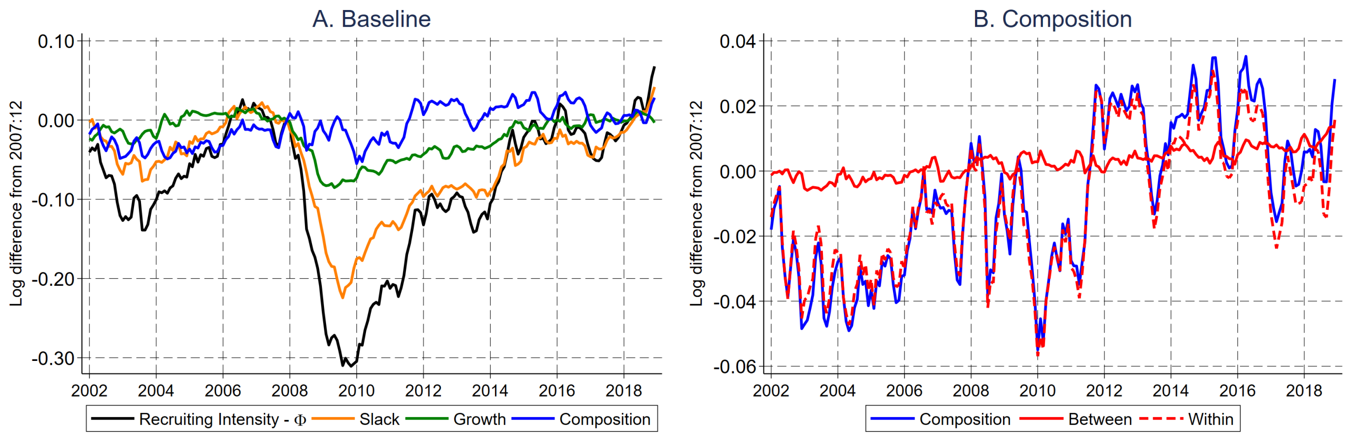


Figure 6: Decomposing aggregate recruiting intensity

Notes: Panels A and B present an example of the components of equations (11) and (15). 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. Time-series are first deseasonalised using X13-ARIMA-SEATS. For presentation only we then apply a three month centered moving average to each series.

across different groupings of j and i. Here we take a particular case as a representative example. We choose the case where j denotes quintiles of firm size, and within j we aggregate at the NAICS4 level to form (ijt) data (corresponding to line 11 in Table 2). Panel A shows the slackness component closely following Φ_t. A sizable drop in the growth component also contributes to the decline in ARI over the Great Recession. Panel B shows that, for this case, almost 100 percent of the composition term is driven by within size-quantile, across-NAICS4 variation in recruiting intensity.

In summary, we find that empirically, the components of aggregate recruiting intensity that do not reflect firm heterogeneity per se are the dominant forces that shape aggregate recruiting intensity. This result is robust to the manner in which permanent heterogeneity in recruiting efficiency is handled.

Finally, we note that this finding has a counterpart in direct survey evidence. There is a tradition in labor economics of designing small-scale ad-hoc surveys to investigate recruitment methods of firms. Some 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) where 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."

5 Robustness

5.1 Parameters and assumptions

First, we find that these results are robust to the value of the matching function elasticity α that we use. Appendix Table A6 and Table A7 replicate Table 2 using values of α of 0.25 and 0.75, respectively. The share of the variance accounted for by $Slack_t$ alone is 50% in the first case and 66% in the second. We can show that the share of the variance due to $Comp_t$ is invariant to α, at 0.066.[24] Second, that $Comp_t$ accounts for little of the fluctuations in ARI is not due to our estimates of γ deviating from the level found in DFH. Appendix Table A8 replicates Table 2 under γ of 0.82. Averaging across specifications, the share of fluctuations due to $Slack_t$ alone increases from 50% (Table 2) to 64% as recruiting decisions become more elastic with respect to market tightness. Third, using regressions with (ij)-fixed effects (Table A2) and using estimates of these in the construction of $Comp_t$ does not affect results. Appendix Table A9 sees the variance component due to $Slack_t$ fall by only 4 ppt.[25] Fourth, using regressions with groupings j by residualized wages and residualized wage growth (as in Table A4), does not affect results. Appendix Table A10 shows that under these groupings the share of the variance due to $Slack_t$ slightly increases to 0.51, as does the $Within_t$ piece of $Comp_t$.

5.2 Why is the composition effect small?

One of our main results is that the composition effect accounts for very little of the variation in aggregate recruiting intensity, but why is this? For intuition we rely on the quantitative model in our existing work Gavazza, Mongey, and Violante (2018, henceforth GMV). In GMV

[24] From equation (11), if we exponentiate all right hand-side terms by $(1-\gamma(1-\alpha))/\alpha$, then α disappears from the righthand-side. Then, when taking logs and decomposing the variance into shares, α does not change the share due to the $Comp_t$ variance. The allocation of the remainder to $Slack_t$ and $Growth_t$ change due to the overall solution under the substitution of the matching function (12).

[25] We can not conduct this decomposition exercise using the estimated ϕ_{jt} fixed effects associated with Table A1, since time variation in these terms cannot be separated from the aggregate terms.

we decompose the response of aggregate recruiting intensity following two aggregate shocks: a drop in TFP and a tightening of financial constraints. In both cases the slackness component dominates, which Table 2 of this paper verifies empirically. In GMV we then use the model to decompose the composition effect into two pieces: direct and indirect. The indirect effect is due to counterfactual changes in the hiring rate that would occur under the equilibrium path for market tightness, counterfactually holding the aggregate shock fixed. The direct effect is the residual. Note that this decomposition is not possible empirically.

Key to understanding the small role of $Comp_t$ is the fact that these two forces have strongly off-setting effects. The *direct effect* is strongly pro-cyclical, as one would expect: as financial constraints tighten or TFP declines, hiring rates fall, and along with this, so does recruiting intensity (recall Figure 2(a)). More surprising is that the *indirect effect* is strongly counter-cyclical: markets slacken, so firms that plan on hiring in fact hire more, pushing up hiring rates, and increasing recruiting intensity. We point out that one of the driving forces of this result is that, as is standard in models with heterogeneous firms, idiosyncratic productivity shocks are 'more important' to the firm's decisions than aggregate shocks. Hence, most of the hiring is done by firms that have realized, say, a persistent 10 percent increase in productivity. In slacker labor markets, these firms face a lower cost of hiring and hence hire more.[26]

Empirically, we can observe the outcome of these offsetting effects by noting small changes to the distribution of establishment growth rates, hiring rates and vacancy shares over the Great Recession (Figure 7). The distribution of establishments across establishment growth rates changed only slightly over the Great Recession, with a small shift of mass to the left (Panel A). Hiring rates fell across the distribution of growth rates, and most significantly at shrinking plants, nevertheless the heterogeneity pre-Great Recession remained largely intact (Panel B). Conditional on these hiring rates, however, vacancy rates fell across the board, consistent with vacancy posting optimality in a slacker labor market (Panel C). However, the overall distribution of openings moved very little (Panel D). Overall, we think this indicates an economy in which idiosyncratic factors dominate the cross-sectional heterogeneity in firm hiring decisions,

[26]Despite the fact that GMV is a model of a single representative sector without heterogeneity in ϕ_i, our empirics in this paper suggest that the logic outlined above should carry over. In an economy with no heterogeneity in ϕ_i, all fluctuations in $Comp_t$ are accounted for by $Within_t$, consistent with what we found in Table 2.

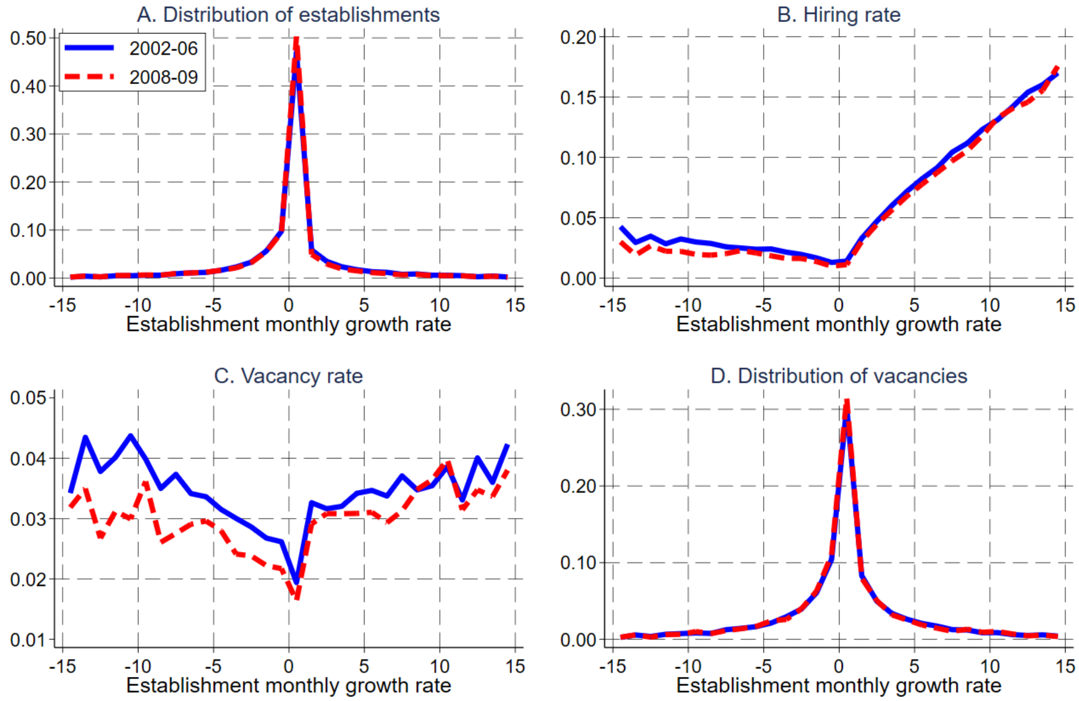


Figure 7: Cross-section of firms before and during the Great Recession

Notes: Establishment growth rates are computed monthly as $g_{it} = (n_{it} - n_{it-1})/(0.5(n_{it-1} + n_{it}))$, and establishments are binned by 1 percent increments. **Panel A., D.** In each bin we compute the total share of establishments (vacancies) across the given period. **Panel B., C.** In each bin we aggregate total hires, total vacancies and total employment across the given period and plot ratios of these. Only 5.6% (6.4%) of vacancies are outside of $\pm15\%$ growth rates in 2002-06 (2008-09).

while aggregate factors impact overall levels. In such an economy we may be surprised if the $Comp_t$ played a strong role in shaping aggregate recruiting intensity.

6 Applications

We use the above empirical results to construct an easily computable index of ARI. We test this index against the exact time-series for ARI that we have constructed, and show that it corresponds to true ARI in a representative firm model. We then use this formulation to conduct a simple counterfactual exercise to understand the role that ARI played in unemployment in the Great Recession.

6.1 An easily computable index of ARI

We build on the results of Section 4 to produce an easy to measure, microfounded, *index* of aggregate recruiting intensity which we denote Φ_t^{Index}. Our microdata exercise has taught us that we can capture the true empirical measure of Φ_t with only $Slack_t$ and $Growth_t$ and their covariance. Abstracting from the composition factor in (11), we obtain

$$\Phi_t^{Index} = \underbrace{Q\left(A_t, \theta_t\right)^{-\frac{\gamma\alpha}{1-\gamma(1-\alpha)}}}_{Slack_t} \underbrace{\left(\frac{H_t}{N_t}\right)^{\frac{\gamma\alpha}{1-\gamma(1-\alpha)}}}_{Growth_t} \tag{16}$$

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 $Q\left(A_t, \theta_t\right)$:

$$\frac{H_t}{V_t} = \Phi_t^{Index} Q\left(A_t, \theta_t\right). \tag{17}$$

Substituting (17) into (16) via $Q(A_t, \theta_t)$, it is clear that H_t drops out and we are left with a convenient expression that depends only on the aggregate *vacancy rate*. This expression is indexed by the elasticity of the matching function (α) and the micro-elasticity of recruiting intensity (γ). It is consistent with how firm behavior (16) depends on aggregates, and how aggregates depend on firm behavior (17):

$$\Phi_t^{Index} = \left(\frac{V_t}{N_t}\right)^{\frac{\gamma\alpha}{1-\gamma}}. \tag{18}$$

Figure 8 plots Φ_t^{Index}, alongside our empirical measure Φ_t. We plot the mean of all the different time series for Φ_t obtained under the different specifications in Table 2. The index closely tracks Φ_t. On average across the specifications of i and j in Table 2, Φ_t^{Index} accounts for 93.2 percent of the time-series variance of Φ_t, with a correlation of 0.97. We conclude that the index delivers an excellent approximation of the overall measure of aggregate recruiting intensity.

Comparison. By comparison, the index computed by DFH is $\Phi_t^{DFH} = (H_t/N_t)^{0.82}$. The foundation for their index is as follows. As discussed earlier, from JOLTS microdata they estimate equation (5) and obtain a micro-elasticity of the job filling rate to the gross hiring rate of 0.82.

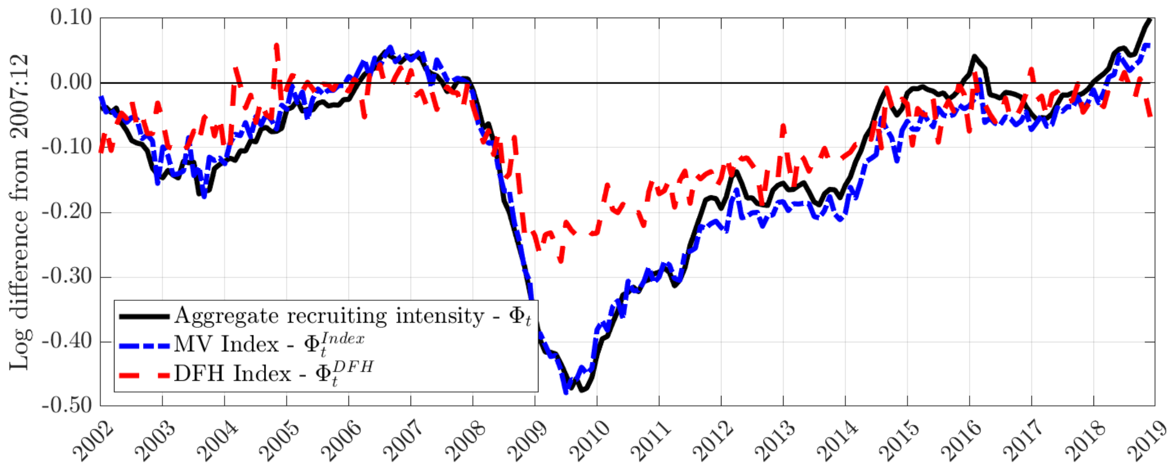


Figure 8: Indexes of aggregate recruiting intensity

Notes: This figure plots our estimated measure of ARI (Φ_t), alongside our empirical index Φ_t^{Index}, and that constructed by DFH. Time-series are first deseasonalised using X13-ARIMA-SEATS. For presentation only, we also apply a three month centered moving average to each series.

They then set the macro elasticity equal to this micro-elasticity.[27] Our measure fundamentally differs. We find that the main contributing factor to the variation of job filling rates is the response of firm recruiting choices to equilibrium aggregate market tightness. This is not captured by the DFH measure as they extrapolate from cross-sectional regression to aggregate time-series.

Representative firm. To further ground our index in theory, we show that in general equilibrium a representative firm model delivers Φ_t^{Index} as the exact measure of aggregate recruiting intensity. This formulation may be used by future researchers to represent firm recruiting choices in arbitrarily rich DSGE environments with frictional labor markets.

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. They then choose 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. For any given pair (h_t, n_t) the firm solves:

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

[27] Put differently, they observe that the elasticity of h_{it}/v_{it} to h_{it}/n_{it} at the micro-level is 0.82. They then construct an index based on H_t/V_t having an elasticity of 0.82 with respect to H_t/N_t at the macro-level.

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

$$e_t = Const. \times \left(Q_t^*\right)^{-\gamma} \left(\frac{h_t}{n_t}\right)^{\gamma}. \tag{19}$$

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 $E_t = (V_t^*/V_t) = \Phi_t^{1/\alpha}$. 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 (19) imply:

$$\Phi_t = Q_t^{*-\gamma\alpha} \left(\frac{H_t}{N_t}\right)^{\gamma\alpha} = Q(A_t, \theta_t)^{-\frac{\gamma\alpha}{1-\gamma(1-\alpha)}} \left(\frac{H_t}{N_t}\right)^{\frac{\gamma\alpha}{1-\gamma(1-\alpha)}}. \tag{20}$$

This expression contains the slackness and growth components of our general model, and corresponds exactly to Φ_t^{Index} in equation (16).

6.2 A Great Recession Counterfactual

As a second application, we seek to isolate the role of aggregate recruiting intensity for the dynamics of the job finding rate and the unemployment rate in the Great Recession. Besides unemployment, there are three other inputs into the evolution of job finding rate: vacancies V_t, aggregate recruiting intensity Φ_t, and residual match efficiency A_t.

Formally, 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 at their pre-recession level?

To answer this question we consider the following dynamic system:

$$H_t = \Phi_t A_t U_t^{\alpha} V_t^{1-\alpha} \tag{21}$$

$$U_{t+1} = (1 - F_t) U_t + S_t \quad , \quad \text{where} \quad F_t := H_t / U_t. \tag{22}$$

First, 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 (21), and derive a consistent series for separations S_t from ob-

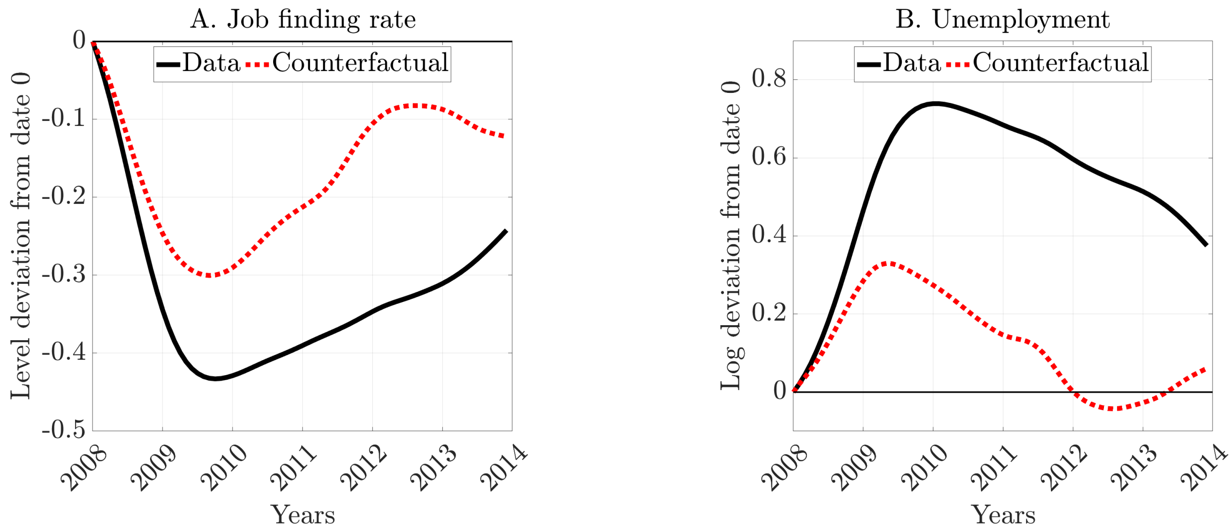


Figure 9: Counterfactual job finding rate and unemployment due only to the decline in Φ_t

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.

served unemployment dynamics (22). Second, we construct our counterfactual series for residual match efficiency and vacancies, by fixing values at their pre-recession levels: $\widetilde{A}_t = A_{2008:1}$ and $\widetilde{V}_t = V_{2008:1}$ for all t. Hence, the only time-varying input into hiring is Φ_t. Third, we construct our counterfactual series for our variables of interest by starting from $\widetilde{U}_{2008:1}$, and using $\left\{\widetilde{A}_t, \widetilde{V}_t, \Phi_t, S_t\right\}$ along with (21) and (22) to construct counterfactual $\left\{\widetilde{F}_t, \widetilde{U}_t\right\}_{t=2008:1}^{2018:12}$ (for more details see the footnote of Figure 9).[28]

Figure 9 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 over 40 percent of the increase in unemployment at the onset of the recession. However, as the vacancy rate recovers quickly and the labor market starts tightening again, recruiting intensity rebounds as firms once more

[28]Consistent with the previous figures we use the series for Φ_t constructed using the employment quintile (j), NAICS4 (i).

increase their recruiting inputs to realize hires. Thus under our counterfactual, unemployment returns to near its pre-recession level by 2012. In the data 2012 unemployment is still 60 percent above its pre-recession level. We conclude that the decline in ARI is important in explaining unemployment dynamics at the onset of the recession, but not its slow recovery

7 Discussion

Before we conclude, we (i) discuss alternative theories for the relationship between hiring rates and vacancy yields, and (ii) study the empirical properties of overall match efficiency and the residual A_t term.

7.1 Alternative theories

Our empirical facts document that heterogeneity in vacancy yields across different groups of firms—age, size, separation rate, quit rate, wage, wage growth—can be explained entirely by heterogeneity in *hiring rates* across these groups. Our theory is one of firms' choices of recruiting intensity, although other theories may be consistent with this behavior, which calls for further empirical and theoretical analysis. First, faster growing firms may have lower recruiting standards, and hence fill their vacancies more quickly. Such channels are considered in Carrillo-Tudela, Kaas, and Lochner (2024) and Carrillo-Tudela, Kaas, and Gartner (2023) and found to have positive effects on vacancy yields. Second, from the perspective of a multi-worker firm job ladder model (Bilal, Engbom, Mongey, and Violante, 2022), firms may grow quickly because they have a high marginal value of additional employee, which also increases their ability to fill vacancies via poaching from other firms. Third, from the perspective of a multi-worker firm directed search model Kaas and Kircher (2015), firms with a high desired hiring rate may post in high wage markets which deliver higher vacancy filling rates. Finally, it could be the case that idiosyncratic shocks to firm-level match efficiency cause both hiring rates and vacancy yields to comove, however we find that our results held while including (jt) fixed effects.

While each of these explanations are appealing, the fact that we find a robust relationship of hiring rates and vacancy yields within and between many different categorizations of firms by observable characteristics means that each could not be the *only* reason for this relationship.

Categories for j are quintiles of	Aggregation level for i	A. Decomposition of $var(\mathcal{M}_t)$				Correlation with unemp.	
		$var(A_t)$	$var(\Phi_t)$	Cov.	β_Φ	A_t	Φ_t
Industry	NAICS2	0.017	0.026	0.025	0.571	-0.825	-0.929
	NAICS3	0.015	0.031	0.022	0.615	-0.763	-0.927
	NAICS4	0.023	0.020	0.025	0.478	-0.863	-0.909
Age	NAICS1	0.014	0.065	-0.011	0.875	-0.196	-0.915
	NAICS2	0.018	0.027	0.023	0.565	-0.790	-0.920
	NAICS3	0.020	0.023	0.025	0.526	-0.828	-0.918
	NAICS4	0.028	0.018	0.022	0.426	-0.840	-0.859
Size	NAICS1	0.010	0.055	0.003	0.833	-0.361	-0.935
	NAICS2	0.018	0.024	0.026	0.541	-0.840	-0.926
	NAICS3	0.033	0.009	0.026	0.327	-0.940	-0.922
	NAICS4	0.036	0.008	0.024	0.296	-0.937	-0.889
Wage	NAICS1	0.018	0.028	0.022	0.572	-0.782	-0.912
	NAICS2	0.025	0.018	0.025	0.449	-0.871	-0.896
	NAICS3	0.022	0.023	0.023	0.509	-0.817	-0.898
	NAICS4	0.026	0.017	0.025	0.429	-0.873	-0.893
Separation rate	NAICS1	0.028	0.014	0.026	0.398	-0.900	-0.898
	NAICS2	0.026	0.017	0.025	0.435	-0.873	-0.892
	NAICS3	0.023	0.022	0.023	0.489	-0.828	-0.893
	NAICS4	0.028	0.016	0.024	0.419	-0.868	-0.877
Quit rate	NAICS1	0.025	0.016	0.027	0.439	-0.886	-0.915
	NAICS2	0.025	0.017	0.026	0.440	-0.880	-0.911
	NAICS3	0.022	0.022	0.024	0.496	-0.826	-0.901
	NAICS4	0.026	0.019	0.023	0.446	-0.841	-0.875
Turnover rate	NAICS1	0.046	0.004	0.018	0.188	-0.961	-0.845
	NAICS2	0.038	0.008	0.022	0.277	-0.934	-0.851
	NAICS3	0.034	0.011	0.023	0.336	-0.908	-0.857
	NAICS4	0.033	0.012	0.023	0.348	-0.901	-0.860
Emp. growth rate	NAICS1	0.028	0.012	0.028	0.382	-0.929	-0.922
	NAICS2	0.027	0.014	0.027	0.406	-0.913	-0.918
	NAICS3	0.024	0.016	0.028	0.442	-0.900	-0.930
	NAICS4	0.025	0.016	0.027	0.433	-0.883	-0.909
Average		0.025	0.020	0.023	0.464	-0.831	-0.900

Table 3: Decomposing aggregate match efficiency

Notes: This table presents the time-series variance decomposition of equation (23). The coefficient β_Φ is obtained from a regression of de-meaned $\log \mathcal{M}_t$ on de-meaned $\log \Phi_t$, this gives an alternative expression for the share of the variance of $\log \mathcal{M}_t$ attributed to $\log \Phi_t$ (see Hottman, Redding, and Weinstein (2016) and description in footnote 23).

For example, controlling for wages —which is a strong predictor of fill rates in directed search models— we still find that higher hiring rate firms have higher vacancy yields. And controlling for establishment age—which is a strong predictor of marginal value of additional employee in Bilal, Engbom, Mongey, and Violante (2022)—we still find that higher hiring rate firms have higher vacancy yields.

7.2 Overall aggregate match efficiency

So far, the focus of the paper has been on aggregate recruiting intensity. In this section, we expand it to overall aggregate match efficiency. Given the matching function $H_t = \Phi_t A_t V_t^{1-\alpha} U_t^{\alpha}$, overall match efficiency is $\mathcal{M}_t = \Phi_t A_t$. Here we take an agnostic view of the determinants of A_t, and estimate $\mathcal{M}_t$ residually from hires, vacancies and unemployment. Then, given our measure of Φ_t, we recover the implied path for A_t and show that: (a) around half of fluctuations in $\mathcal{M}_t$ are due to recruiting intensity Φ_t, (b) the residual portion A_t is pro-cyclical, (c) around half of fluctuations in A_t are accounted for by a simple measure of worker search effort and composition based on (7), leaving ample room for other pro-cyclical theories, such as mismatch, to explain the remainder.

Table 3 repeats the decomposition exercise of our main results in Table 2, but now breaking down $\mathcal{M}_t$ into fluctuations in Φ_t, A_t and their covariance:

$$Var\Big(\log \mathcal{M}_t\Big) = Var\Big(\log \Phi_t\Big) + Var\Big(\log A_t\Big) + 2Cov\Big(\log \Phi_t, \log A_t\Big). \tag{23}$$

Recall that obtaining A_t requires an estimate of $Comp_t$, and hence for every grouping of types of firms we obtain a different estimate of A_t. Both A_t and Φ_t are strongly procyclical: the last two columns show that the correlation with unemployment is close to one in both cases. Across groupings we find that, on average, around 40% of fluctuations in overall match efficiency are accounted for by changes in Φ_t.

Figure 10 depicts these results graphically by plotting $\mathcal{M}_t$ (blue line in both panels) along with paths for A_t (panel A) and Φ_t (panel B) obtained for each of our groupings of fixed effects j across all NAICS aggregation levels for i, and their mean paths (in red).

In the Great Recession, aggregate recruiting intensity Φ_t falls quickly, whereas the residual factors are slower to decline and also more persistent. As explained, the residual A_t is a catch-all for further features of the economy that may lead to a variation in match efficiency. First, we construct a sub-component of A_t which captures changes in job-seekers search effort and composition. Using (7), and taking into account $K = 3$ types of workers, unemployed U, employed

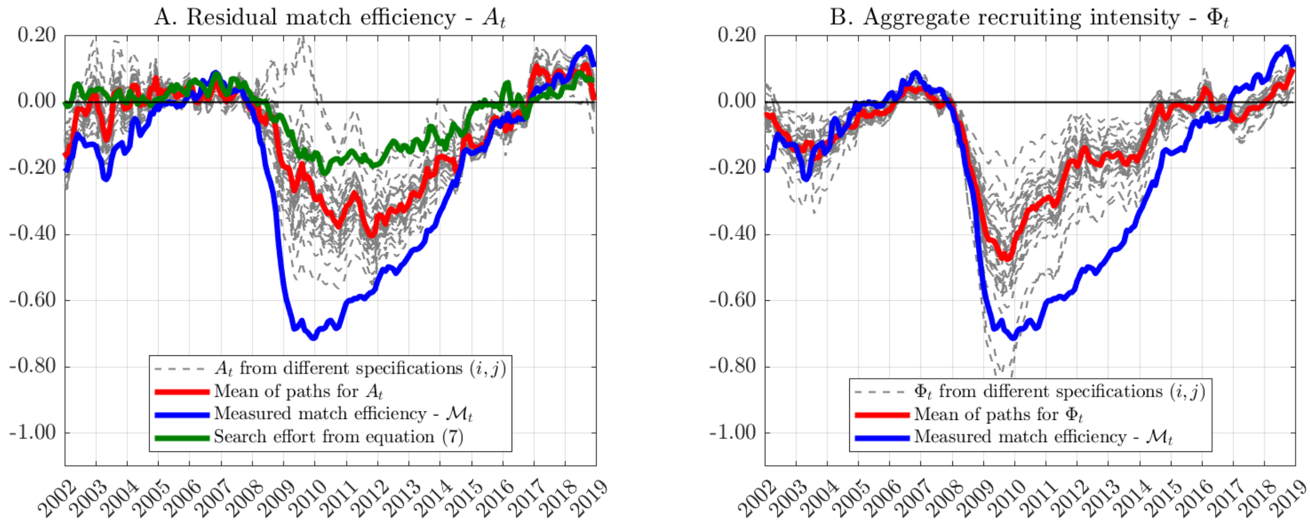


Figure 10: Decomposing aggregate match efficiency into recruiting intensity and residual

Notes: Each of the eight dashed line corresponds to the A_t (left panel) or Φ_t (right panel) obtained under all different grouping of firms j and industry categorizations to define i considered in Table 2. The red line is the average of the dashed lines. The blue line gives measured aggregate match efficiency $\mathcal{M}_t = A_t\Phi_t$. The green line in Panel A plots $\tilde{A}_t$ constructed directly using equation (24), where we construct groups $k \in \{\text{Unemployed, Non-employment, Employed}\}$.

E and non-employed N, yields the index $\widetilde{A}_t$:

$$\widetilde{A}_t = \left[\sum_{k=1}^{K} a_{kt}\frac{S_{kt}}{U_t}\right]^{1-\alpha} = \left[1 + a_{Et}\frac{E_t}{U_t} + a_{Nt}\frac{N_t}{U_t}\right]^{1-\alpha} \text{ where } a_{Et} = \frac{EE_t/E_t}{UE_t/U_t} \quad , \quad a_{Nt} = \frac{NE_t/N_t}{UE_t/U_t}. \tag{24}$$

Since the matching function is constant returns to scale, we can measure a_{Et} and a_{Nt} from relative flows. We use the adjusted employed-to-employed transition rate EE_t/E_t from Fujita, Moscarini, and Postel-Vinay (2024). The green line in Figure 10 plots $\widetilde{A}_t$. This time series shares the same pro-cyclicality of the measures of A_t backed out from our recruiting intensity exercises and, in the Great Recession, accounts for around half of the decline in average A_t (red line).[29] Second, although not in the figure, we note that what remains of A_t after subtracting the job-seeker composition term $\widetilde{A}_t$ is also procyclical. This result is consistent with additional explanations of fluctuations in $\mathcal{M}_t$, such as worsening mismatch (Şahin, Song, Topa, and Violante, 2014) or a decline in poaching (Bilal, Engbom, Mongey, and Violante, 2022).[30]

[29] We find that search efficiencies a_{Et} and a_{Nt} both increase in the Great Recession. However, since the levels of both are much lower than one (i.e. the normalized search efficiency of the unemployed), these increases in search efficiency are dominated in the construction of $\widetilde{A}_t$ by the shift in composition toward non-employment.

[30] In Bilal, Engbom, Mongey, and Violante (2022), a job ladder exists across firms, ranked by the marginal surplus

8 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 offered wages, non-pecuniary job amenities, and screening standards, may be important too. There is currently no representative microdata for the U.S. that allows researchers to disentangle these different mechanisms, but progress has being made for other countries, such as Austria and Germany (Mueller, Kettemann, and Zweimuller, 2018; Carrillo-Tudela, Kaas, and Gartner, 2023). This promising line of research that digs deeper into the black box of firm-level recruiting decisions could lead 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, which is what is ultimately important 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 composition of the pool of job seekers, in worker's search effort, and in mismatch. 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 or in offsetting each other—would be another welcome advancement in the literature (see Crump, Eusepi, Giannoni, and Sahin (2019), Leduc and Liu (2020) and Barnichon and Figura (2015) for first steps in this direction).

of additional employment. Firms at the top of the ladder post the most vacancies and fill their jobs most quickly as they can hire from any other firm below them. A financial crisis most steeply reduces the marginal surplus of jobs at firms at the top of the ladder, reducing their vacancies, which shifts the distribution of vacancies toward firms with lower job filling rates.

References

BARLEVY, G. (2011): "Evaluating the Role of Labor Market Mismatch in Rising Unemployment," *Economic Perspectives*, 35(3).

BARNICHON, R., AND A. FIGURA (2015): "Labor Market Heterogeneity and the Aggregate Matching Function," *American Economic Journal: Macroeconomics*, 7(4), 222–249.

BILAL, A., N. ENGBOM, S. MONGEY, AND G. L. VIOLANTE (2022): "Firm and Worker Dynamics in a Frictional Labor Market," *Econometrica*, 90(4), 1425–1462.

CARRILLO-TUDELA, C., L. KAAS, AND H. GARTNER (2023): "Recruitment Policies, Job-Filling Rates and Matching Efficiency," *Journal of the European Economic Association*, 21(6), 2413–2459.

CARRILLO-TUDELA, C., L. KAAS, AND B. LOCHNER (2024): "Matching Through Search Channels," Discussion Paper 16583, IZA Discussion Paper.

CRUMP, R. K., S. EUSEPI, M. GIANNONI, AND A. SAHIN (2019): "A Unified Approach to Measuring u," *Brookings Papers on Economic Activity*, 50(1 (Spring), 143–238.

DAVIS, S. J., R. J. FABERMAN, AND J. C. HALTIWANGER (2012): "Labor Market Flows in the Cross Section and Over Time," *Journal of Monetary Economics*, 59(1), 1–18.

——— (2013): "The Establishment-Level Behavior of Vacancies and Hiring," *Quarterly Journal of Economics*, 128(2), 581–622.

DAVIS, S. J., R. J. FABERMAN, J. C. HALTIWANGER, AND I. RUCKER (2010): "Adjusted Estimates of Worker Flows and Job Openings in JOLTS," in *Labor in the New Economy*, ed. by K. G. Abraham, J. R. Spletzer, and M. Harper, pp. 187–216. Chicago, IL: University of Chicago Press.

ELSBY, M. W., R. MICHAELS, AND D. RATNER (2015): "The Beveridge Curve: A Survey," *Journal of Economic Literature*, 53(3), 571–630.

——— (2018): "Vacancy Chains," Working paper, University of Edinburch.

FABERMAN, R. J. (2014): "Recruiting Intensity," *IZA World of Labor*, pp. 1–21.

FABERMAN, R. J., AND E. NAGYPAL (2008): "Quits, Worker Recruitment, and Firm Growth: Theory and Evidence," Working Paper 08-12, Federal Reserve Bank of Philadelphia.

FORSYTHE, E., AND R. WEINSTEIN (2018): "Recruiting Intensity Over the Business Cycle," Working Paper, University of Illinois at Uraban-Champaign.

——— (2021): "Recruiting Intensity, Hires, and Vacancies: Evidence from Firm-Level Data," Discussion paper, IZA.

FUJITA, S., G. MOSCARINI, AND F. POSTEL-VINAY (2024): "Measuring Employer-to-Employer Reallocation," *American Economic Journal: Macroeconomics*, 16(3), 1–51.

GAVAZZA, A., S. MONGEY, AND G. L. VIOLANTE (2018): “Aggregate Recruiting Intensity,” *American Economic Review*, 108(8), 2088–127.

HALL, R. E., AND S. SCHULHOFER-WOHL (2018): “Measuring Job-Finding Rates and Matching Efficiency with Heterogeneous Jobseekers,” *American Economic Journal: Macroeconomics*, 10(1), 1–32.

HERZ, B., AND T. VAN RENS (2019): “Accounting for Mismatch Unemployment,” *Journal of the European Economic Association*, Forthcoming.

HORNSTEIN, A., M. KUDLYAK, AND F. LANGE (2016): “Estimating Matching Efficiency with Variable Search Effort,” Working Paper 2016-24, Federal Reserve Bank of San Francisco.

HOTTMAN, C. J., S. J. REDDING, AND D. E. WEINSTEIN (2016): “Quantifying the Sources of Firm Heterogeneity,” *The Quarterly Journal of Economics*, 131(3), 1291–1364.

KAAS, L., AND P. KIRCHER (2015): “Efficient Firm Dynamics in a Frictional Labor Market,” *American Economic Review*, 105(10), 3030–60.

KOTHARI, S., I. SAPORTA-EKSTEN, AND E. YU (2013): “The (Un) Importance of Geographical Mobility in the Great Recession,” *Review of Economic Dynamics*, 16(3), 553–563.

LEDUC, S., AND Z. LIU (2020): “The Weak Job Recovery in a Macro Model of Search and Recruiting Intensity,” *American Economic Journal: Macroeconomics*, 12(1), 310–343.

LOCHNER, B., C. MERKL, H. STUBER, AND N. GURTZGEN (2019): “A Note on Recruiting Intensity and Hiring Practices: Cross-Sectional and Time-Series Evidence,” FAU Discussion Papers in Economics 04/2019, Friedrich-Alexander University Erlangen-Nuremberg, Institute for Economics.

MALM, F. T. (1954): “Recruiting Patterns and the Functioning of Labor Markets,” *Industrial and Labor Relations Review*, 7(4), 507–525.

MUELLER, A., A. KETTEMANN, AND J. ZWEIMULLER (2018): “Vacancy Durations and Entry Wages: Evidence from Linked Vacancy-Employer-Employee Data",” Working paper, University of Texas (Austin), Unpublished.

MUKOYAMA, T., C. PATTERSON, AND A. ŞAHIN (2018): “Job Search Behavior over the Business Cycle,” *American Economic Journal: Macroeconomics*, 10(1), 190–215.

O’LEONARD, K., J. KRIDER, AND R. ERICKSON (2015): “Talent Acquisition Factbook 2015: Benchmarks and Trends of Spending, Staffing and Key Recruiting Metrics,” Discussion paper, Bersin and Associates.

PETRONGOLO, B., AND C. A. PISSARIDES (2001): “Looking into the Black Box: A Survey of the Matching Function,” *Journal of Economic Literature*, 39(June), 390–431.

PISSARIDES, C. A. (2000): *Equilibrium Unemployment Theory*. Cambridge, MA: MIT Press.

ŞAHIN, A., J. SONG, G. TOPA, AND G. L. VIOLANTE (2014): “Mismatch Unemployment,” *American Economic Review*, 104(11), 3529–64.

SHIMER, R. (2005): "The Cyclical Behavior of Equilibrium Unemployment and Vacancies," *American Economic Review*, 95(1), 25–49.

——— (2012): "Reassessing the Ins and Outs of Unemployment," *Review of Economic Dynamics*, 15(2), 127–48.

Appendix For Online Publication

This Appendix is organized as follows. Section A contains additional figures and tables. Section B provides details on our analytical derivations. Section C provides additional details on variable construction.

A Additional figures and tables

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

Categories for j are quintiles of:	Level of aggregation for i			
	NAICS1	NAICS2	NAICS3	NAICS4
Industry	-	0.77 (0.009)	0.79 (0.007)	0.74 (0.004)
Age	0.84 (0.009)	0.77 (0.006)	0.76 (0.004)	0.73 (0.003)
Size	0.83 (0.011)	0.77 (0.009)	0.66 (0.005)	0.65 (0.004)
Wage	0.78 (0.010)	0.74 (0.006)	0.76 (0.004)	0.72 (0.003)
Separation rate	0.70 (0.011)	0.72 (0.007)	0.75 (0.004)	0.73 (0.003)
Quit rate	0.73 (0.012)	0.73 (0.008)	0.77 (0.004)	0.77 (0.003)
Turnover rate	0.48 (0.027)	0.62 (0.017)	0.68 (0.007)	0.69 (0.005)
Emp. growth rate	0.71 (0.011)	0.71 (0.008)	0.72 (0.005)	0.72 (0.003)

Table A1: Coefficient estimates - With jt fixed effects

Notes: This table replicates Table 1, but with the following modification. In each case equation (14), but with fixed effects δ_t and ξ_j replaced with the joint fixed effect δ_{jt}. This implies that the only variation used to estimate the coefficient β presented in this table is: *within-group-j-month-t*, *across-industries-i*.

Categories for j are quintiles of:	Level of aggregation for i			
	NAICS1	NAICS2	NAICS3	NAICS4
Industry	-	0.78 (0.013)	0.75 (0.008)	0.75 (0.004)
Age	0.78 (0.011)	0.80 (0.007)	0.75 (0.004)	0.73 (0.003)
Size	0.83 (0.011)	0.78 (0.009)	0.69 (0.006)	0.68 (0.004)
Wage	0.75 (0.011)	0.75 (0.007)	0.74 (0.004)	0.73 (0.003)
Separation rate	0.78 (0.012)	0.77 (0.008)	0.76 (0.004)	0.74 (0.003)
Quit rate	0.72 (0.014)	0.73 (0.009)	0.76 (0.004)	0.76 (0.003)
Turnover rate	0.71 (0.024)	0.72 (0.016)	0.72 (0.007)	0.73 (0.004)
Emp. growth rate	0.62 (0.011)	0.67 (0.009)	0.70 (0.005)	0.73 (0.003)

Table A2: Coefficient estimates - With ij and t fixed effects

Notes: This table replicates Table 1, but with the following modification. In each case equation (14), but with fixed effect ξ_j replaced with the joint fixed effect ξ_{ij}. This implies that the only variation used to estimate the coefficient β presented in this table is: *within-group-j-industry-i*, *across-months-t*.

Categories for j are quintiles of:	Level of aggregation for i			
	NAICS1	NAICS2	NAICS3	NAICS4
Industry	-	71228	17245	5553
Age	27303	14758	3546	1134
Size	27303	14758	3608	1178
Wage	22753	12318	2989	956
Separation rate	22753	12135	2941	936
Quit rate	22753	12225	2984	952
Turnover rate	22752	12135	2936	936
Emp. growth rate	22753	12602	3138	1099

Table A3: Sample size in each ij cell

Notes: In the estimation described in Table A2, we estimate fixed effects ϕ_{ij}. For each estimation, this table gives the average number of observations in each (ij)-cell.

Categories for j are quintiles of:	Level of aggregation for i			
	NAICS1	NAICS2	NAICS3	NAICS4
A. **Grouped by establishment's current residual**				
Within-NAICS3-month log wage residual quantile	0.78 (0.010)	0.74 (0.006)	0.76 (0.004)	0.72 (0.003)
Within-NAICS3-month wage growth $(t-1,t)$ residual quantile	0.71 (0.011)	0.71 (0.008)	0.72 (0.005)	0.72 (0.003)
Within-NAICS3-month wage growth $(t,t+1)$ residual quantile	0.70 (0.011)	0.71 (0.008)	0.71 (0.005)	0.72 (0.003)
B. **Grouped by establishment's average residual**				
Within-NAICS3-month log wage residual quantile	0.80 (0.010)	0.75 (0.006)	0.76 (0.004)	0.72 (0.003)
Within-NAICS3-month wage growth $(t-1,t)$ residual quantile	0.76 (0.011)	0.78 (0.008)	0.74 (0.005)	0.74 (0.003)
Within-NAICS3-month wage growth $(t,t+1)$ residual quantile	0.73 (0.010)	0.75 (0.007)	0.74 (0.005)	0.74 (0.003)

Table A4: Coefficient estimates - Grouping by residualized wages and wage growth

Notes: This table replicates Table 1, but with the following modification. The variables that we use to group firms into groups j are residuals. Take a variable x_{emt} for establishment e in NAICS3 industry m in period t. We regress x_{emt} on mt-fixed effects, call the residual $\widetilde{x}_{emt}$. We then group firms into groups j by quintiles of either: (Panel A) grouped every period by $\widetilde{x}_{emt}$, (Panel B) grouped by the establishment mean of $\widetilde{x}_{emt}$ over the sample. For x we consider (a) log $Wage_{emt}$, where $Wage_{emt} = Payroll_{emt} / Employment_{emt}$, (b) growth in $Wage_{emt}$ between $t-1$ and t (where t is a quarter), (c) growth in $Wage_{emt}$ between t and $t+1$.

Categories for j are quintiles of:	Level of aggregation for i			
	NAICS1	NAICS2	NAICS3	NAICS4
A. **Grouped by establishment's current residual**				
Within-NAICS3-month log wage residual quantile	0.75 (0.011)	0.75 (0.007)	0.74 (0.004)	0.73 (0.003)
Within-NAICS3-month wage growth $(t-1,t)$ residual quantile	0.62 (0.011)	0.67 (0.009)	0.70 (0.005)	0.73 (0.003)
Within-NAICS3-month wage growth $(t,t+1)$ residual quantile	0.61 (0.011)	0.66 (0.009)	0.69 (0.005)	0.73 (0.003)
B. **Grouped by establishment's average residual**				
Within-NAICS3-month log wage residual quantile	0.78 (0.011)	0.78 (0.007)	0.75 (0.004)	0.74 (0.003)
Within-NAICS3-month wage growth $(t-1,t)$ residual quantile	0.71 (0.011)	0.77 (0.008)	0.75 (0.005)	0.76 (0.003)
Within-NAICS3-month wage growth $(t,t+1)$ residual quantile	0.68 (0.011)	0.75 (0.008)	0.75 (0.005)	0.75 (0.003)

Table A5: Coefficient estimates - Grouping by residualized wages and wage growth - With jt fixed effects

Notes: This replicates the above Table A4, with the addition of jt fixed effects, as in Table A1, above.

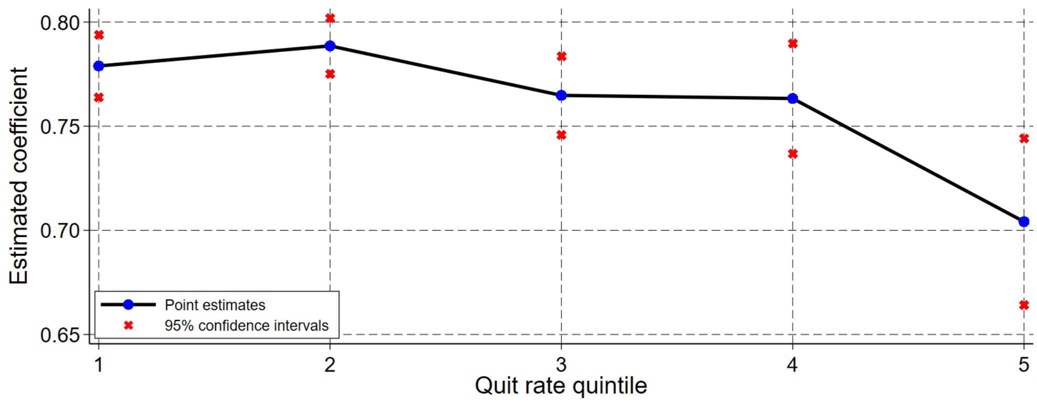


Figure A1: Coefficient estimates - Separately for quit rate quintiles

Notes: This figures provides point estimates similar to Table 1, but with the following modification. In each case we run the entire analysis *only* for establishments within a particular quintile of quit rates q_{it}.

Categories for j	**Aggregation**	**1. Aggregate recruiting intensity**					**2. Composition**		
are quintiles of	**level for i**	Slack	Growth	Comp.	Cov.	β_{Comp}	Between	Within	Cov.
Industry	NAICS2	0.42	0.09	0.02	0.47	0.098	0.39	0.24	0.37
	NAICS3	0.42	0.08	0.03	0.47	0.109	0.29	0.37	0.34
	NAICS4	0.40	0.10	0.05	0.45	0.119	0.32	0.64	0.04
Age	NAICS1	0.52	0.07	0.06	0.35	0.079	0.19	0.38	0.43
	NAICS2	0.47	0.09	0.04	0.40	0.063	0.14	0.51	0.35
	NAICS3	0.45	0.10	0.04	0.41	0.070	0.10	0.68	0.22
	NAICS4	0.42	0.10	0.14	0.34	0.139	0.13	0.52	0.35
Size	NAICS1	0.53	0.07	0.02	0.38	0.038	0.09	0.68	0.23
	NAICS2	0.46	0.10	0.03	0.41	0.057	0.49	1.24	-0.73
	NAICS3	0.39	0.12	0.05	0.44	0.095	0.21	1.01	-0.22
	NAICS4	0.38	0.12	0.08	0.42	0.116	0.05	0.82	0.13
Wage	NAICS1	0.48	0.09	0.04	0.39	0.052	0.22	0.41	0.37
	NAICS2	0.46	0.11	0.05	0.38	0.059	0.26	0.48	0.26
	NAICS3	0.46	0.10	0.05	0.39	0.071	0.12	0.72	0.16
	NAICS4	0.43	0.11	0.08	0.38	0.098	0.07	0.80	0.13
Separation rate	NAICS1	0.40	0.11	0.06	0.43	0.111	0.47	0.20	0.33
	NAICS2	0.41	0.10	0.07	0.42	0.108	0.42	0.25	0.33
	NAICS3	0.45	0.10	0.07	0.38	0.081	0.38	0.40	0.22
	NAICS4	0.47	0.11	0.09	0.33	0.065	0.36	0.64	0.00
Quit rate	NAICS1	0.48	0.11	0.05	0.36	0.036	0.32	0.29	0.39
	NAICS2	0.48	0.11	0.06	0.35	0.037	0.30	0.44	0.26
	NAICS3	0.56	0.11	0.07	0.26	-0.008	0.40	0.76	-0.16
	NAICS4	0.63	0.13	0.12	0.12	-0.053	0.48	1.03	-0.51
Turnover rate	NAICS1	0.28	0.12	0.14	0.46	0.229	1.15	0.31	-0.46
	NAICS2	0.36	0.12	0.12	0.40	0.150	0.88	0.29	-0.17
	NAICS3	0.41	0.12	0.11	0.36	0.106	0.76	0.31	-0.07
	NAICS4	0.43	0.12	0.11	0.34	0.097	0.47	0.25	0.28
Emp. growth rate	NAICS1	0.43	0.12	0.03	0.42	0.055	0.27	0.48	0.25
	NAICS2	0.44	0.12	0.04	0.40	0.056	0.28	0.55	0.17
	NAICS3	0.42	0.11	0.04	0.43	0.085	0.06	0.77	0.17
	NAICS4	0.42	0.11	0.07	0.40	0.099	0.03	0.82	0.15
Average		0.44	0.105	0.065	0.39	0.08	0.33	0.56	0.12

Table A6: Decomposing aggregate recruiting intensity - ALTERNATIVE $\alpha = 0.15$

Notes: This table replicates Table 2 from the main text with the following difference. For every row, we assume that the matching function elasticity $\alpha = 0.15$ when constructing all terms that enter the variance decomposition.

Categories for j are quintiles of	Aggregation level for i	1. Aggregate recruiting intensity					2. Composition		
		Slack	Growth	Comp.	Cov.	β_{Comp}	Between	Within	Cov.
Industry	NAICS2	0.57	0.03	0.02	0.38	0.098	0.13	0.47	0.40
	NAICS3	0.57	0.03	0.03	0.37	0.109	0.09	0.57	0.34
	NAICS4	0.54	0.03	0.05	0.38	0.119	0.11	0.73	0.16
Age	NAICS1	0.69	0.02	0.06	0.23	0.079	0.05	0.64	0.31
	NAICS2	0.64	0.03	0.04	0.29	0.063	0.05	0.69	0.26
	NAICS3	0.62	0.03	0.04	0.31	0.070	0.03	0.79	0.18
	NAICS4	0.57	0.04	0.14	0.25	0.139	0.05	0.69	0.26
Size	NAICS1	0.72	0.02	0.02	0.24	0.038	0.02	0.81	0.17
	NAICS2	0.63	0.03	0.03	0.31	0.057	0.16	1.02	-0.18
	NAICS3	0.52	0.05	0.05	0.38	0.095	0.09	0.99	-0.08
	NAICS4	0.51	0.06	0.08	0.35	0.116	0.02	0.87	0.11
Wage	NAICS1	0.66	0.03	0.04	0.27	0.052	0.07	0.62	0.31
	NAICS2	0.63	0.04	0.05	0.28	0.059	0.09	0.63	0.28
	NAICS3	0.63	0.03	0.05	0.29	0.071	0.04	0.81	0.15
	NAICS4	0.58	0.04	0.08	0.30	0.098	0.02	0.87	0.11
Separation rate	NAICS1	0.54	0.04	0.06	0.36	0.111	0.18	0.39	0.43
	NAICS2	0.56	0.04	0.07	0.33	0.108	0.15	0.45	0.40
	NAICS3	0.61	0.03	0.07	0.29	0.081	0.13	0.56	0.31
	NAICS4	0.63	0.04	0.09	0.24	0.066	0.13	0.71	0.16
Quit rate	NAICS1	0.65	0.04	0.05	0.26	0.036	0.11	0.50	0.39
	NAICS2	0.65	0.04	0.06	0.25	0.037	0.11	0.60	0.29
	NAICS3	0.76	0.04	0.07	0.13	-0.008	0.13	0.76	0.11
	NAICS4	0.86	0.04	0.13	-0.03	-0.053	0.15	0.90	-0.05
Turnover rate	NAICS1	0.35	0.07	0.14	0.44	0.229	0.66	0.25	0.09
	NAICS2	0.48	0.06	0.12	0.34	0.150	0.40	0.33	0.27
	NAICS3	0.56	0.05	0.11	0.28	0.106	0.31	0.37	0.32
	NAICS4	0.58	0.05	0.11	0.26	0.097	0.18	0.41	0.41
Emp. growth rate	NAICS1	0.58	0.05	0.03	0.34	0.055	0.11	0.61	0.28
	NAICS2	0.60	0.04	0.04	0.32	0.056	0.11	0.65	0.24
	NAICS3	0.57	0.04	0.04	0.35	0.085	0.02	0.85	0.13
	NAICS4	0.57	0.04	0.07	0.32	0.099	0.01	0.88	0.11
Average		0.60	0.039	0.066	0.29	0.08	0.13	0.66	0.22

Table A7: Decomposing aggregate recruiting intensity - ALTERNATIVE $\alpha = 0.50$

Notes: This table replicates Table 2 from the main text with the following difference. For every row, we assume that the matching function elasticity $\alpha = 0.50$ when constructing all terms that enter the variance decomposition.

Categories for j are quintiles of	**Aggregation level for i**	**1. Aggregate recruiting intensity**					**2. Composition**		
		Slack	Growth	Comp.	Cov.	β_{Comp}	Between	Within	Cov.
Industry	NAICS2	0.56	0.05	0.01	0.38	0.063	0.17	0.42	0.41
	NAICS3	0.54	0.04	0.02	0.40	0.082	0.13	0.53	0.34
	NAICS4	0.58	0.05	0.04	0.33	0.066	0.11	0.77	0.12
Age	NAICS1	0.56	0.04	0.06	0.34	0.089	0.13	0.45	0.42
	NAICS2	0.61	0.05	0.04	0.30	0.035	0.08	0.62	0.30
	NAICS3	0.61	0.05	0.04	0.30	0.034	0.06	0.74	0.20
	NAICS4	0.61	0.05	0.13	0.21	0.080	0.06	0.64	0.30
Size	NAICS1	0.59	0.05	0.02	0.34	0.044	0.06	0.72	0.22
	NAICS2	0.62	0.05	0.03	0.30	0.023	0.25	1.06	-0.31
	NAICS3	0.67	0.05	0.04	0.24	-0.007	0.12	0.83	0.05
	NAICS4	0.68	0.05	0.08	0.19	0.000	0.05	0.79	0.16
Wage	NAICS1	0.62	0.05	0.03	0.30	0.027	0.12	0.52	0.36
	NAICS2	0.66	0.05	0.05	0.24	0.008	0.13	0.57	0.30
	NAICS3	0.62	0.05	0.05	0.28	0.035	0.07	0.76	0.17
	NAICS4	0.63	0.05	0.08	0.24	0.039	0.03	0.84	0.13
Separation rate	NAICS1	0.62	0.05	0.06	0.27	0.037	0.18	0.39	0.43
	NAICS2	0.61	0.05	0.06	0.28	0.049	0.17	0.43	0.40
	NAICS3	0.62	0.05	0.06	0.27	0.040	0.17	0.51	0.32
	NAICS4	0.67	0.05	0.09	0.19	0.011	0.14	0.67	0.19
Quit rate	NAICS1	0.68	0.05	0.05	0.22	-0.016	0.15	0.44	0.41
	NAICS2	0.69	0.05	0.06	0.20	-0.012	0.14	0.53	0.33
	NAICS3	0.73	0.06	0.07	0.14	-0.038	0.20	0.70	0.10
	NAICS4	0.82	0.07	0.13	-0.02	-0.083	0.23	0.86	-0.09
Turnover rate	NAICS1	0.68	0.05	0.10	0.17	0.009	0.30	0.34	0.36
	NAICS2	0.67	0.05	0.10	0.18	0.024	0.28	0.38	0.34
	NAICS3	0.67	0.05	0.10	0.18	0.018	0.27	0.38	0.35
	NAICS4	0.67	0.05	0.10	0.18	0.018	0.18	0.41	0.41
Emp. growth rate	NAICS1	0.68	0.05	0.03	0.24	-0.021	0.16	0.53	0.31
	NAICS2	0.67	0.05	0.03	0.25	-0.011	0.15	0.58	0.27
	NAICS3	0.62	0.05	0.03	0.30	0.024	0.05	0.83	0.12
	NAICS4	0.63	0.05	0.06	0.26	0.038	0.02	0.86	0.12
Average		0.64	0.050	0.060	0.25	0.02	0.14	0.62	0.24

Table A8: Decomposing aggregate recruiting intensity - ALTERNATIVE $\gamma = 0.82$

Notes: This table replicates Table 2 from the main text with the following difference. We assume that $\gamma = 0.82$ in every row, rather than the value presented in Table 1.

Categories for j are quintiles of	Aggregation level for i	1. Aggregate recruiting intensity					2. Composition		
		Slack	Growth	Comp.	Cov.	β_{Comp}	Between	Within	Cov.
Industry	NAICS2	0.49	0.06	0.02	0.43	0.091	0.29	0.22	0.49
	NAICS3	0.45	0.06	0.03	0.46	0.117	0.33	0.18	0.49
	NAICS4	0.42	0.06	0.05	0.47	0.149	0.33	0.18	0.49
Age	NAICS1	0.50	0.05	0.04	0.41	0.100	0.28	0.22	0.50
	NAICS2	0.52	0.05	0.03	0.40	0.093	0.25	0.25	0.50
	NAICS3	0.45	0.06	0.03	0.46	0.123	0.33	0.18	0.49
	NAICS4	0.37	0.06	0.08	0.49	0.200	0.36	0.16	0.48
Size	NAICS1	0.55	0.04	0.02	0.39	0.086	0.20	0.31	0.49
	NAICS2	0.48	0.05	0.03	0.44	0.105	0.29	0.21	0.50
	NAICS3	0.39	0.07	0.05	0.49	0.155	0.42	0.13	0.45
	NAICS4	0.34	0.06	0.09	0.51	0.218	0.42	0.12	0.46
Wage	NAICS1	0.47	0.06	0.03	0.44	0.104	0.33	0.18	0.49
	NAICS2	0.47	0.06	0.04	0.43	0.108	0.33	0.18	0.49
	NAICS3	0.46	0.06	0.06	0.42	0.122	0.34	0.18	0.48
	NAICS4	0.40	0.06	0.07	0.47	0.172	0.36	0.16	0.48
Separation rate	NAICS1	0.53	0.06	0.03	0.38	0.070	0.28	0.22	0.50
	NAICS2	0.51	0.06	0.04	0.39	0.085	0.29	0.21	0.50
	NAICS3	0.49	0.06	0.06	0.39	0.103	0.31	0.19	0.50
	NAICS4	0.40	0.06	0.11	0.43	0.194	0.34	0.17	0.49
Quit rate	NAICS1	0.51	0.08	0.02	0.39	0.043	0.37	0.15	0.48
	NAICS2	0.50	0.08	0.03	0.39	0.064	0.36	0.16	0.48
	NAICS3	0.54	0.07	0.05	0.34	0.061	0.31	0.20	0.49
	NAICS4	0.50	0.06	0.08	0.36	0.108	0.31	0.20	0.49
Turnover rate	NAICS1	0.49	0.08	0.09	0.34	0.089	0.38	0.14	0.48
	NAICS2	0.50	0.08	0.10	0.32	0.094	0.37	0.15	0.48
	NAICS3	0.48	0.07	0.14	0.31	0.132	0.37	0.16	0.47
	NAICS4	0.40	0.06	0.17	0.37	0.219	0.36	0.16	0.48
Emp. growth rate	NAICS1	0.38	0.09	0.04	0.49	0.134	0.50	0.08	0.42
	NAICS2	0.41	0.08	0.04	0.47	0.118	0.45	0.11	0.44
	NAICS3	0.43	0.07	0.05	0.45	0.127	0.39	0.14	0.47
	NAICS4	0.40	0.06	0.06	0.48	0.169	0.35	0.17	0.48
Average		0.46	0.064	0.057	0.42	0.12	0.34	0.18	0.48

Table A9: Decomposing aggregate recruiting intensity - Baseline has (ij)-fixed effects

Notes: This table replicates Table 2, but with the following modification. In each case equation (14), but with fixed effect ξ_j replaced with the joint fixed effect ξ_{ij}. This implies that the only variation used to estimate the coefficient β presented in this table is: *within-group-j-industry-i*, *across-months-t*. The ϕ_{ij} terms are then computed and used in the decomposition.

Categories for j are quintiles of	Aggregation level for i	1. Aggregate recruiting intensity				2. Composition		
		Slack	Growth	Comp.	Cov.	Between	Within	Cov.
A. **Grouped by establishment's current residual**								
Within-NAICS3-month log wage residual quantile	NAICS1	0.55	0.06	0.04	0.35	0.15	0.49	0.36
	NAICS2	0.52	0.08	0.05	0.35	0.18	0.53	0.29
	NAICS3	0.52	0.07	0.05	0.36	0.08	0.75	0.17
	NAICS4	0.49	0.08	0.08	0.35	0.05	0.83	0.12
Within-NAICS3-month wage growth $(t-1,t)$ residual quantile	NAICS1	0.49	0.09	0.03	0.39	0.20	0.52	0.28
	NAICS2	0.50	0.08	0.04	0.38	0.20	0.58	0.22
	NAICS3	0.47	0.08	0.04	0.41	0.04	0.80	0.16
	NAICS4	0.48	0.08	0.07	0.37	0.02	0.84	0.14
Within-NAICS3-month wage growth $(t,t+1)$ residual quantile	NAICS1	0.48	0.09	0.03	0.40	0.26	0.51	0.23
	NAICS2	0.50	0.09	0.04	0.37	0.25	0.60	0.15
	NAICS3	0.46	0.08	0.03	0.43	0.06	0.78	0.16
	NAICS4	0.47	0.07	0.07	0.39	0.03	0.83	0.14
B. **Grouped by establishment's average residual**								
Within-NAICS3-month log wage residual quantile	NAICS1	0.57	0.06	0.03	0.34	0.13	0.52	0.35
	NAICS2	0.53	0.07	0.05	0.35	0.16	0.50	0.34
	NAICS3	0.52	0.07	0.05	0.36	0.08	0.72	0.20
	NAICS4	0.49	0.08	0.08	0.35	0.04	0.80	0.16
Within-NAICS3-month wage growth $(t-1,t)$ residual quantile	NAICS1	0.54	0.07	0.04	0.35	0.16	0.50	0.34
	NAICS2	0.56	0.06	0.04	0.34	0.13	0.61	0.26
	NAICS3	0.51	0.07	0.03	0.39	0.06	0.78	0.16
	NAICS4	0.50	0.07	0.08	0.35	0.02	0.83	0.15
Within-NAICS3-month wage growth $(t,t+1)$ residual quantile	NAICS1	0.50	0.08	0.03	0.39	0.18	0.52	0.30
	NAICS2	0.52	0.07	0.04	0.37	0.16	0.65	0.19
	NAICS3	0.49	0.07	0.03	0.41	0.05	0.79	0.16
	NAICS4	0.48	0.07	0.08	0.37	0.02	0.84	0.14
Average		0.51	0.075	0.048	0.37	0.11	0.67	0.22

Table A10: Decomposing aggregate recruiting intensity - Grouping by residualized wages and wage growth

Notes: This table replicates Table 2, but with the following modification. The variables that we use to group firms into groups j follow Table A4.

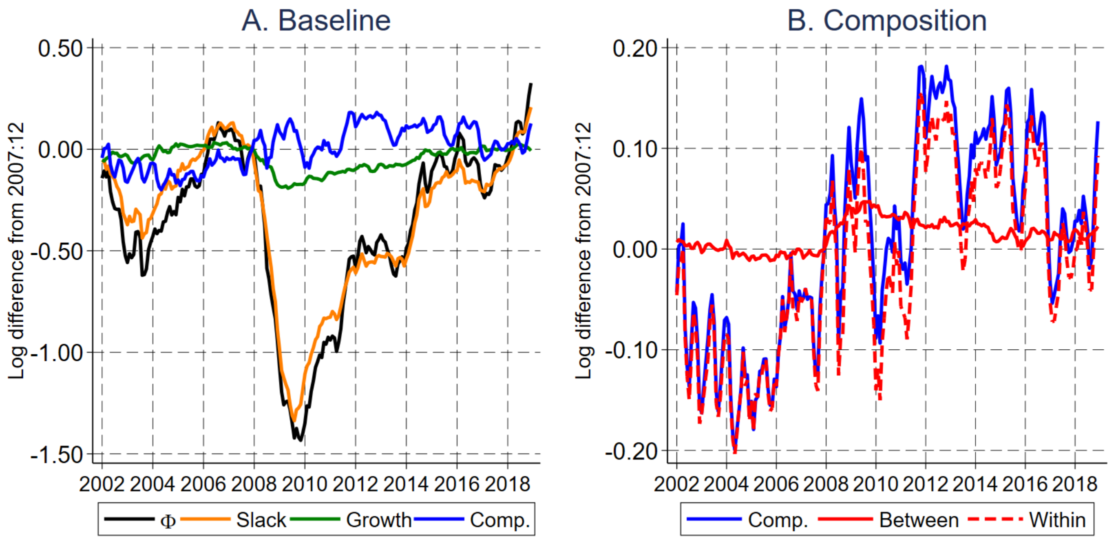


Figure A2: Decomposing aggregate recruiting intensity - ALTERNATIVE $\gamma = 0.82$

Notes: This figure replicates Figure 6 from the main text with the following difference. We assume that $\gamma = 0.82$ rather than the value presented in Table 1.

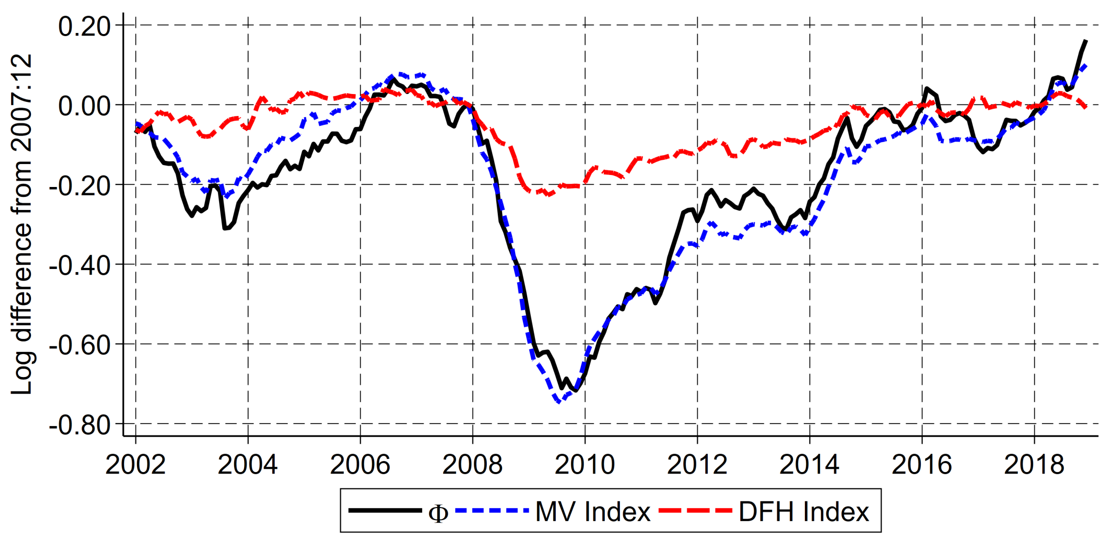


Figure A3: Indexes of aggregate recruiting intensity - ALTERNATIVE $\gamma = 0.82$

Notes: This figure replicates Figure 8 from the main text with the following difference. We assume that $\gamma = 0.82$ rather than the value presented in Table 1.

B Mathematical details

This section contains (1) the proof of Proposition 1 and (2) 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 functions, with elasticities γ_m, γ_v and γ_e respectively, this condition 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: $C(e, v, n) = \left[g(e) + f\left(\frac{v}{n}\right)\right]$. 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 $C(e, \widetilde{v}) = m\left(g(e) + f(\widetilde{v})\right)$, 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 $e = \Omega \widetilde{v}^{\omega}$. 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.[31]

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*

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

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* $\log h_2(y)$*:*

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

[31] 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.

Exponentiating delivers our the functional form we wished to establish:

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

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:

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

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

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

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

B.2 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:

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

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

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

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 ℓ_{it} divided by employment n_{it} and then dividing by τ: $\xi_{it} = (\ell_{it}/\tau n_{it})$. 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

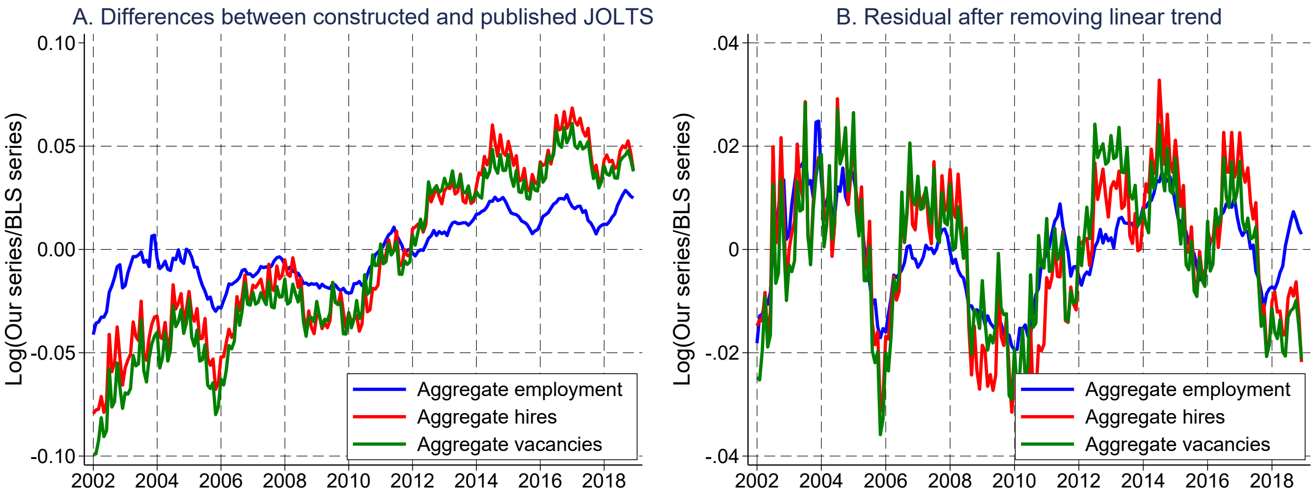


Figure C1: Trends in our data relative to published JOLTS aggregates

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 C1B, 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 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.

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

- 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.
- 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*.