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Jobs and Matches: Quits, Replacement Hiring, and Vacancy Chains†

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In the canonical DMP model of job openings, all job openings stem from new job creation. Jobs denote worker-firm matches, which are destroyed following worker quits. Yet, employers classify 56 percent of vacancies as quit-driven replacement hiring into old jobs, which evidently outlived their previous matches. Accordingly, aggregate and firm-level hiring tightly track quits. We augment the DMP model with longer-lived jobs arising from sunk job creation costs and replacement hiring. Quits trigger vacancies, which beget vacancies through replacement hiring. This vacancy chain can raise total job openings and net employment. The procyclicality of quits can thereby amplify business cycles. (*JEL* E24, E32, J23, J31, J63)

In matching models of the labor market, firms post vacancies to recruit workers into newly created jobs. A job is a match between a particular worker and particular firm, and disappears whenever that first match dissolves. This paper studies a more realistic notion of *longer-lived jobs that outlive matches*. Job openings then comprise new jobs as well as reposted old jobs.

A central and motivating contribution of this paper is our new, direct job-level evidence for replacement hiring: 56 percent of real-world job vacancies are for old jobs vacated by quits—rather than 100 percent new job creation as in the standard model. Our source is the IAB Job Vacancy Survey, in which German employers directly classify the nature of a given job opening, distinguishing such replacement hiring from creation of a new job. This composition is masked in standard, catch-all measures of vacancies. In an event study design, we estimate that at the establishment level, one incremental quit triggers almost perfect replacement hiring.

In the aggregate, quits, which are dramatically procyclical, comove nearly one to one with hires and job openings. Our paper explores the possibility that part of this comovement causally goes *from* quits *to* hiring. In fact, we construct a

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counterfactual time series of job openings and hires that shuts off procyclical replacement hiring; job openings and hiring would be much smoother, falling by a *third* less during recessions.

We then formally study the aggregate effects of longer-lived jobs and replacement hiring by introducing *two* parsimonious refinements into the textbook DMP model. First, some employed workers quit, accepting outside job offers.

Second, longer-lived jobs arise from a one-time, sunk job creation cost, not due when firms repost *old* jobs. Hence vacancies, once created, command a strictly positive equilibrium value, and firms optimally *replacement-hire* following quits. Intuitively, job creation corresponds to constructing a new office from scratch; replacement hiring is to fill an empty existing office. Zero job creation costs, implying zero value of vacancies and jobs as mere matches, nest the standard DMP model.

A *vacancy chain* emerges: quitters leave behind valuable vacant jobs, which firms repost, some of which are filled by employed job seekers, who in turn leave behind their old jobs, and so forth. Vacancies beget vacancies.

In equilibrium, replacement hiring and vacancy chains can raise employment by boosting total job openings. This aggregate net effect depends on the crowd-out response of new job creation, in our model guided by the adjustment cost parameter for new job creation. We conduct a meta study of 15 empirical studies, finding that such crowd-out appears very limited in the short run. For instance, temporary hiring boosts due to targeted policy incentives do not crowd out hiring by ineligible employers (Cahuc, Carcillo, and Barbanchon 2019), and sharp labor demand reductions by some employers do not lead other employers to expand in the short run in the same local labor market (e.g., Mian and Sufi 2014, Gathmann, Helm, and Schönberg 2018), even among tradables. Consequently, in the calibrated model, quit-driven replacement hiring partially passes through into total job openings, and ultimately into aggregate net employment.

By accommodating equilibrium net effects, our model also overcomes Robert Hall's critique of the original fixed-jobs and pure-churn vacancy chains in Akerlof, Rose, and Yellen (1988, p. 589): "The explanation given for a vacancy chain [...] is defective because it does not recognize stochastic equilibrium. As long as the unemployment rate is not changing over time, the chain does not end when someone moves from unemployment to employment: that move has to be counterbalanced by another move from employment to unemployment, which keeps the chain going." The aggregate net effects of our calibrated model are also consistent with the empirical causal effect of job-to-job transitions on net employment levels established by Shimer (2001) and Davis and Haltiwanger (2014) across US states, for which our model's vacancy chain mechanism therefore suggests a novel rationalization.

The model additionally implies amplification of business cycles that stems from the procyclicality of quits. In our model, recessions are times when fewer jobs open up because incumbents stay put, cutting short the vacancy chain and reducing job opportunities available to the unemployed, raising unemployment. In upswings, the tightening labor market pulls employed workers out of their matches, and the vacancies they leave behind add to the surge in vacancies, pushing down unemployment further than without replacement hiring.

We close by speculating that the trend decline in churn (Davis 2008, Davis and Haltiwanger 2014, Moscarini and Postel-Vinay 2016, Mercan 2018) may, by determining the strength of the vacancy chain, amplify labor market fluctuations, consistent with the correlations in Galí and Van Rens (2017) for the United States. Similarly, while worker flow rates in Germany—the context of our vacancy survey—are comparable to many OECD countries (Elsby, Hobijn, and Şahin 2013), replacement hiring may play an even larger role in higher-churn labor markets such as the United States.

Related Literature.—Faberman and Nagypál (2008) investigate establishment-level links between employment growth, quits, and job openings, and build a micro model fitting cross-sectional establishment-level patterns. Akerlof, Rose, and Yellen (1988) examine vacancy chains focusing on the match quality improvements (amenities) with a fixed number of jobs (not studying equilibrium). Lazear and Spletzer (2012) and Lazear and McCue (2017) study explicitly "pure churn," while our paper presents an equilibrium model and assesses potential net effects. Our paper is most closely related to Elsby, Michaels, and Ratner (2019), who study vacancy chains in a rich model featuring on-the-job search and large heterogeneous firms. Workers switch jobs to climb the productivity ladder. Firms replacement-hire because of sticky employment-level targets, which the authors support with establishment-level evidence on net employment persistence despite turnover. Reicher (2011) investigates hiring chains with heterogeneous firms and on-the-job search. Krause and Lubik (2006), Nagypál (2008), Menzio and Shi (2011), Eeckhout and Lindenlaub (2018), and Moscarini and Postel-Vinay (2018) present models featuring the labor *supply* channel, by which increased on-the-job-search during upswings stimulates new job creation. Krause and Lubik (2006) feature a mechanism akin to replacement hiring from a "bad" sector into a "good" sector due to complementarities in final-goods production. Burgess and Turon (2010) study on-the-job search and finite supply of job vacancies, but not procyclical quits and recycled jobs. Fujita and Ramey (2007) introduce adjustment costs in vacancies into a DMP model to generate empirically realistic hump-shaped impulse responses of vacancies, but do not focus on reposting of vacancies or quits. Coles and Moghaddasi-Kelishomi (2018) study layoffs and job destruction with inelastic job creation, but do not feature quits and vacancy chains. Acharya and Wee (2018) study the wage growth trend effects of an alternative notion of replacement hiring by which employers search "on the job" for better workers.

I. Replacement Hiring in the Data

(i) At the job level, surveyed employers classify the majority of job openings as replacement hiring. (ii) An establishment-level event study estimates essentially one new hire per quit. At the (iii) aggregate level, hiring and job opening time series tightly track quits, and (iv) they might be much smoother in a no-replacement-hiring counterfactual.

A. *Job-Level Evidence on Replacement Hiring from an Employer Survey*

A central contribution and motivation of the paper is our novel direct evidence on the prevalence of old jobs and replacement hiring in total job openings. Our source is a representative annual employer survey of 7,500 to 15,000 establishments from 2000 to 2015 (German IAB Job Vacancy Survey). We exploit a variable on the *reason* for the job opening, part of a section with details on the last filled job opening in the last 12 months.

The bar chart in Figure 1, panel A, shows that 56 percent of job openings are posted in response to quits.[1] Of these, 47 percentage points (9 percentage points) are permanent (temporary). Around 35 percent of vacancies target permanent net job creation, and around 8 percent in response to temporary demand increases. The composition is quite stable between 2000 and 2015 (online Appendix Figure A.1, panel A).

B. *Establishment-Level Effects of Quits on Hiring*

At the establishment level, we estimate an almost one-to-one effect of quits on replacement hiring. We use another annual representative establishment panel survey (LIAB, from the German IAB), from 1993 to 2008, on *annual cumulative* gross flows by type (quits, layoffs, hires), a "German JOLTS."[2] We focus on hiring outcomes since the point-in-time vacancy variable comes with temporal mismatch, estimating an event study for establishment e's year-t outcome for leads/lags $L \in \{0,1,2,3\}$:

$$(1) \quad \frac{\{Hires_{e,t}, Job\ Openings_{e,t}\}}{Emp_{e,t-1}} = \beta_0 + \sum_{s=-L}^{+L} \nu_s \frac{Quits_{e,t+s}}{Emp_{e,(t+s)-1}} + \alpha_e + \alpha_t + \varepsilon_{e,t}.$$

The variable ν_s measures the amount of (replacement) hires (or job openings) per quit at event time s; α_e (α_t) are establishment (year) fixed effects.

Figure 1, panel B, plots the estimates (complemented by regression results in online Appendix Tables A.1 and A.2).[3] One incremental quit is associated with between 0.74 and 1.0 additional hires (p-value $<$ 0.1 percent). Cumulating coefficients around $t = 0$ would imply even larger replacement hiring effects. The small coefficients on the leads and lags confirm that replacement hiring occurs within the year of the quit, making reverse causality (past hires triggering quits) unlikely.

Moreover, the binned scatter plots in online Appendix Figure A.1, panel B (C), reveal a strikingly *linear* shape of the replacement hiring (job posting) relationship, consistent with *job-level* replacement hiring, and motivating our model of atomistic firm-jobs rather than multi-worker firms in Section II.[4]

[1] The vacancy survey does not definitely distinguish quits from layoffs, but the connotation of examples given (e.g., maternity leave is offered as an example cause for temporary replacement hiring, and later survey rounds separate out retirement from permanent worker departures) suggests this quit interpretation.

[2] We restrict our analysis to West Germany and establishments with at least 50 employees. We exclude extreme observations ($|d \ln Emp_{e,t}| \geq 40$ percent employment growth and $Quits_{e,t}/Emp_{e,t-1} \geq 20$ percent).

[3] Online Appendix Table A.1, panel B, shows estimates for job openings consistent with the hiring effects if annualized (multiplied by 12, supposing one-month vacancy duration), but noisier likely because job openings are measured point-in-time.

[4] Ancillary evidence by Isen (2013); Doran, Gelber, and Isen (2015); and Jäeger and Heining (2019) is consistent with one-to-one replacement hiring.

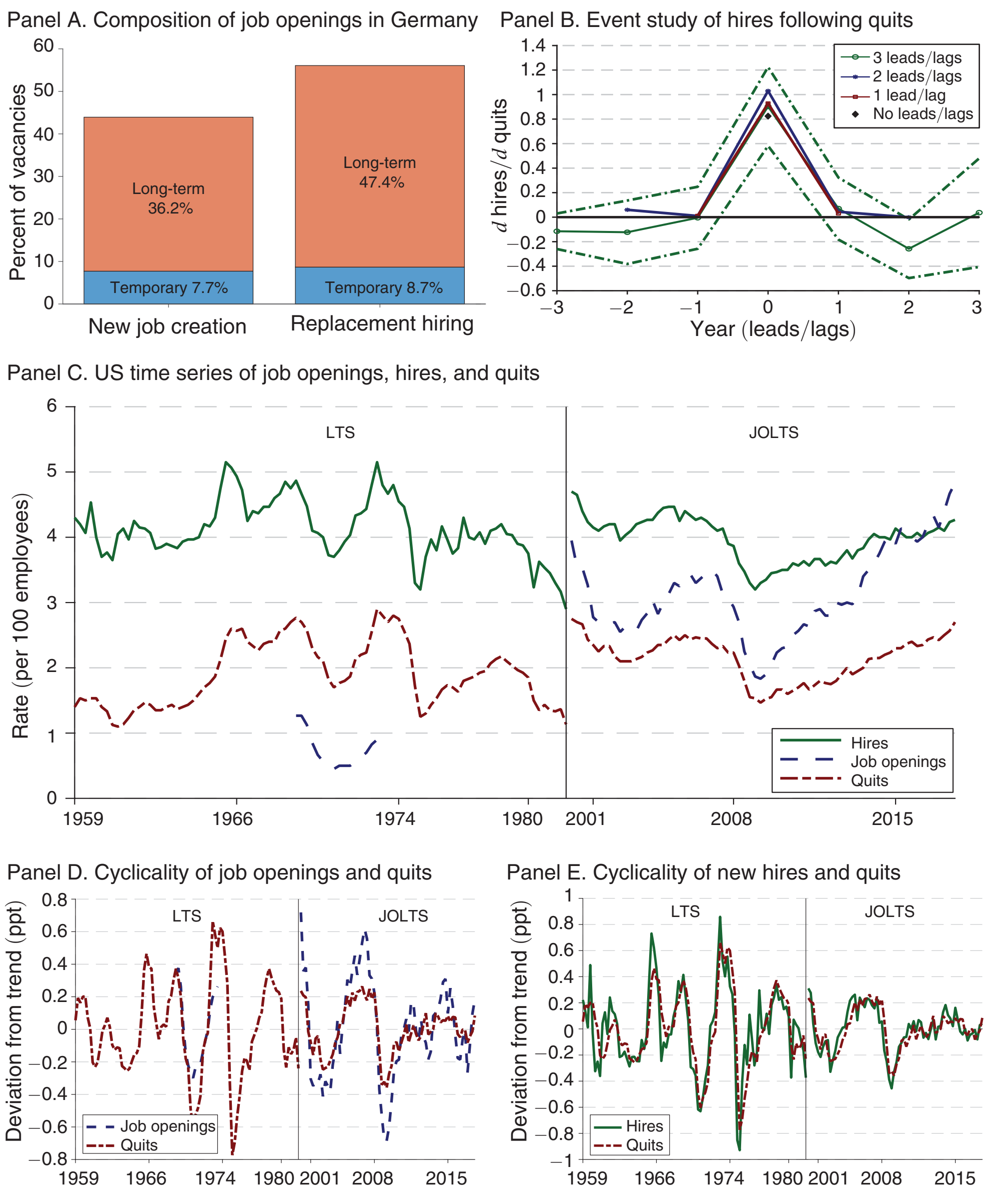

FIGURE 1. REPLACEMENT HIRING IN THE DATA

Notes: Panel A: Composition of job openings (last filled job at establishment) by reason, 2000–2015 averages. The temporary category includes seasonal factors. New job creation is phrased as a labor-demand increase ("Mehrbedarf"); replacement hiring is literal translation ("Ersatz"), where the temporary category includes maternity leave and sickness. The survey excludes apprentices, "mini-jobs," contract renewals or temp.-to-perm. switches, temp workers, and subsidized ("1 euro") jobs. Panel B: Establishment level event study of hires (per year) on quits (per year). We plot 95 percent confidence bands for the 3-lag/lead specification, estimating regression model (1), detailed in text. Panel C: Time series of quarterly averages of monthly data on job openings (point in time), and hires (count per month), and quits (count per month), all as rates (per 100 employees). Panels D and E plot detrended versions (HP-filtered with parameter 1,600).

Sources: IAB Job Vacancy Survey, IAB LIAB, BLS Labor Turnover Survey, and JOLTS.

C. *Time Series Comovement*

Figure 1, panel C, plots the US time series of quits (count per month), job openings (point in time) and new hires (count per month), averaged at the quarterly frequency. Figure 1, panels D and E, plot the detrended versions (HP-filtered, smoothing parameter of 1,600).[5] Aggregate quit rates are highly procyclical, and comove around one to one with hiring and job vacancy rates. For example, during the Great Recession, monthly quits per 100 workers fell from 2.5 to 1.5. Job openings per 100 workers moved almost in lockstep, falling from 3.3 to 2, similarly for monthly hires. The post-2000 data are from Job Turnover and Layoff Survey (JOLTS) for the private sector; the earlier data are from the BLS Labor Turnover Survey (LTS), which covers the manufacturing sector. Online Appendix Figure A.1, panel D, confirms similar aggregate cyclical patterns for Germany; panel E (F) does so for quits and hires (job openings) in response to regional business cycles (municipalities).

D. *Counterfactual Time Series without Replacement Hiring*

Building on the previous empirical facts, we next present reduced-form counterfactual time series that would arise absent replacement hiring fluctuations—i.e., if reposted vacancies were stable, and *only* new job creation fluctuated. We will study the *equilibrium* counterfactual in the cyclical analysis of the calibrated model in Section IIID.

Total vacancies $v = r + n$ consist of reposted old jobs r and new jobs n. Our job-level evidence suggests a share of reposted vacancies $\rho = r/(r+n) = 0.56$ in Germany. Percent deviations from trend in total vacancies are a ρ-weighted average of those in r and n:

$$\frac{dv}{v} = \rho \frac{dr}{r} + (1-\rho)\frac{dn}{n}, \tag{2}$$

where in practice we study deviations from an HP trend with quarterly log time series (smoothing parameter of 1,600).

The object of interest is the counterfactual vacancy time series that would mechanically emerge if $dr = 0$ at all points while n's path remained unaffected. We back out new job creation as total-vacancy growth net of growth in repostings by rearranging identity (2), then proxying for reposted vacancies with worker quits (exploiting the one-to-one, linear replacement hiring estimated in Section IB):

$$\left.\widetilde{\frac{dv}{v}}\right|_{dr=0} = (1-\rho)\frac{dn}{n} = \frac{dv}{v} - \rho\frac{dr}{r} \approx \frac{dv}{v} - \rho\frac{dQuits}{Quits}. \tag{3}$$

Figure 2, panel A, presents this counterfactual vacancy series along with the empirical one, relying on JOLTS quit and vacancy data from 2000 through 2018. The graph reveals amplification potential: during the Great Recession, total job openings

[5] We have found similar results with the detrending procedure advocated by Hamilton (2018), with overall larger, yet proportional, amplitudes.

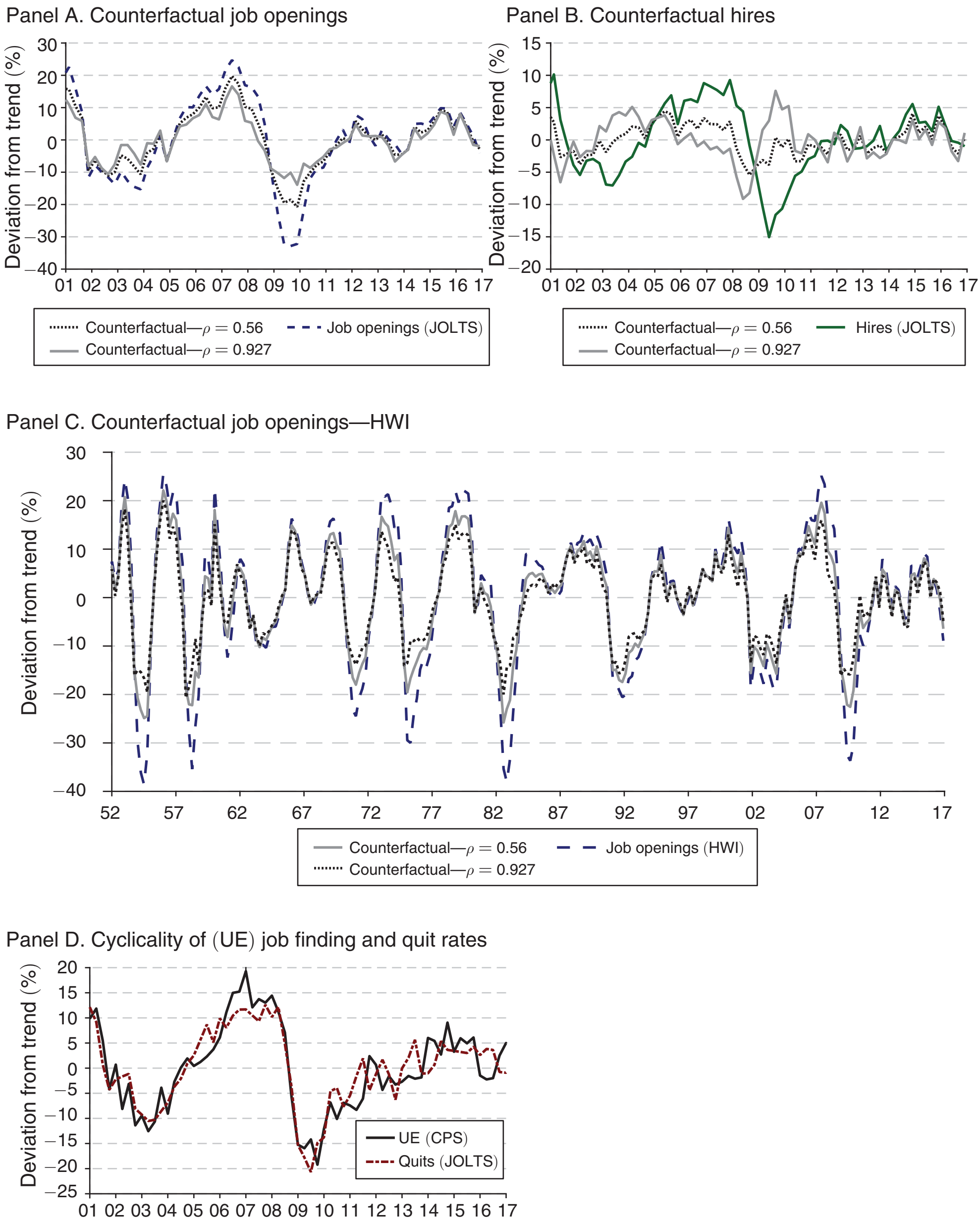

Figure 2. Counterfactual Time Series and Quit Cyclicality

Notes: All time series are quarterly, logged and HP-filtered with smoothing parameter $\lambda = 1{,}600$. Consistent with the decomposition exercise, they are in levels (counts), rather than rates (per 100 workers). The monthly time series (JOLTS, CPS) have been averaged at the quarterly frequency. Panel A: Actual and counterfactual job openings from JOLTS. Panel B: Actual and counterfactual hires from JOLTS. Panel C: Actual and counterfactual job openings from the Help Wanted Index. Panel D: Cyclical component of UE job finding rates (CPS, our construction) and quit rates (JOLTS, count of quits per month per 100 employees). A regression reveals a linear coefficient of UE on quit rates of 0.985 ($R^2 = 0.77$).

would have only dropped by 20 percent instead of 30 percent. Panel B illustrates the smoothing predicted for hires. Panel C extends the vacancy time series to 1951 using the Help Wanted Index (Barnichon 2010), confirming the role of replacement hiring in all post-War recessions.[6]

The Role of Churn ρ.—The amplification potential naturally depends on ρ, the share of reposted vacancies in total vacancies. Our baseline calibration to $\rho = 0.56$, from the German context, is likely a lower bound for higher-churn economies such as the United States. A back of the envelope extrapolation suggests a US ballpark $\rho^{US} \approx 0.93$.[7] Figure 2 panels A–C also plot this more speculative counterfactual, illustrating the potential range of amplification.

II. A Model of Jobs, Matches, and Replacement Hiring

We introduce longer-lived jobs, a distinction between jobs and matches, and replacement hiring into the DMP model, and then study their equilibrium consequences quantitatively in Section III.

Preview.—We add a one-time, sunk cost per new job created, $k(n_t)$, with $k'(n_t) \geq 0$, where n_t denotes the number of new, initially vacant, jobs. The net value of a newly created job, N_t, is the value of a vacant job V_t minus upfront cost $k(n_t)$: $N_t = V_t - k(n_t)$. Free entry for *new* job creation pushes equilibrium N_t to zero, and hence if $k(0) > 0$, the equilibrium value of a vacant job is strictly positive:

$$V_t = k(n_t). \tag{4}$$

Here, when a worker-firm *match* dissolves that leaves the *job* intact, the firm optimally reposts the valuable vacancy—i.e., engages in replacement hiring. Jobs outlive matches.

Such longer-lived jobs render the vacancy stock v_t predetermined, following law of motion:

$$v_t = n_t + (1 - q_{t-1}) v_{t-1} + r_t, \tag{5}$$

where q and r denote the vacancy filling rate and newly reposted vacancies, respectively.

A *vacancy chain* emerges: vacancies can meet employed workers, who quit to switch jobs, leaving their jobs vacant, which firms optimally repost, and so forth. Vacancies beget vacancies.

[6] To extrapolate the quit time series to the pre-JOLTS time period, we estimate an "Okun's law" for quits. Specifically, we regress the quarterly JOLTS detrended log quit level on the detrended unemployment rate ($R^2 = 0.88$). We then project that estimated semi-elasticity (-0.1) onto the full unemployment time series.

[7] Online Appendix Figure A.1, panel D, highlights that German churn is an order of magnitude below the US ones (since it represents *annual* hires while JOLTS is *monthly*), consistent with cross-country evidence on worker flows (Elsby, Hobijn, and Şahin 2013). Let $\rho^i = r^i/(r^i + n^i)$ denote the share of repostings in total job openings for country i. Under the approximation of one-to-one quit-replacement hiring, ρ can be stated in terms of quit rate Q^i and new job creation rate C^i: $\rho^i = Q^i/(Q^i + C^i)$, such that $C^i = Q^i[1/\rho^i - 1]$. Under the perhaps extreme assumption $C^i = C^j = C$, we can express: $\rho^j = Q^j/(Q^j + C) = Q^j/(Q^j + Q^i[1/\rho^i - 1]) = 1/(1 + Q^i/Q^j[1/\rho^i - 1])$. For the United States and Germany, $Q^{US}/Q^{DE} \approx 10$, and then $\rho^{DE} = 0.56$ implies $\rho^{US} = 0.9272$.

This vacancy chain can have *aggregate net effects* beyond churn, on total vacancies—depending on the response by *new* jobs:

$$\frac{dv_t}{dr_t} = \overbrace{\underbrace{\frac{dn_t}{dr_t}}_{\in[-1,0]} + 1}^{\in[0,1]}. \tag{6}$$

In our model, this "crowd-out" dn_t/dr_t is guided by the shape of job creation cost $k(n_t)$. Since empirical crowd-out—we show in Section IIIC—appears small in the short run, replacement hiring passes through into total job openings, some of which are filled by the unemployed, hence raising aggregate net employment.

A. *Environment*

Time is discrete. There is a unit mass of workers, with risk neutral preferences and discount factor β, who are either employed or unemployed. There is a larger mass of potential firm entrants. Firms are single-worker jobs, owned by workers.

Jobs, Matches, Separations, and Vacancies.—*Jobs* denote long-lasting entities that can be vacant or matched. *Matches* denote a job that is filled by a particular worker. In each period, jobs are exogenously destroyed with probability δ: the worker becomes unemployed, the job disappears forever without replacement hiring. Matches moreover dissolve with probability σ (the worker becomes unemployed), or through a worker job-to-job transition (described below). These jobs—vacated by what we label "quits" going forward—remain intact with probability γ and trigger replacement hiring (while $(1-\gamma)$ of match dissolutions destroy the job).

Job Creation.—One new job (aggregate count n) can be created at sunk cost $k(n)$. Note, $k(n) = 0$ nests standard DMP.[8] If $k(n) > 0$, firms will repost jobs vacated by quits. All vacancies also require the standard per-period maintenance cost κ.

Matching.—Both unemployed and employed workers look for jobs. Employed workers search with intensity λ relative to unemployed workers. Meetings between vacancies and workers follow a constant returns matching function $M(s,v) < \min\{s,v\}$. Labor market tightness $\theta = v/s$ is the ratio of vacancies v to searchers $s = u + \lambda e$. The job [worker] finding probability for an unemployed (employed) worker [vacancy] is $f(\theta) = M/s = M(1,\theta)$ $(\lambda f(\theta))$ $[q(\theta) = M/v = M(1/\theta,1)]$.

Timing.—The timing of events within period t is:

(i) $\mathbf{s}_t$, the state of the economy, is realized, including unemployment u_t and beginning-of-period (inherited) vacancies $\tilde{v}_t$.[9]

[8] Fujita and Ramey (2007) use a similar cost to smooth out vacancy responses in a model without replacement hiring.

[9] Our experiments will comprise perfect foresight transition dynamics, so we do not make $\mathbf{s}_t$ explicit here.

(ii) Employed workers consume a bargained wage w_t and produce y_t, unemployed workers receive unemployment benefit b.

(iii) Firms create n_t new jobs at cost $k(n_t)$ each, and pay flow cost κ per vacancy. This determines total vacancies $v_t = \tilde{v}_t + n_t$ and market tightness $\theta_t = v_t/(u_t + \lambda(1 - u_t))$.

(iv) $f(\theta_t)u_t$ of unemployed workers find jobs, $\lambda f(\theta_t)e_t$ of employed workers switch jobs.

(v) Fraction δ of jobs are exogenously destroyed; these workers become unemployed.

(vi) Fraction σ of matches are exogenously dissolved; these workers become unemployed. Share γ $(1 - \gamma)$ of jobs hit by EE quits or σ shocks can be reposted as vacancies (are destroyed).

The law of motion for unemployment is

$$u_t = \underbrace{\big(1 - (1 - \delta)(1 - \sigma)f(\theta_{t-1})\big)\, u_{t-1}}_{\text{stay unemployed}} + \underbrace{\delta(1 - u_{t-1})}_{\text{EU: job destruction}} + \underbrace{(1 - \delta)\sigma(1 - u_{t-1})}_{\text{EU: match separation}}. \tag{7}$$

Due to sunk cost $k(n)$, the vacancy stock is predetermined, with law of motion:

$$v_t = \underbrace{n_t}_{\text{new}} + \underbrace{(1-\delta)\left(\underbrace{\big(1-(1-\sigma)q(\theta_{t-1})\big)v_{t-1}}_{\text{unfilled}} + \overbrace{\gamma\left(\underbrace{\lambda f(\theta_{t-1})e_{t-1}}_{\text{reposted: EE}} + \underbrace{\sigma\big(1-\lambda f(\theta_{t-1})\big)e_{t-1}}_{\text{reposted: EU}}\right)}^{=\gamma(\sigma+(1-\sigma)\lambda f(\theta_{t-1}))e_{t-1}}\right)}_{\text{beginning-of-period (inherited) vacancies } \tilde{v}_t}. \tag{8}$$

Below, we drop time subscripts and use primes ($'$) to denote the next period.

B. *Value Functions*

Value functions are expressed recursively, after the aggregate state is realized (i.e., after subperiod i).

Worker Problem.—The worker when unemployed consumes unemployment benefit b. She may match with a job, to start work next period (unless a match/job shock hits), or stays unemployed:

$$U(\mathbf{s}) = b + \beta(1 - \delta)(1 - \sigma)f(\theta)E[W(\mathbf{s}')] + \beta(1 - (1 - \delta)(1 - \sigma)f(\theta))E[U(\mathbf{s}')]. \tag{9}$$

An employed worker consumes wage $w(\mathbf{s})$, and then may stay, quit to another job, or become unemployed:

$$W(\mathbf{s}) = w(\mathbf{s}) + \beta(\delta + (1-\delta)\sigma)E[U(\mathbf{s}')] + \beta(1-\delta)(1-\sigma)\underbrace{\left(\overbrace{1-\lambda f(\theta)}^{\text{stay}} + \overbrace{\lambda f(\theta)}^{\text{quit}}\right)}_{=1} E[W(\mathbf{s}')]. \tag{10}$$

Maximally Parsimonious On-the-Job Search.—We present a parsimonious version of job-to-job quits because its hard-wired unit-elasticity between job-to-job quit $(\lambda f(\theta))$ and unemployed job finding $(\text{UE}, f(\theta))$ turns out to produce empirically realistic quits, as shown in panel D of Figure 2, where we plot log deviations from trend of the quarterly quit rate (based on the JOLTS) against the job finding rate (based on the CPS) of the unemployed (regression coefficient of UE on quit rates of 0.985, $R^2 = 0.77$).[10]

Online Appendix E presents a richer model that explicitly rationalizes job switching with heterogeneity in match quality, and features endogenous job search effort—with similar amplification results.

Firm Problem.—Newly created jobs have value

$$N(\mathbf{s}) = -k(n) + V(\mathbf{s}). \tag{11}$$

Once created, a vacancy carries value

$$V(\mathbf{s}) = -\kappa + \beta(1-\delta)\Big[q(\theta)(1-\sigma)E[J(\mathbf{s}')] + \big(1-q(\theta)(1-\sigma)\big)E[V(\mathbf{s}')]\Big]. \tag{12}$$

A vacancy incurs flow cost κ and matches with a worker with probability $q(\theta)$; otherwise it stays vacant or is destroyed.

A filled job produces output y and pays wage w. If the *match* separates (σ shock or job-to-job quit), the *job* enters next period as a vacancy with probability γ (and otherwise becomes destroyed and is worth 0), hence its value is:

$$J(\mathbf{s}) = y - w(\mathbf{s}) + \beta(1-\delta)\Big[\gamma\big(\sigma + (1-\sigma)\lambda f(\theta)\big)E[V(\mathbf{s}')] + (1-\sigma)(1-\lambda f(\theta))E[J(\mathbf{s}')]\Big]. \tag{13}$$

Free Entry.—Free entry in job creation drives new job values $N(\mathbf{s}) = -k(n) + V(\mathbf{s})$ to zero:

$$V(\mathbf{s}) = k(n). \tag{14}$$

[10] CPS job-to-job transition measures (with short/no nonemployment spell) are slightly smoother than quits but include layoffs/job destruction, not exclusively quits.

C. *Match Surplus and Wage Bargaining*

The worker's outside option is unemployment, *even for a job switcher*, who must renounce her old job before bargaining with the new employer (rather than permitting sequential bargaining as in Postel-Vinay and Robin 2002; our simplification is also used in Fujita and Ramey 2012). Joint match surplus $S(\mathbf{s})$ is

$$S(\mathbf{s}) \;=\; J(\mathbf{s}) - V(\mathbf{s}) + W(\mathbf{s}) - U(\mathbf{s}). \tag{15}$$

Wages are determined according to generalized Nash Bargaining with worker share $\phi \;\in\; (0,1)$ to maximize

$$\big(W(\mathbf{s}) - U(\mathbf{s})\big)^{\phi}\big(J(\mathbf{s}) - V(\mathbf{s})\big)^{1-\phi}, \tag{16}$$

implying linear surplus sharing, worker (firm) capturing share ϕ $(1 - \phi)$ of joint surplus S:[11]

$$\phi S(\mathbf{s}) \;=\; W(\mathbf{s}) - U(\mathbf{s}), \tag{18}$$

$$(1 - \phi)S(\mathbf{s}) \;=\; J(\mathbf{s}) - V(\mathbf{s}). \tag{19}$$

D. *Stationary Equilibrium Definition*

We solve the model in steady state. The stationary equilibrium of the model is a set of value functions $W(\mathbf{s})$, $U(\mathbf{s})$, $J(\mathbf{s})$, and $V(\mathbf{s})$, wage function w, and new job creation n such that: (i) Worker and firm values satisfy Bellman Equations (9), (10), (12), and (13). (ii) Wage w maximizes equation (16). (iii) Unemployment u and vacancies v follow the laws of motion (7) and (8). (iv) New job creation n satisfies free entry condition (14).

E. *Calibration*

Panel A of online Appendix Table B.1 summarizes the calibration; Panel B reports the targeted moments and the model fit. We discuss below, formally and informally, how these target moments help identify the model parameters. Computational details are in online Appendix B. We relegate the specification and calibration of job creation cost $k(n)$ to Section III.

[11] Using (9), (10), (12), (13), (15), (18), and (19), joint surplus is

$$\begin{aligned} S(\mathbf{s}) \;=\;& y - b + \kappa + \beta(1-\delta)(1-\sigma)\big[1 - \lambda f(\theta) - f(\theta)(1-\lambda)\phi - q(\theta)(1-\phi)\big]E\big[S(\mathbf{s}')\big] \\ &+ \beta(1-\delta)\big[(1-\sigma)\big(1-\lambda f(\theta)\big) + \gamma\sigma - 1 + \gamma(1-\sigma)\lambda f(\theta)\big]E\big[V(\mathbf{s}')\big], \end{aligned} \tag{17}$$

where $V(\mathbf{s}) \;=\; -\kappa + \beta(1-\delta)\big[q(\theta)(1-\sigma)(1-\phi)E\big[S(\mathbf{s}')\big] + E\big[V(\mathbf{s}')\big]\big]$.

We start with standard DMP parameters set outside of the model. Our model period is a month. Discount factor $\beta = 0.9967$ targets an annual interest rate of 4 percent. Standard Cobb-Douglas matching function $M(s,v) = \mu s^{\eta} v^{1-\eta}$ features elasticity of matches with respect to total search effort η and matching efficiency μ. Unemployed (employed) job finding [vacancy filling] rate is $f(\theta) = \mu\theta^{1-\eta}$ ($\lambda f(\theta) = \lambda\mu\theta^{1-\eta}$) [$q(\theta) = \mu\theta^{-\eta}$]. We set $\eta = 0.5$, as standard. Inconsequential for our study of *relative* amplification, we set $\phi = 0.5$ (Hosios condition) and pragmatically $b = 0.9$ following Fujita and Ramey (2007), who in turn follow Hagedorn and Manovskii (2008) for sizable amplification.

GMM sets the remaining DMP parameters. Targeting a monthly UE rate of 45 percent (Shimer 2005) with model counterpart $(1-\delta)(1-\sigma)f(\theta) = (1-\delta)(1-\sigma)\mu\theta^{1-\eta}$, yields $\mu = 0.6542$. Steady-state unemployment rate $EU/(EU+UE) = 5.7$ percent disciplines EU rate $\delta + (1-\delta)\sigma = 2.72$ percent. Targeting job filling rate $(1-\delta)(1-\sigma)q(\theta) = 0.9$ (Fujita and Ramey 2007) normalizes steady-state market tightness $\left((1-\delta)(1-\sigma)f(\theta)\right)/\left((1-\delta)(1-\sigma)q(\theta)\right) = \theta = 0.45/0.9 = 0.5$. We then find a vacancy posting cost $\kappa = 0.1611$ consistent with free entry and this tightness, given job creation costs $k(n)$, discussed below. We pin down on-the-job search efficiency $\lambda = EE/UE = 0.056$, targeting an average monthly quit rate of 2.5 percent (CPS EE, Fujita and Nakajima 2016, and JOLTS quit rate). To separately identify match-separation $\sigma = 0.0051$ and job-destruction $\delta = 0.0222$ rates, we target a vacancy reposting share $\rho = \frac{\gamma(1-\delta)\left[\lambda f + \sigma(1-\lambda f)\right]e}{n + \gamma(1-\delta)\left[\lambda f + \sigma(1-\lambda f)\right]e} = 56$ percent (see Section IA).

III. Aggregate Effects of Replacement Hiring and Vacancy Chains

Job Creation Cost $k(n)$.—We organize our discussion of the aggregate implications of replacement hiring and vacancy chains around job creation cost $k(n)$, specifying it in terms of deviations from steady-state $\bar{n}$:

$$k(n) = k_1 + k_2 \times \frac{n - \bar{n}}{\bar{n}}. \tag{20}$$

The variable k_1 guides (micro) replacement hiring by generating positively valued vacancies, which we discuss and calibrate first below. We then move to equilibrium aggregate consequences of replacement hiring by calibrating k_2, the degree to which hiring costs are increasing in n, e.g., due to adjustment costs.

A. *Firm-Level Replacement Hiring*

Free entry (14) implies that firms create vacancies until the "$k(n)$-profit" condition (replacing the standard DMP zero-profit) is satisfied in all periods:

$$\begin{aligned} \kappa + (1-\beta(1-\delta))\,k_1 + \left(1 - \beta(1-\delta)E\left[\frac{n' - \bar{n}}{n - \bar{n}}\right]\right)\frac{n - \bar{n}}{\bar{n}}k_2 \\ = \beta(1-\delta)q(\theta)(1-\phi)E\left[S(\mathbf{s}')\right]. \end{aligned} \tag{21}$$

Parameter $k_1 > 0$ ensures a positive ex post value of vacancy in steady state. As a result, jobs vacated by quits are reposted. We set k_1 to 0.1, large enough to ensure that $k(n) > 0$ and thus $n > 0$ in all our subsequent experiments. Equilibrium entry condition (21) clarifies that κ and k_1 affect steady-state surplus similarly, and we let $\kappa = 0.1611$ be estimated to target normalized $\theta = 1/2$. We also set $\gamma = 1$ to match the $\sim$1.0 (cumulative) estimate from Section IB.

B. *Vacancy Chains*

Our model features a *vacancy chain*, by which vacancies beget vacancies through quits and the associated replacement hiring. Formally, the chain tracks a single vacancy and all the additional vacancies it triggers by meeting employed workers (probability $1 - \Upsilon$), who quit and leave behind another vacancy, which we then track, and so forth. The chain ends when it meets an unemployed searcher (probability $\Upsilon = u/(u + \lambda(1 - u))$), or is destroyed by a δ-shock. The chain *length C* counts these vacancies, obtained recursively:[12]

$$E[C] = 1 \cdot [\delta + (1-\delta)q\Upsilon] + (1-\delta)q(1-\Upsilon)(E[C] + \gamma) + (1-\delta)(1-q)E[C] = \frac{\delta + (1-\delta)q\big(\Upsilon + \gamma(1-\Upsilon)\big)}{1 - (1-\delta)(1-q\Upsilon)}. \tag{23}$$

In our calibrated model, this length is 1.88, i.e., one vacancy entails 0.88 vacancies in excess of itself.

C. *Aggregate Equilibrium Effects*

The vacancy chain is a microeconomic concept tracking the life cycle of a single vacancy and its "offspring." To study the equilibrium implications of the vacancy chain, we consider a one-time exogenous addition to the stock of inherited vacancies.[13] Whether and how much such a vacancy "injection" actually adds to the total stock on net (and then affects other quantities) depends on the response in new job creation.

Crowd-Out by New Job Creation: Model.—The key response to a vacancy injection—and in fact the only *contemporaneous* one in the vacancy law of motion—stems from the *crowd-out* response by new job creation. In terms of

[12] If $\delta = 0$ and $\gamma = 1$, $E[C] = \big(0.057 + 0.0556 \times (1 - 0.057)\big)/0.057 = 1.92 \approx 1.88$ since $\delta \ll \Upsilon$. Alternatively, the length can be calculated as a binomial sum of iso-length paths:

$$E[C] = \sum_{c=1}^{\infty} c \cdot \Pr(C = c) = \sum_{c=1}^{\infty} c \sum_{t=c-1}^{\infty} \left(\binom{t}{t-(c-1)} \frac{(\delta + (1-\delta)q\Upsilon)(\gamma(1-\delta)q(1-\Upsilon))^{c-1}}{((1-\delta)(1-q) + (1-\delta)q(1-\Upsilon)(1-\gamma))^{(c-1)-t}} \right). \tag{22}$$

[13] This ad hoc experiment may capture, e.g., cyclical shifts in public employment or sectoral shocks.

beginning-of-period vacancy shifts $d\tilde{v}$, one additional vacancy is crowded out by $dn/d\tilde{v} \in [-1,0]$, and *on net* raise the vacancy stock only by $(1 + dn/d\tilde{v}) \leq 1$. Crowd-out $dn_t/d\tilde{v}_t$ is an equilibrium outcome and depends on k_2, the increasing degree of hiring cost. In panel A of Figure 3 we plot $dn_t/d\tilde{v}_t$ for various values of k_2, along with total-vacancy response $dv_t/d\tilde{v}_t = 1 - dn_t/d\tilde{v}_t$, where $dx = x_t - \bar{x}$ denotes level deviation from steady state. The simulated data plots the first-period (hence largest) response to a (beginning-of-period) "vacancy injection" $\varepsilon_t^{\tilde{v}}$ shock:[14]

$$v_t = n_t + (1-\delta)\Big(\big(1-(1-\sigma)q(\theta_{t-1})\big)v_{t-1} + \gamma\big(\sigma + (1-\sigma)\lambda f(\theta_{t-1})\big)e_{t-1}\Big) \boxed{+\,\varepsilon_t^{\tilde{v}}}. \tag{24}$$

In calculating the underlying impulse responses, we focus on perfect foresight transition dynamics following one-time, unanticipated shocks out of steady state, using a shooting algorithm (details in online Appendix B.3). We plot and discuss the full impulse response functions (IRFs) for new job creation (and unemployment and vacancies) in online Appendix C.

The case of $k_2 = 0$ provides an extreme benchmark of *perfect neutrality* of vacancy inflows such as from replacement hiring: full crowd-out ($dn/d\tilde{v} = -1$) and no pass-through into total vacancies ($dv/d\tilde{v} = 0$), since n adjusts such that $v^* = \theta^* \cdot u$, and θ remains—as in the standard DMP model—the equilibrating variable. Reposting then merely tilts the *composition* from new to old jobs in the economy, despite longer-lived jobs and reposting.

By contrast, for all $k_2 > 0$, replacement hiring has net effects on aggregate labor market outcomes. Intuitively, at the original $\bar{n}$, a vacancy injection incipiently lowers V a lot (as q falls and w increases due to higher θ), beyond the original free entry consistent $k(n)$. Free entry leads n to fall, the process that drives the adjustment to the new equilibrium by again raising V and, due to $k_2 > 0$, also lowering $k(n)$. The incidence between $k(n)$ and V—whether new jobs fully restore the original total-vacancy level, and V and $k(n)$ to the original levels—depends on the shape of $k(n)$. When $k'(n) > 0$ ($k_2 > 0$), the fall in new job creation stops "prematurely," at a lower equilibrium $k(n) = V$, hence implying higher *total* job openings. Under $k_2 > 0$ ($k_2 \to \infty$), repostings are offset less than one to one (not at all) and thus pass through (completely) into total job openings and aggregate employment.

Empirical Evidence for Crowd-Out, and Calibration of k_2.—We calibrate k_2 by matching the model crowd-out to empirical targets. In Figure 3, panel B, we conduct a meta study and convert 15 suitable empirical studies into implied crowd-out measures. Strikingly, nearly every study points toward *zero* (if not positive) short-run crowd-out. For example, subsidies boosting hiring among eligible firms do not curb hiring by ineligible employers in the same labor market (Cahuc, Carcillo, and Barbanchon 2019), and sharp hiring (employment) reductions

[14] The shock hits in period $t = 1$ (beginning of period), and is zero for all $t \neq 1$. We consider a shock small enough, specifically 1 percent of steady-state vacancy stock, to not crowd out n_1 below zero, although we have checked that crowd-out is quite stable in shock size.

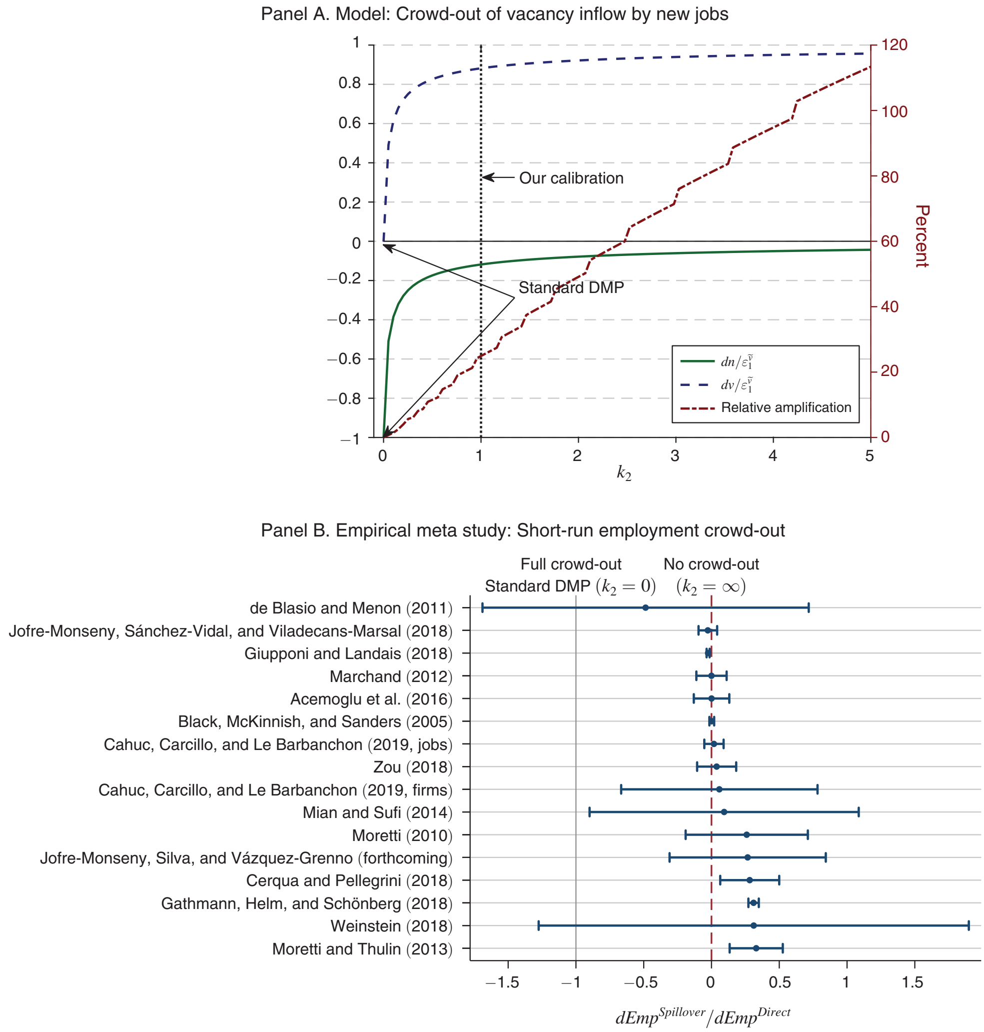

Figure 3. Short-Run Employment Crowd-Out in the Model and the Data

Notes: Panel A presents simulated model responses of new job creation n and total vacancy stock v upon impact to an exogenous injection of vacancies as a function of the vacancy cost creation parameter k_2. The right y-axis plots the corresponding relative amplification of the baseline model compared to a no-reposting counterfactual, in response to a productivity shock, described in Section IIID. Panel B presents a meta study of *empirical estimates* speaking to employment crowd-out underlying our calibration of k_2. We describe the papers and detail our calculations of the spillover effects in online Appendix D. Some sensitivities are backed out from elasticities. Most studies report crowd-out effects with SEs. For the others, we either replicate results (Mian and Sufi 2014, Acemoglu et al. 2016) and estimate crowd-out SEs in an IV strategy to estimate crowd-out as the ratio of spillover to direct effects $\beta^{Spillover}/\beta^{Direct}$ for some instrument affecting a subset of employers, and report SEs of the IV effect. In cases where we cannot access the data directly to reestimate IV SEs (Gathmann et al. 2018; Cahuc, Carcillo, and Barbanchon 2019; Weinstein 2018; Giupponi and Landais 2018), we could construct SEs with the Delta method as follows (i.e., be forced to assume a zero covariance term): $\mathrm{SE}\left(\beta^{S(pillover)}/\beta^{D(irect)}\right) = \mathrm{SE}^D/\beta^S \cdot \sqrt{1+\left(\beta^S/\beta^D\right)^2 \cdot \left(\mathrm{SE}^S/\mathrm{SE}^D\right)^2} = \mathrm{SE}^D/\beta^S \cdot \sqrt{1+\left(t^S/t^D\right)^2}$. In practice, since spillover effects are small compared to direct effects, and since direct effects are precisely estimated, these SEs are close to $\mathrm{SE}^{Direct}/\beta^{Spillover}$, which we therefore report for this subset.

do not lead unaffected employers in the same local labor market to expand in the short run even within the tradable sector (e.g., Mian and Sufi 2014, Gathmann et al. 2018). Some caveats apply to our extrapolation from local to aggregate crowd-out.[15] Based on the preponderance of the evidence, we set $k_2 = 1$, still implying some crowd-out, $dn_t/d\tilde{v} = -0.1183$.

Equilibrium Effects of Reposting: The Vacancy Multiplier.—To investigate the dynamic equilibrium effects of a (one-time, perfectly transitory) vacancy injection $\varepsilon^{\tilde{v}}$ such as arising from reposting, we define a *vacancy multiplier*, which cumulates the vacancy *inflows* generated by the shock (as deviations from steady-state $\bar{v}^{inflow}$) over horizon h,

$$M(h) = \frac{\sum_{s=1}^{h}\left(v_s^{inflow} - \bar{v}^{inflow}\right)}{\varepsilon_1^{\tilde{v}}}, \tag{25}$$

where $v_s^{inflow} = n_s + (1-\delta)\gamma\left(\sigma + (1-\sigma)\lambda f(\theta_{s-1})\right)e_{s-1} + \varepsilon_s^{\tilde{v}}$ captures the total inflow of newly created and reposted vacancies (with $\varepsilon_s^{\tilde{v}} = 0\,\forall s \neq 1$).

In addition, we *decompose* the multiplier. First, we plot the "one-only" multiplier that would arise *if only one of the variables shifted* (the rest held at steady state). Second, we plot the "all-but-one" complementary multiplier: if all variables adjusted *except for the variable of interest kept at its steady state*.

Figure 4, panel C (impulse response in companion panel A), reveals that the equilibrium multiplier reaches around 1.37. The immediate vacancy pass-through in period one is $0.88 = 1 + dn/d\tilde{v}$, and after 3 (6) [12] months the multiplier has reached 1.03 (1.16) [1.29]. The first implication is the positive level: rather than being crowded out as in the standard DMP model, an exogenous vacancy injection raises the aggregate vacancy stock. This result motivates our discussion of business-cycle amplification in Section IIID below.

Second, the multiplier *exceeds* 1.00, implying that the model features amplification akin to the micro vacancy chain: a given vacancy injected into the economy "generates" an additional 0.37 vacancies in excess of itself. The "one-only" decompositions in panel C clarify that much of the multiplier is due to the job finding boost—the equilibrium analogue of the micro vacancy chain. Still, at 1.37 the equilibrium multiplier remains below the micro vacancy chain (1.88), confirming the importance of the equilibrium perspective. Here, the "all-but-one" decomposition panel D (IRFs in B) clarifies that crowd-out by new job creation is the culprit: if n were held at steady state, the multiplier would reach around 2.25, even exceeding the micro vacancy chain (1.88). Hence our limited crowd-out calibration of k_2 leaves new job creation with a quantitatively important role.

[15] First, most studies do not differentiate between employment and hiring (although Cahuc, Carcillo, and Barbanchon 2019 do and find similar estimates (Table 3)). Second, we do not rescale the spillover-treated (e.g., tradable) sector to the full labor market (e.g., by $1/$*Share Tradable*), which would further increase the positive estimates. Third, agglomeration forces may mask crowd-out (Moretti 2010, Gathmann et al. 2018). Fourth, non-local other (e.g., capital) markets may imply larger crowd-out for national experiments. Fifth, mismeasured labor market overlaps may bias crowd-out away from -1, although matching functions appear consistent across levels of aggregation (Petrongolo and Pissarides 2001). Moreover, e.g., Gathmann et al. (2018) show robustness to year-industry-location cells.

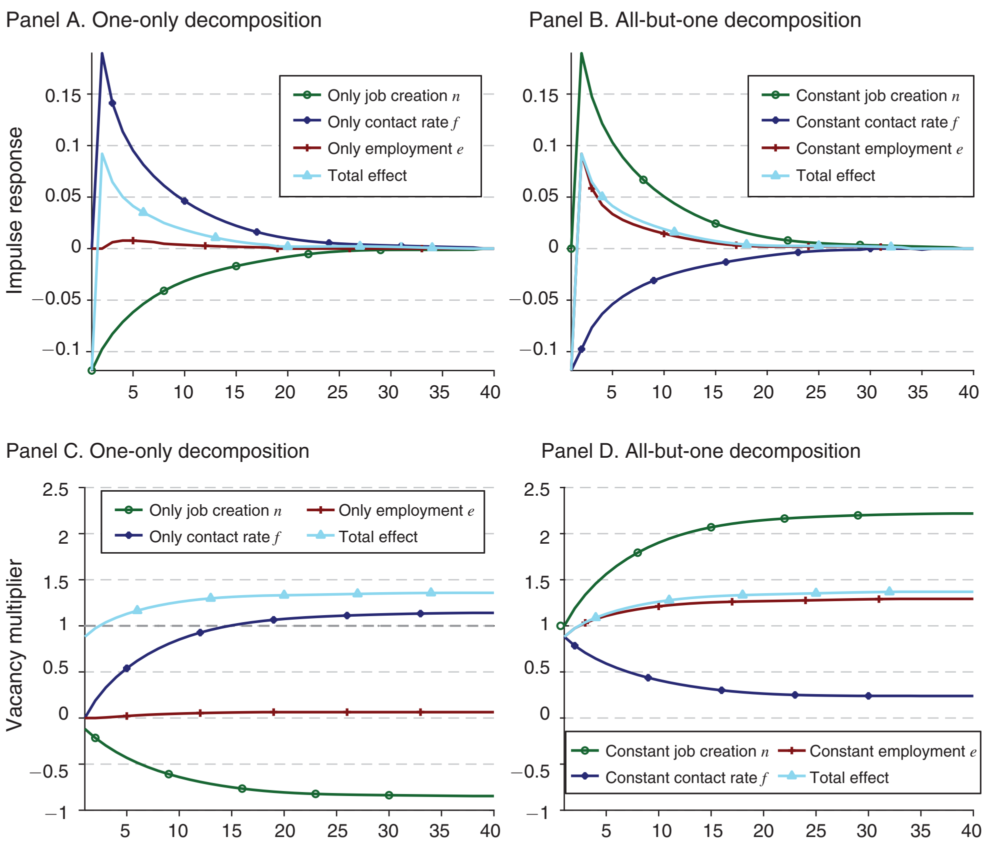

FIGURE 4. DECOMPOSING THE VACANCY MULTIPLIER

Notes: The figure presents impulse responses (panels A and B) and cumulative vacancy multipliers (panels C and D) of vacancy inflows in response to a perfectly transitory exogenous increase in the vacancy stock by 1 percent, for simulated time series and its components. The variables are normalized by the size of vacancy injection $\varepsilon_1^{\tilde{v}}$, which is not plotted. Panels A and C additionally present "one-only" inflows (that only permit one variable to move from steady state); panels B and D present "all-but-one" inflows (that keep only one variable at steady state). The *total effect* is $\left(n_t + (1-\delta)\gamma\left(\sigma + (1-\sigma)\lambda f_{t-1}\right)e_{t-1} + \varepsilon_1^{\tilde{v}} - \bar{v}^{Inflow}\right)/\varepsilon_1^{\tilde{v}}$. We then decompose this total effect. The one-only decomposition features (i) the only job creation n effect $(n_t - \bar{n})/\varepsilon_1^{\tilde{v}}$; (ii) the only contact rate f effect $(1-\delta)\gamma(1-\sigma)\lambda\left(f_{t-1} - \bar{f}\right)\bar{e}/\varepsilon_1^{\tilde{v}}$; (iii) the *only employment e* term, where we plot the sum of (iiia) the mechanical employment rate effect $(1-\delta)\gamma(1-\sigma)\lambda\bar{f}\left(e_{t-1} - \bar{e}\right)/\varepsilon_1^{\tilde{v}}$, (iiib) the small effect of the employment change on quits through σ shocks $(1-\delta)\gamma\sigma\left(e_{t-1} - \bar{e}\right)/\varepsilon_1^{\tilde{v}}$, as well as (iiic) the small interaction between the two $(1-\delta)\gamma(1-\sigma)\lambda\left(f_{t-1} - \bar{f}\right)\left(e_{t-1} - \bar{e}\right)/\varepsilon_1^{\tilde{v}}$.

Online Appendix Figure F.1 illustrates the larger multiplier in an economy with lower crowd-out of 5.95 percent (rather than 11.83 percent, using $k_2 = 3.1$).

D. *Business Cycle Implications*

We close with a natural application: amplification of business cycle shocks stemming from the dramatic procyclicality of quits and hence of replacement hiring, as foreshadowed in the empirical counterfactual in Section ID.

Figure 5 presents the impulse responses from three experiments. To isolate the incremental amplification from the vacancy multiplier, we juxtapose our model (green solid lines) with two benchmarks that deactivate it, but otherwise feature the

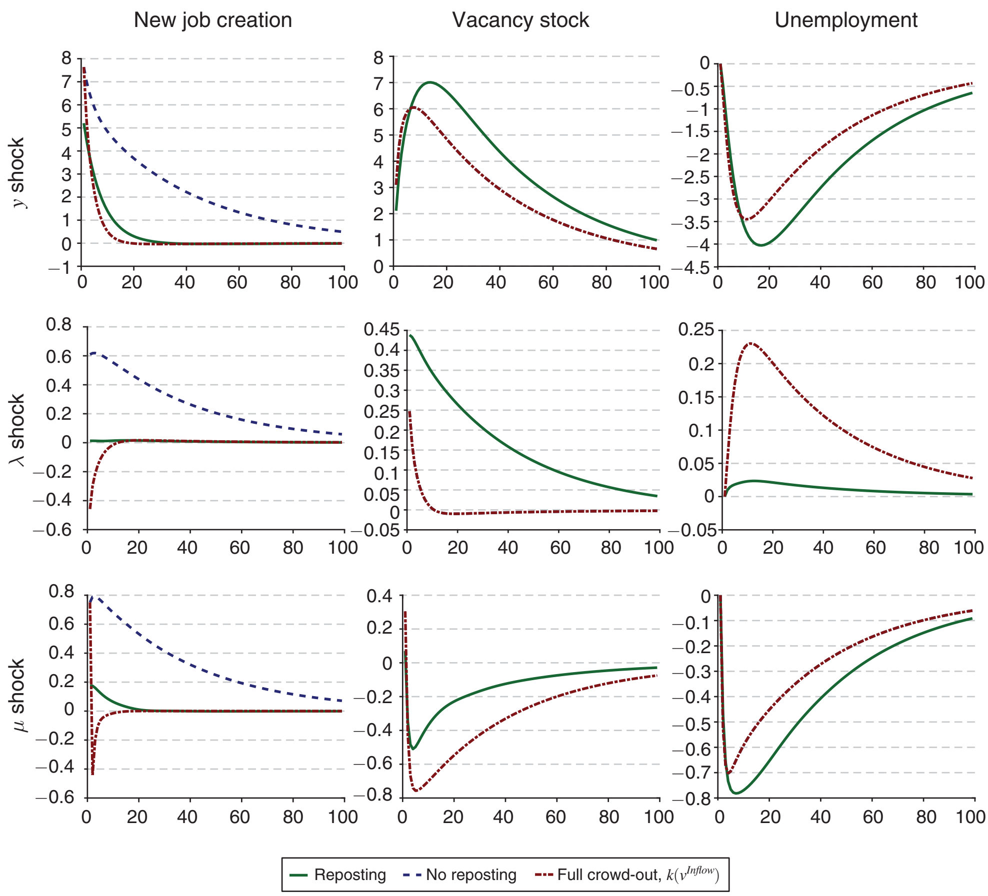

FIGURE 5. IMPULSE RESPONSES: THE ROLE OF REPOSTING AND LIMITED CROWD-OUT

Notes: Impulse response functions of new job creation, vacancy stock and unemployment to aggregate productivity, on-the-job search intensity and matching efficiency shocks. y-axes measure percent deviations from steady state. The graphs arise from three model variants: the *baseline* model with reposting and imperfect crowd-out (green solid line), the *no-incremental-reposting* economy (blue dashed, where repostings are held at steady state yet the job creation cost mirrors the baseline model), and the *full-crowd-out* economy (red dash-dotted, where job creation costs depend on total inflows rather than new job creation, yet there is reposting).

same steady state and adjustment costs. (While $k_2 = 0$ *would* generate neutrality, it would also shut off adjustment cost $k'(n)$, independently generating amplification. While $\gamma = 0$ would shut off reposting, it would also change steady-state flows, surplus and the discounting of the shock process.)

First, in the "*no* (*incremental*) *reposting* economy" (blue dashed lines), we artificially *hold acyclical* (at steady state) any fluctuations in reposting *inflows* in the vacancy law of motion.[16] Second, we add a "*full crowd-out* economy" (red dash-dotted lines), where vacancy creation costs $k(\cdot)$ depend on *total* vacancy

[16]Here perhaps an unmodelled actor neutralizes reposting fluctuations by adding and subtracting to $\tilde{v}_t$ (but not to n_t) to obtain: $v_t = n_t + (1-\delta)\Big(\big(1-(1-\sigma)q(\theta_{t-1})\big)v_{t-1} + \gamma\big(\sigma + (1-\sigma)\lambda f(\bar{\theta})\big)\bar{e}\Big)$.

inflows rather than only newly created job openings n, generating full crowd-out as new and reposted inflows are perfect substitutes therein.[17]

Aggregate Productivity.—The first row of Figure 5 presents IRFs to productivity shocks (Shimer 2005, Hagedorn and Manovskii 2008; similar results for discount factor shocks as in Hall 2017), where y increases exogenously by 1.5 percent at $t = 1$ (log persistence $\rho_z = 0.975$, following Fujita and Ramey 2007).

Higher productivity stimulates job creation. Labor market tightness and job finding rates increase, lowering unemployment but also raising job-to-job quits. In the full model, the quitters leave vacancies behind, boosting total vacancies, some of which the unemployed fill, amplifying the unemployment response. The amplification from the vacancy chain becomes clear when compared to the smoother no-incremental-reposting variant (where repostings do not enter) and in the full-crowd-out economy (where repostings exist but are fully crowded out). These two economies only differ in n, where the absence of reposting forces new job creation to adjust total vacancies.

A *relative* response of the economies with and without reposting isolates the incremental amplification potential of the mechanism. As an amplification statistic, we consider the peak of the cycle in the reposting economy, where the unemployment rate is 4.0 percent below trend, while in this period the unemployment rate is 3.2 percent below trend in the no-reposting economy, i.e., 0.8 percentage points lower. That is, the reposting mechanism provides $0.8/3.2 = 25$ percent relative amplification. We have confirmed that this relative statistic is invariant to the absolute amplification (conditional on a given crowd-out level), which can be scaled arbitrarily by, e.g., shifting b (e.g., Hagedorn and Manovskii 2008, Ljungqvist and Sargent 2017).

By contrast, lowering crowd-out (by adjusting k_2) dramatically increases relative amplification. Figure 3, panel A, plots this relative amplification statistic as a function of crowd-out-guiding parameter k_2. Online Appendix Figure F.2 illustrates the cyclical behavior in an economy with half the crowd-out of our baseline model (i.e., 5.95 percent rather than 11.83 percent, using $k_2 = 3.1$ rather than one). Here, this amplification statistic rises to 77.1 percent.

On-the-Job Search and Quits.—In the second row of Figure 5, we increase on-the-job search efficiency λ by 1 percent at $t = 1$ (returning to its steady-state level at rate $\rho_\lambda = 0.975$).

Vacancies increase through a conventional "labor supply" channel by facilitating vacancy filling (lowering labor market tightness $\theta = \mathit{Job\ Openings}/\big(\mathit{Unemployed} + \mathit{On\text{-}the\text{-}Job\ Searchers}\big)$, as in, e.g., Shimer 2001, Krause and Lubik 2006, Nagypál 2008, Eeckhout and Lindenlaub 2018, and Moscarini and Postel-Vinay 2018). In the no-reposting model, new job creation achieves this vacancy increase. In the full crowd-out model, new job creation actually *falls* to offset the surge in repostings. Note that n is stable in the full model on net, balancing limited crowd-out with the labor supply channel. Interestingly, due

[17] Specifically, creation costs become $k(\iota) = k_1 + k_2 \frac{\iota_t - \bar{\iota}}{\bar{n}}$, where inflows $\iota_t = n_t + \gamma\big(\sigma + (1-\sigma)\lambda f(\theta_{t-1})\big)e_{t-1}$.

to random search, the employed searchers crowd out their unemployed peers, dramatically *raising* unemployment in the models without the vacancy chain and with full crowd-out. By contrast, the full model nearly *eliminates* this spillover, as the job-to-job quitters free up job opportunities for the unemployed.

Matching Efficiency.—The last row of Figure 5 raises matching efficiency μ by 1 percent (persistence $\rho_{\mu} = 0.975$), discussed as a potential cyclical driver in, e.g., Barnichon and Figura (2011), Davis, Faberman, and Haltiwanger (2013), Cheremukhin and Restrepo-Echavarria (2014), and Furlanetto and Groshenny (2016).

Higher matching efficiency stimulates job creation and—unlike the asymmetric λ shock—lowers unemployment. But faster matching also depletes the vacancy stock. Replacement hiring replenishes the vacancy stock, pushing the unemployment rate even lower. Interestingly, the no-reposting economy has a strong new job creation response, whereas the full-crowd-out economy spikes and then sharply drops.

IV. Conclusion

Our paper has presented evidence on the role of quits and replacement hiring in the behavior of job openings. We have integrated these features into a matching model that distinguishes between short-lived worker-firm matches, and longer-lived jobs that persist even after a given match dissolves. In our model, quits trigger vacancies, which in turn beget other vacancies through replacement hiring.

Amplification arises, as during recessions incumbents hold on to their jobs, cutting short the vacancy chain and the job opportunities available to the unemployed, raising unemployment. Conversely, in upswings, the tightening labor market pulls workers out of their matches, leaving behind additional jobs for the unemployed to fill.

The amplification potential of the vacancy chain falls in the degree of short-run crowd-out between the reposted vacancies for old jobs, and new job creation. Our meta study of employment spillover estimates suggests this crowd-out to be low.

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Online Appendix of:

New Jobs and Old Jobs: Quits, Replacement Hiring and Vacancy Chains

Yusuf Mercan
Benjamin Schoefer

A Supplementary Evidence on Replacement Hiring

Table A.1: Establishment-level Regressions

A. Dependent Variable: $\frac{\text{New Hires}_{et}}{\text{Emp.}_{et-1}}$

	All			Positive Quits		
	(1)	(2)	(3)	(1)	(2)	(3)
$\frac{\text{Quits}_{et}}{\text{Emp.}_{et-1}}$	.736	.727	.733	.824	.817	.821
	(.067)	(.068)	(.068)	(.086)	(.086)	(.085)
Establishment FE	✓	✓	✓	✓	✓	✓
Year FE	✓			✓		
Year x Industry FE		✓			✓	
Year x State FE			✓			✓
N	24509	24509	24509	18015	18015	18015
R^2	.64	.64	.64	.66	.67	.67

B. Dependent Variable: $\frac{\text{Job Openings}_{et}}{\text{Emp.}_{et-1}}$

	All			Positive Quits		
	(1)	(2)	(3)	(1)	(2)	(3)
$\frac{\text{Quits}_{et}}{\text{Emp.}_{et-1}}$	.048	.046	.047	.071	.069	.068
	(.026)	(.027)	(.026)	(.035)	(.035)	(.035)
Establishment FE	✓	✓	✓	✓	✓	✓
Year FE	✓			✓		
Year x Industry FE		✓			✓	
Year x State FE			✓			✓
N	23209	23209	23209	16964	16964	16964
R^2	.37	.37	.37	.35	.36	.35

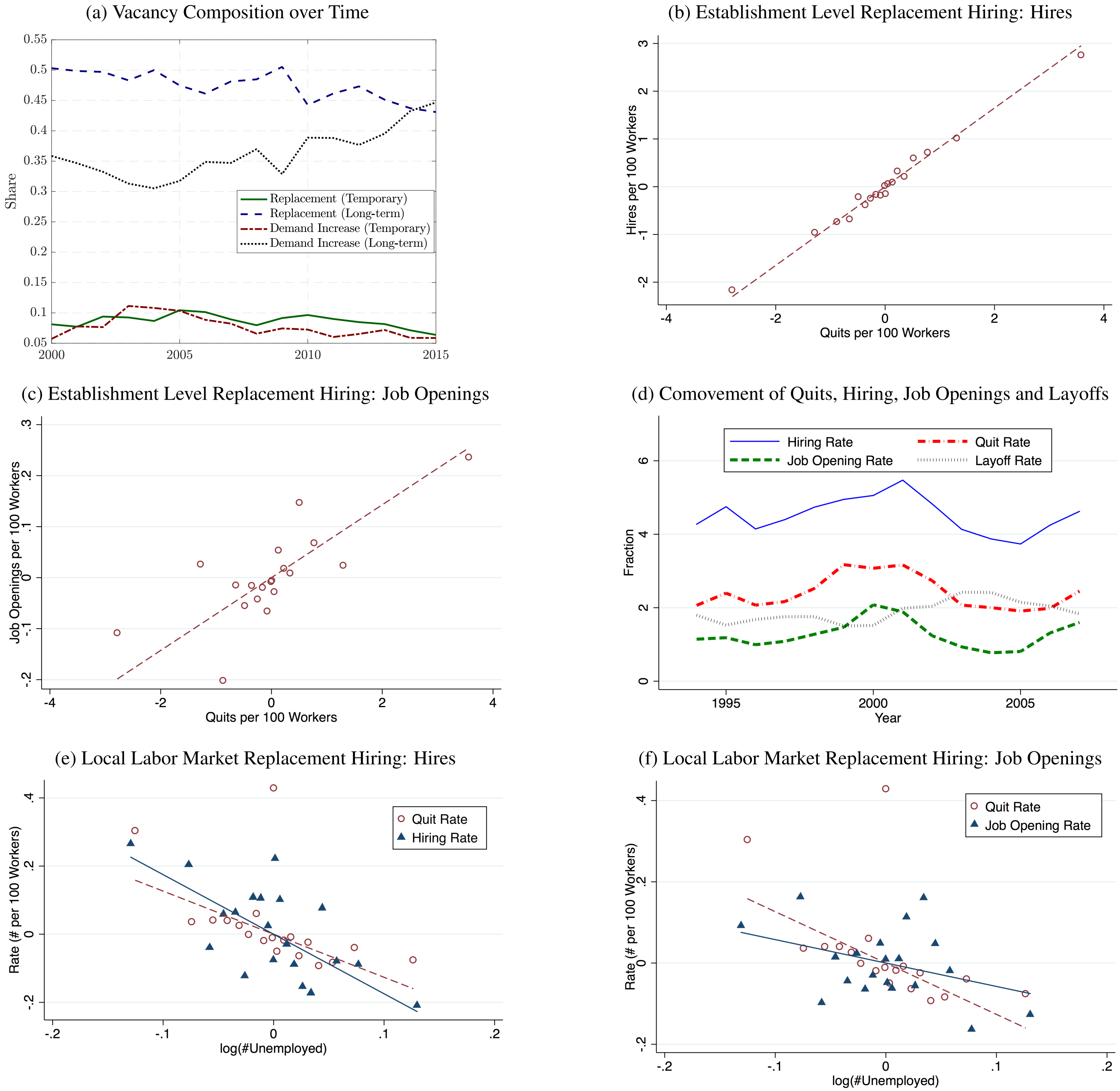
Notes: Regressions run at the establishment level. Standard errors reported in parenthesis and clustered around establishments. Sample restricted to West German establishments with at least 50 employees and less than 40 percent absolute employment change. Data are annual covering 1993-2008. Source: LIAB sample of the IAB Establishment Survey.

Table A.2: Event Study: Timing of Hires and Quits

	Dependent Variable: $\frac{\text{New Hires}_{et}}{\text{Emp.}_{et-1}}$							
	All				Positive Quits			
Lead/Lag	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
−3				−.060				−.115
				(.067)				(.074)
−2			.016	−.008			.060	−.123
			(.096)	(.086)			(.158)	(.132)
−1		.051	.064	.078		.011	.010	−.005
		(.057)	(.098)	(.091)		(.089)	(.150)	(.129)
0	.736	.753	.815	.818	.824	.928	1.03	.903
	(.067)	(.068)	(.095)	(.127)	(.086)	(.097)	(.140)	(.164)
+1		.050	.079	.192		0.030	.044	.070
		(.069)	(.086)	(.104)		(.102)	(.136)	(.129)
+2			.086	−.055			−.001	−.258
			(.085)	(.088)			(.122)	(.122)
+3				.161				.037
				(.139)				(.226)
Establishment FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
N	24509	11414	5732	2832	18015	6433	2912	1385
R^2	.64	.67	.63	.65	.66	.64	.62	.73

Notes: Regressions run at the establishment level. Standard errors reported in parenthesis and clustered around establishments. Sample restricted to West German establishments with at least 50 employees and less than 40 percent absolute employment change. Data are annual covering 1993-2008. Source: LIAB sample of the IAB Establishment Survey.

Figure A.1: Further Evidence on Quits, Hiring, Job Openings and Layoffs from Germany



Notes: Panel (a) plots the time series of breakdown of last filled job, 2000-15. The shift in the later years is perhaps due to a redesign of the survey introducing a subcategory for death/retirement-triggered replacement hiring (a smaller share, here subsumed in total long-term replacement hiring). Source: IAB Job Vacancy Survey. Panels (b) and (c) present binned scatter plots illustrating the replacement-hiring/quit sensitivity estimated using establishment–year observations in regression model in Appendix Table A.1 Column (1), i.e. all variables are residualized. Panel (d) plots aggregate (average) quit, hiring, job opening and layoff rates in Germany. Panels (e) and (f) plot the establishment hires/job opening rates with respect to district (Kreis) level economic conditions, again binned scatter plots of the underlying micro observations (residualized by year and establishment fixed effects), i.e. we estimate establishment e's year-t worker flow outcome to the log unemp. in location l (Source: Regional Database Germany (Federal Statistical Office and the Statistical Offices of the Länder)): $\frac{\text{Outcome}_{e,t}}{\text{Emp}_{e,t-1}} = \beta_0 + \beta_1 \ln(\text{Unemp.}_{l(e),t}) + \alpha_e + \alpha_t + \varepsilon_{e,t}$ Hires' cyclical behavior moves in lock-step with the quit rate in response to local business cycles. Source for panels (b)-(f): LIAB Establishment Survey, West Germany, annual data, 1993–2008.

B Computational Details

B.1 Calibration

Table B.1: Calibration and Model Fit of Baseline Model

(a) Calibrated Parameters and Values

A. PREDETERMINED		
Discount factor	β	0.9967
Worker bargaining share	ϕ	0.5
Elasticity of matching function	η	0.5
Unemployment benefit	b	0.9
Reposting rate	γ	1
Vacancy creation cost	k_1	0.1
	k_2	1
B. ESTIMATED		
Relative efficiency of OJS	λ	0.0556
Scale of matching function	μ	0.6542
Job destruction	δ	0.0222
Match separation	σ	0.0051
Vacancy posting cost	κ	0.1611

(b) Target Moments and Model Fit

Target	Data	Model	Source
Unemployment rate	0.057	0.057	CPS - Shimer (2005)
Job-to-job rate	0.025	0.025	CPS - Fujita and Nakajima (2016)
Unemployed job finding rate	0.45	0.45	CPS - Shimer (2005)
Reposted vacancy share	0.56	0.56	IAB German Job Vacancy Survey
Job filling rate	0.9	0.9	Fujita and Ramey (2007)

B.2 Solution: Steady State

Instead of working with individual Bellman Equations for workers and firms, we work with the value of surplus from a match, which is sufficient to characterize worker decisions. This approach has the added advantage of not requiring wage levels while solving the model. We use value function iteration to solve the model. We outline the algorithm below.

1. For a given parameterization of the model, start with an initial guess of market tightness θ_0.

2. For each guess of θ_n in iteration n:

   (a) Iterate on $S(\mathbf{s})$ given in Footnote 11 to solve for match surplus.

   (b) Iterate on the law of motion in equation (7) to compute the steady-state values of employment and unemployment rates.

   (c) Solve the market tightness level $\tilde{\theta}_{n+1}$ that satisfies the free-entry condition in equation (14), and law of motion for vacancies in equation (8). Calculate its absolute deviation from θ_n.

   (d) If the deviation is less than the tolerance level, stop. Otherwise update the guess for market tightness to $\theta_{n+1} = \omega\theta_n + (1-\omega)\tilde{\theta}_{n+1}$ with a dampening parameter $\omega < 1$.

B.3 Solution: Transition Dynamics

In this section we outline the algorithm used to solve for the transition path of the model to a one-time unanticipated shock.

1. Fix the number of time periods it takes to reach the new steady state, T.

2. Compute the steady state equilibrium for a given set of model parameters according to the algorithm in Section B.2. Since we are interested in transitory shocks, the new steady state at T will be the same.

3. Guess a sequence of market tightness, $\{\theta_t^0\}_{t=1}^{T-1}$.

4. Solve for the sequence of match surplus, $\{S_t\}_{t=1}^{T-1}$ and vacancy values $\{V_t\}_{t=1}^{T-1}$ backwards, given path $\{\theta_t^0\}_{t=1}^{T-1}$, the shock, and the terminal values of S_T and V_T.

5. Compute the sequence of market tightness $\{\theta_t^1\}_{t=1}^{T-1}$ consistent with the worker and vacancy laws of motion, induced by the decisions implied by $\{S_t\}_{t=1}^{T-1}$ and $\{V_t\}_{t=1}^{T-1}$.

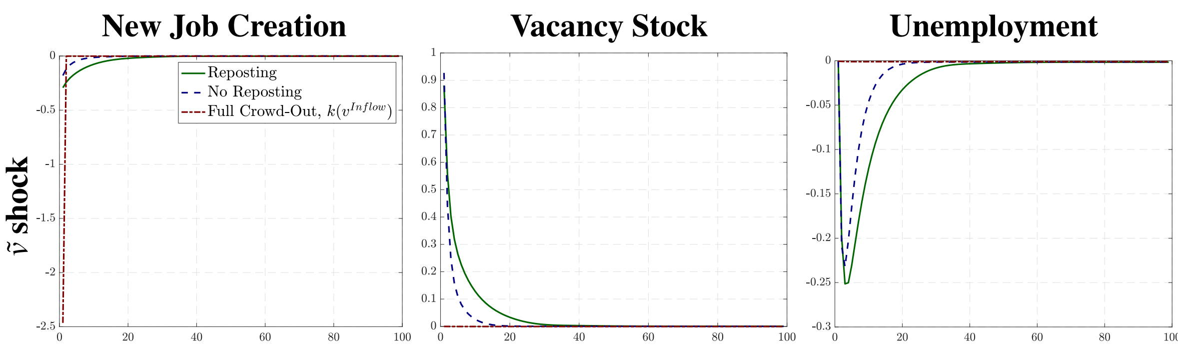
6. Check if $\max_{1\leq t<T} |\theta_t^1 - \theta_t^0|$ is less than a predetermined tolerance level. If yes, continue, if no update $\{\theta_t^0\}_{t=1}^{T-1}$ and go back to step 3.

7. Check if $|\theta_T^1 - \theta_T^0|$ is less than a predetermined tolerance level. If yes stop, if not increase T and go back to step 1.

C Additional Results on Vacancy Injection Experiment

This section completes the discussion of the equilibrium multiplier from Section C. In Figure C.1, we present the IRFs following the vacancy injection shock. In the baseline model, labor market tightness, job finding and quits increase, hence repostings boost total vacancies, such that unemployment falls further. The smaller and shorter-lived response of the no-incremental-reposting economy clarifies the incremental amplification as well as internal propagation from the vacancy multiplier.[1] Lastly, in the full-crowd-out economy n fully neutralizes the injection.

Figure C.1: Impulse Responses from Vacancy Injection



Notes: Impulse response functions of new job creation, vacancy stock and unemployment to an exogenous vacancy injection shock. Y-axes measure percent deviations from steady state. The graphs arise from three model variants: the *baseline* model with reposting and imperfect crowd-out (green solid line), the *no-incremental-reposting* economy (blue dashed, where repostings are held at steady state yet the job creation cost mirrors the baseline model), and the *full-crowd-out* economy (red dash-dotted, where job creation costs depend on total inflows rather than new job creation, yet there is reposting).

[1] In the no-reposting counterfactual follows law of motion $v_t = n_t + (1-\delta)\Big((1-(1-\sigma)q(\theta_{t-1}))v_{t-1} + \gamma\big(\sigma+(1-\sigma)\lambda f(\bar{\theta})\big)\bar{e}\Big) + \varepsilon_t^{\tilde{v}}$, where $\varepsilon_t^{\tilde{v}} > 0$ in the first period and zero afterwards.

D Description of Papers Reported in the Meta Analysis of Spillovers in Figure 3 Panel (b)

We describe the papers and detail each calculation of the spillover effects we report in meta analysis in Figure 3 Panel (b).

Blasio and Menon (2011) replicate Moretti (2010) (described below) and estimate a tradable-on-tradable local jobs multiplier, from 1991 to 2001, and to 2007, in Italy. We convert the elasticities into sensitivities because the tradable groups are of similar size.

Giupponi and Landais (2018) study the effects of temporary employment subsidies (short-time work) in Italy. The indirect spillover effect (reduced-form effect of fraction of eligible workers in LLM on ineligible firm employment growth $(dn^{\text{non}}/n^{\text{non}})/(d[N^{\text{elig}}/N^{\text{tot}}]))$ is reported as $\beta^S = -0.00937$ (T.3 C.3, divided by 100); i.e. the market-level sensitivity, normalized by total employment, is $(dN^{\text{non}})/(d[N^{\text{elig}}/N^{\text{tot}}]) = \beta^S \cdot (N^{\text{tot non}}/N^{\text{tot}})$, where $N^{\text{tot non}}/N^{\text{tot}} = 0.75$ (source: correspondence with authors). The market-level direct effect traced out is $\beta^D \times d[N^{\text{elig}}/N^{\text{tot}}]$, where $\beta^D = 0.284$ (T.2 C.1) is the direct firm-level employment effect of subsidy eligibility $(dn^{\text{elig}}/n^{\text{elig}})$. Hence, the implied market-level job-for-job crowd-out of ineligible employment in response to policy-induced direct employment effect, $dN^{\text{non}}/dN^{\text{elig}} = \left[(dn^{\text{non}}/n^{\text{non}})/d[N^{\text{elig}}/N^{\text{tot}}]\right] \times [N^{\text{tot non}}/N^{\text{tot}}]/[dn^{\text{elig}}/n^{\text{elig}}]$, is given by $\beta^I \cdot s^I/\beta^D = (-0.00937) \cdot 0.75/0.284 = -0.025$. We thank the authors for detailing this calculation. We similarly rescale the indirect effect SE (T.3 C.3) by the same factor (given first stage precision) as $0.002161 \cdot 0.75/0.284 = 0.0057$.

Jofre-Monseny et al. (2018a) examine the local labor market effects (LLMEs) of large plant closures in Spain, including spillovers in other sectors/industries such as tradables (manufacturing), 2001-8, in Spain. T.7 C.3 reports a -0.027 employment effect per job loss (SE 0.035) in unaffected manufacturing industries.

Marchand (2012) estimates local job multipliers of the 1971-81 and 1996-2006 booms in the Canadian energy sector; T.4a reports IV estimates the manufacturing employment sensitivity to energy employment.

Acemoglu et al. (2016) examine the LLMEs of import competition from China, from 1999 to 2007/11, in the US. The ratio of employment effects of nonexposed to exposed tradables (T.7 C.6), implies a crowd-out of $-6.928 \cdot 10^{-4}/(-1.68) = 4.112 \cdot 10^{-4}$. We construct clustered by state SE with an IV strategy (tradable as the dependent variable, exposed tradable as endogenous independent variable, instrument being the import shock).

Black et al. (2005) estimate the local labor market effects of coal sector boom-bust cycles in the US from a 1970-89. T.6 C.1, "All Years", "Traded sector" reports the local job multiplier of tradable employment to treated mining employment, 0.002 (SE 0.009).

Cahuc et al. (2019) study a hiring subsidy in France for small firms and low-paying jobs, 2008-9. T.4 Column 4 [T.5 last column] reports the estimates on eligible (small) [ineligible (larger)] firms as 0.138 [0.008], implying 0.008/0.138=0.058 crowd-out. Difference-in-Difference estimates for eligible (0.011) and ineligible (0.002) *jobs* (sorted by wage cutoff) in T.3 C.1 and .2 imply a second crowd-out (-in) estimate of 0.002/0.011=0.0118. T.1 and F.3 suggest that the larger number of small eligible firms roughly makes up for their size discount, implying similar employment shares, so we interpret the percent effects as sensitivities. We provide standard error ballparks by simply rescaling the ineligible-effect SEs by 1/direct effect.

Zou (2018) estimates LLMEs of military employment contractions in the US (counties), 1988-2000. T.3 C.2 reports the sensitivity of tradable civilian employment to military employment as 0.044 (SE 0.085) at the 12-year horizon. We rescale the short-run (year one) effect (and, ad-hoc, the SE) by 1.09/1.26, extrapolating the dynamic effects from the civilian employment (Fig. B.1), where the final year-2000 [one-year 1989) effect is 1.26 (i.e. T.3 C.1) [1.09].

Mian and Sufi (2014) study housing wealth shocks across US regions on nontradables through local aggregate demand. They estimate a 0.19 effect of the instrument on nontradable [tradable] employment (T.5 C.1) [0.018 (precisely: .0177), T.5 C.1]. With nontradable and tradable industries having similar employment shares (a conservative approximation (Moretti (2010)), the coefficient ratio implies crowd-out of 0.0177/0.19 = 0.094. We estimate SEs (clustered by state) by running an IV specification, with tradable [nontradable] employment as the dependent [endogenous independent] variable, and the housing wealth instrument. We disregard the geographic concentration index as the (insignificant negative) effects are inconsistent with the positive slope reported in Fig. 2a.

Moretti (2010) studies the local labor market effects of industry growth, with a shift-share instrument, in US cities for 1980-90, 1990-2000. Model 3 in T.1 C.3 presents the job multipliers for tradable on other tradable industries (Caveat: agglomeration effects.).

Jofre-Monseny et al. (forthcoming) study the effect of quasi-experimental public employment shifts on private sector employment in Spain at 10-year horizons (1980, 1990, 1990-2001). Table 10 Column 1 Row 1 reports effects for nontradable employment (Caveat: migration effects).

Cerqua and Pellegrini (2018) study the local employment effect of business subsidies (capital) in Italy, 1995-2006. In T.3 C.8 shows spillover effects of subsidized tradable firms' employment on non-subsidized tradable firms.

Gathmann et al. (2018) investigate local labor market effects of establishment-level employment contractions in Germany. T.4 C.5,.7 restrict the spillover analysis to the tradable sector. The size of an average mass layoff event is 0.019 of total local employment (T. 1 P.A), and the tradable sector is on average 0.39 of total local employment (fn 36). Hence the tradable employment shock induced is -0.019/0.39=-0.049 (similar to the -0.045 year-0 effect in C.7). The one-year -0.015 log employment effects on other establishments exclude the shrinking firm imply a -0.015/(-0.049)=+0.31 crowd-in (approximation: firm has small initial employment share). We scale the SE by the same factor.

Weinstein (2018) studies LLMEs of an quasi-experimental expansion of the financial sector in Delaware, US; the shortest horizon is 1980-7. The response of directly treated FIRE industries is 0.549 (T.5 C.1), vs. 0.077 on tradable (manufacturing) employment (T.5 C.6), hence a 0.077/0.549=0.141 spillover (positive). We rescale the elasticity (and SEs) by 0.2/0.09 into a sensitivity, where FIRE [manufacturing employment shares in 1990 are 0.09 [0.2] (Appendix Figure A1) (most conservative year, implying the least positive multiplier).

Moretti and Thulin (2013) replicate Moretti (2010) (described above) for Swedish regions, from 1995-2001, and 2001-7. T.8 center C reports the IV estimates for tradable employment on other tradables (we report the least positive among the two industry variants).

E Extended Model: Match Heterogeneity and Endogenous Search

Our extension endogenizes on-the-job search and rationalizes it with heterogeneity in match disamenities. The modified model can be solved similarly using the algorithm in B.2, and IRFs can be generated using the algorithm in B.3. Once calibrated to realistic quit levels and cyclicality, it behaves very similarly to our parsimonious model presented in the main text.

Structure of Extended Model Let $\xi \in [\underline{\xi}, \bar{\xi}]$ denote match disamenity. New jobs start from the lowest disamenity, which then evolves following first order Markov chain $P(\xi'|\xi)$. Hence all new jobs are accepted, and the disamenity distribution over existing matches does not enter the free-entry condition. Workers choose search effort s subject to convex cost $c(s)$. The worker and firm problems then become:

$$
\begin{aligned}
U(\mathbf{s}) &= \max_{s_U \geq 0} \Big\{ b - c(s_U) + \beta(1-\delta)(1-\sigma)s_U f(\theta)\mathbb{E}[W(\underline{\xi}, \mathbf{s}')] + \beta(1-(1-\delta)(1-\sigma)s_U f(\theta))\mathbb{E}[U(\mathbf{s}')] \Big\} \\
W(\xi, \mathbf{s}) &= \max_{s_E \geq 0} \Big\{ w(\xi, \mathbf{s}) - \xi - c(s_E) + \beta\delta\mathbb{E}[U(\mathbf{s}')] + \beta(1-\delta)\sigma\mathbb{E}[U(\mathbf{s}')] \\
&\quad + \beta(1-\delta)(1-\sigma)\Big[(1-s_E\lambda f(\theta))\mathbb{E}\big[\max\{W(\xi', \mathbf{s}'), U(\mathbf{s}')\}\big] + s_E\lambda f(\theta)\mathbb{E}[W(\underline{\xi}, \mathbf{s}')]\Big] \Big\} \\
V(\mathbf{s}) &= -\kappa + \beta(1-\delta)\Big[q(\theta)(1-\sigma)\mathbb{E}[J(\underline{\xi}, \mathbf{s}')] + (1-q(\theta)(1-\sigma))\mathbb{E}[V(\mathbf{s}')]\Big] \\
J(\xi, \mathbf{s}) &= y - w(\xi, \mathbf{s}) + \beta(1-\delta)\Big[\gamma s_E^* \lambda f(\theta)\mathbb{E}[V(\mathbf{s}')] + \gamma\sigma(1-s_E^*\lambda f(\theta))\mathbb{E}[V(\xi', \mathbf{s}')] \\
&\quad + (1-\sigma)(1-s_E^*\lambda f(\theta))\Big\{\mathbb{E}\Big[\mathbb{I}\{W(\xi', \mathbf{s}') > U(\mathbf{s}')\}J(\xi', \mathbf{s}')\Big] + \gamma\mathbb{E}\Big[\mathbb{I}\{W(\xi', \mathbf{s}') \leq U(\mathbf{s}')\}V(\mathbf{s}')\Big]\Big\}\Big]
\end{aligned}
$$

With heterogeneity in matches, we need to keep track of the worker distribution. Accordingly, the laws of motion for vacancies, unemployment and employment now become

$$
\begin{aligned}
v_t &= n_t + (1-\delta)\Big((1-(1-\sigma)q(\theta_{t-1}))v_{t-1} + \gamma\Big(\lambda f(\theta_{t-1})\int_{\tilde{\xi}} s_E(\tilde{\xi})e_{t-1}(\tilde{\xi})d\tilde{\xi} \\
&\quad + \int_{\tilde{\xi}} \Big(\sigma + (1-\sigma)P(\xi > \xi^c|\tilde{\xi})\Big)\big(1-\lambda f(\theta_{t-1})s_E(\tilde{\xi})\big)e_{t-1}(\tilde{\xi})d\tilde{\xi}\Big)\Big) \\
u_t &= \Big(1-(1-\delta)(1-\sigma)s_u f(\theta_{t-1})\Big)u_{t-1} + \delta(1-u_{t-1}) \\
&\quad + (1-\delta)(1-\sigma)\int_{\tilde{\xi}} P(\xi > \xi^c|\tilde{\xi})\big(1-\lambda f(\theta_{t-1})s_E(\tilde{\xi})\big)e_{t-1}(\tilde{\xi})d\tilde{\xi} + (1-\delta)\sigma(1-u_{t-1})
\end{aligned}
$$

$$
e_t(\xi) = (1-\delta)(1-\sigma)\int_{\tilde{\xi}} P(\xi|\tilde{\xi})\big(1-\lambda f(\theta_{t-1})s_E(\tilde{\xi})\big)e_{t-1}(\tilde{\xi})d\tilde{\xi} \;\; \forall \xi \neq \underline{\xi} \text{ and } \xi < \xi^c
$$

$$
e_t(\underline{\xi}) = (1-\delta)(1-\sigma)\Big(\int_{\tilde{\xi}} P(\underline{\xi}|\tilde{\xi})\big(1-\lambda f(\theta_{t-1})s_E(\tilde{\xi})\big)e_{t-1}(\tilde{\xi})d\tilde{\xi} + s_u f(\theta_{t-1})u_{t-1} + \lambda f(\theta_{t-1})\int_{\tilde{\xi}} s_E(\tilde{\xi})e_{t-1}(\tilde{\xi})d\tilde{\xi}\Big)
$$

$$
e_t(\xi) = 0 \;\forall \xi > \xi^c
$$

where $\xi^c(\mathbf{s})$ denotes the endogenous separation cutoff implicitly defined by $W(\xi^c, \mathbf{s}) = U(\mathbf{s})$.

Calibration of Extended Model We now provide *one* specific version of the more general model above to show that the extended model implies a similar amplification role of the replacement hiring channel (conditional on matching similar targets). The calibration strategy is analogous to the baseline except for the process that governs transitions between job types and endogenous on the job search, features we elaborate on below.

To maximize intuition and to economize on free parameters, we assume that there are two match types: good and bad jobs. We set disutility from working in a good job to $\underline{\xi} = 0$ and in a bad job to $\overline{\xi} = 0.1$. As we focus on EE mobility, we ensure that this drop does not merit endogenous separations into unemployment at any point in our transitions. All jobs (whether formed out of unemployment or employment) start off as a good type. A distinct feature of this economy is therefore the evolution of the stock of searchers (in bad jobs), which follows a law of motion, whereas our baseline model has a constant fraction of employed searchers. Each period, the Markov process $P(\xi|\tilde{\xi})$ has good jobs downgrade to a bad type with probability p_D; bad jobs upgrade to the good quality with probability p_U. To jointly identify (p_D, p_U), we target a steady state on-the-job seeker share of 0.23, a number we take from Faberman et al. (2018) as the fraction of employed workers that report to be actively searching for another job – in our model the share of employed workers in the bad job type. We pin down the split between upgrades and downgrades (which can be thought of inflow and outflow probabilities into the bad state, where on-the-job search provides a second outflow margin) by targeting the elasticity of the EE quit rate to the UE job finding rate, depicted in Figure 2 Panel (d), and discussed in the main text in Section II.[2] This target ensures that our model exhibits a realistic quit cyclicality, as well as remains comparable to the baseline model (which we constructed to match the near-unit elasticity between quits and UE rates from the data.)

We further assume that the cost function for job search effort is quadratic $c(s) = 0.5s^2$. (We have also experimented with other functional form choices but prefer the quadratic setup, by which the level of optimal search effort is transparently related to its benefits.) We finally choose k_2 to yield a comparable crowd-out in this economy compared to the

[2] Intuitively, more "churn" between job types related to the Markov process will attenuate the elasticity of the stock of the bad jobs to shifts in EE (which otherwise would unrealistically attenuate the elasticity of EE to UE rates, one of our targets).

baseline economy of -0.1183, which implies $k_2 = 2.85$.[3] We set $b = 0.7$ (but note that the comparison to the baseline model is limited due to the additional job search costs and job qualities).

Table E.1 summarizes model parameters under this calibration and the extended model's fit. We underpredict the elasticity of EE quit to UE rates, implying that the extended model will understate replacement hiring compared to the baseline model.[4]

In response to our aggregate shocks, the extended model exhibits again strong amplification from the vacancy chain, mirroring our discussion in Section D.

Additional Reference for Appendix E

Faberman, Jason, Andreas Mueller, Ayşegül Şahin, and Giorgio Topa. 2018. "Job Search Behavior among the Employed and Non-Employed". Unpublished Manuscript

[3]We again focus on relative/differential amplification, as to net out the inherent attenuation from the adjustment cost nature of k_2 .

[4]Permitting differential job search costs might be another lever to increase the quit/UE elasticity.

Table E.1: Calibration and Model Fit: Extended Model

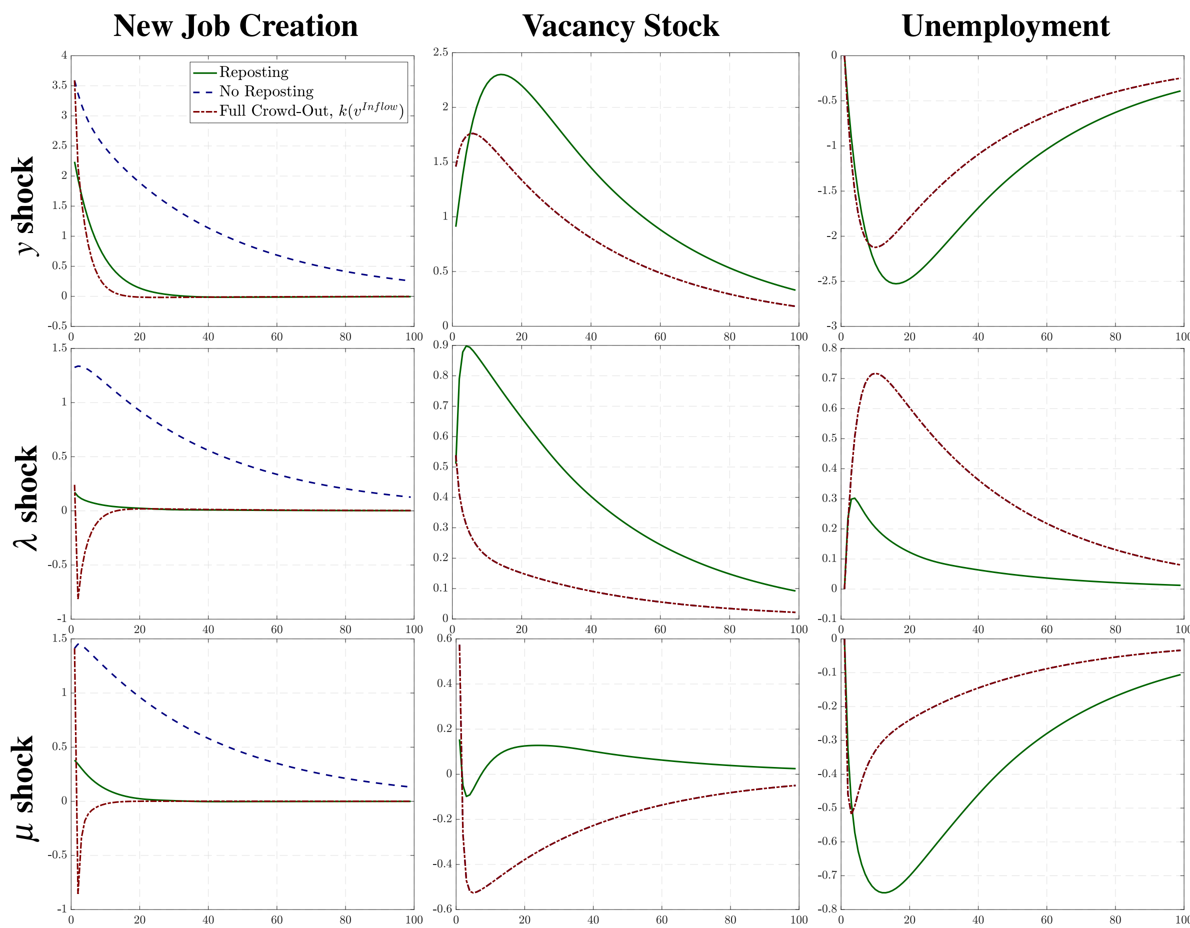
(a) Calibrated Parameters and Values

A. PREDETERMINED		
Discount factor	β	0.9967
Worker bargaining share	ϕ	0.5
Elasticity of matching function	η	0.5
Unemployment benefit	b	0.7
Reposting rate	γ	1
Vacancy creation cost	k_1	0.1
	k_2	2.85
Disutility of work in good job	$\underline{\xi}$	0
Disutility of work in bad job	$\overline{\overline{\xi}}$	0.1
B. ESTIMATED		
Relative efficiency of OJS	λ	1.14
Scale of matching function	μ	0.8188
Job destruction	δ	0.0221
Match separation	σ	0.0046
Vacancy posting cost	κ	0.8
Probability of downgrading to bad job	p_D	0.1248
Probability of upgrading to good job	p_U	0.3159

(b) Target Moments and Model Fit

Target	Data	Model	Source
Unemployment rate	0.057	0.0567	CPS - Shimer (2005)
Job-to-job rate	0.025	0.0252	CPS - Fujita and Nakajima (2016)
Unemployed job finding rate	0.45	0.4425	CPS - Shimer (2005)
Reposted vacancy share	0.56	0.56	IAB German Job Vacancy Survey
Job filling rate	0.90	0.90	Fujita and Ramey (2007)
Share of employed actively searching	0.23	0.2265	Faberman et al. (2018)
Elasticity of EE w.r.t UE rate	1	0.9378	CPS and JOLTS

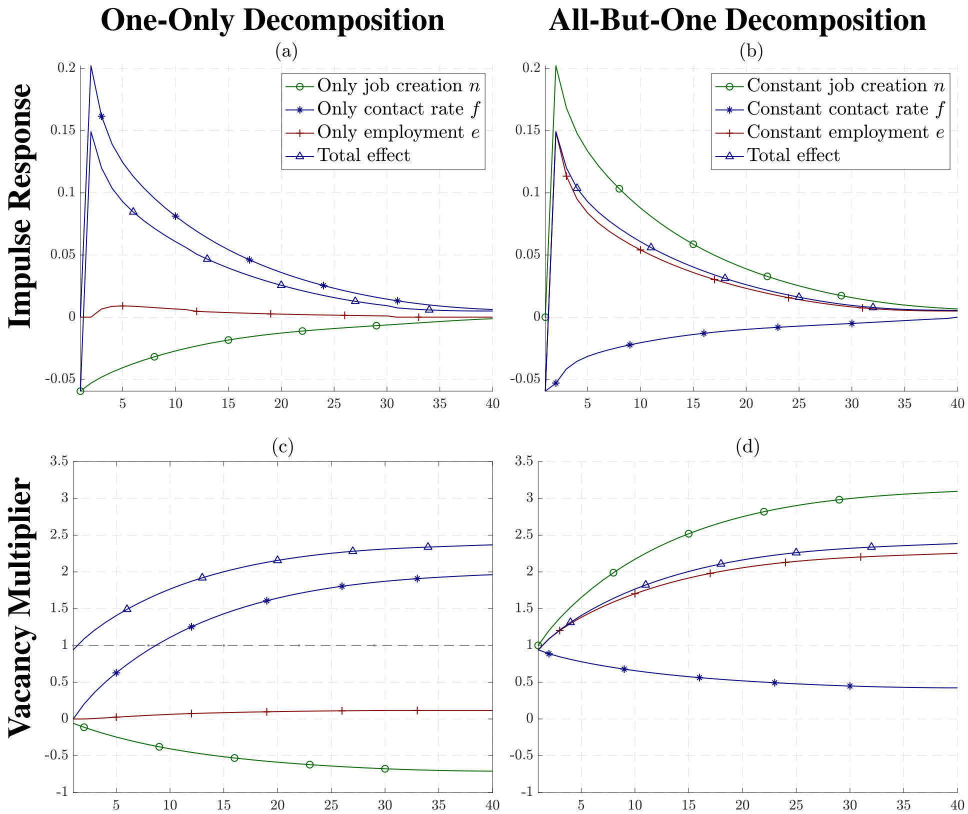
Figure E.1: Impulse Responses: Extended Model



Notes: Impulse response functions of new job creation, vacancy stock and unemployment to aggregate productivity, on-the-job search intensity and matching efficiency shocks. Y-axes measure percent deviations from steady state. The graphs arise from three model variants: the *full* model with reposting and imperfect crowd-out (green solid line), the *no-incremental-reposting* economy (blue dashed, where repostings are held at steady state yet the job creation cost mirrors the baseline model), and the *full-crowd-out* economy (red dash-dotted, where job creation costs depend on total inflows rather than new job creation, yet there is reposting).

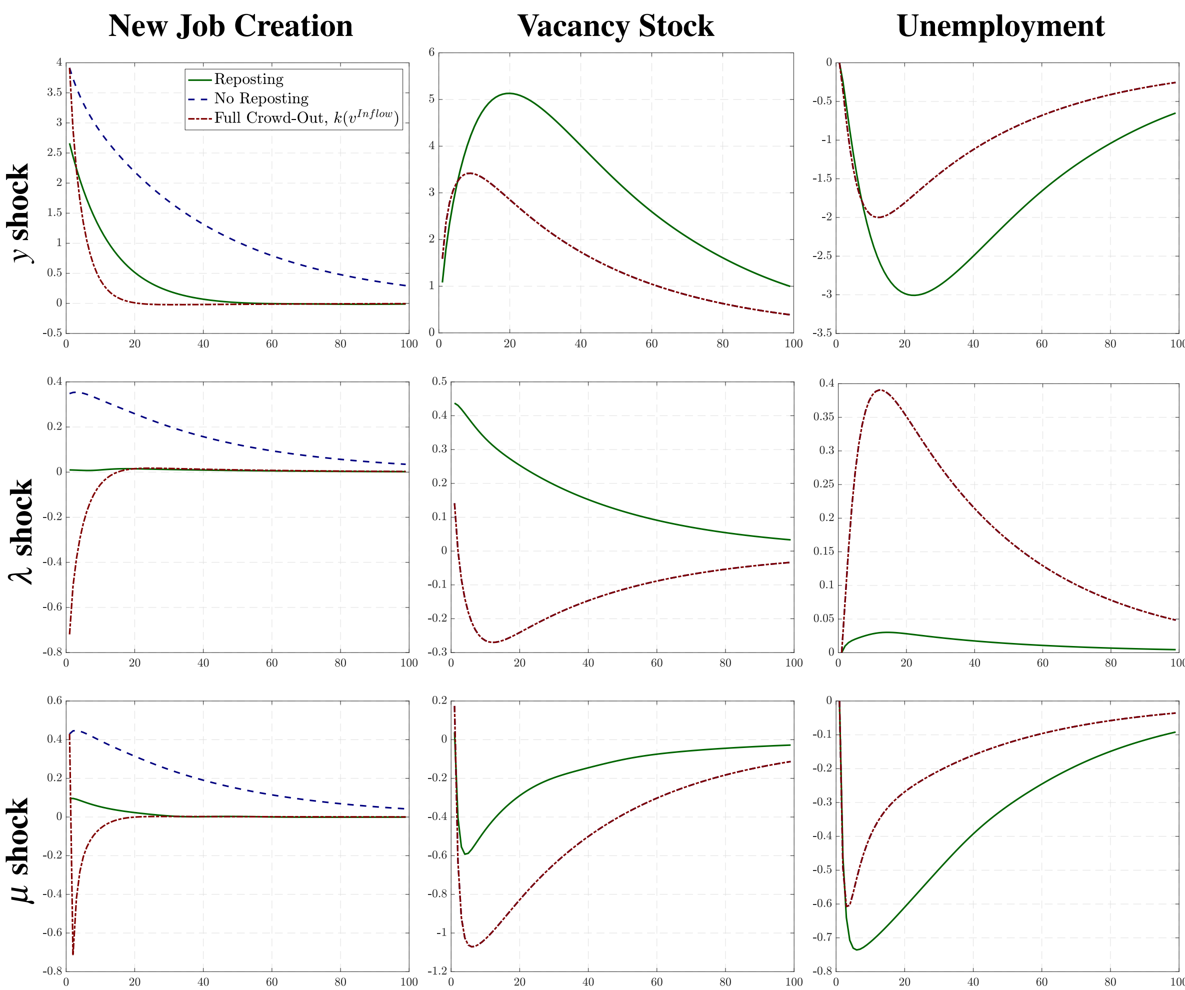
F Low Crowd-Out Economy

Figure F.1: Decomposing the Vacancy Multiplier: Low-Crowd-Out Economy



Notes: The figure presents impulse responses (Panel (a) and (b)) and cumulative vacancy multiplier (Panel (c) and (d)) of vacancy inflows in response to a perfectly transitory exogenous increase in the vacancy stock by 1 percent, for simulated time series and its components. The variables are normalized by the size of vacancy injection $\varepsilon_1^{\tilde{v}}$, which is not plotted.. The left panels additionally present "one-only" inflows (that only permit one variable to move from steady state); the right panels present "all-but-one" inflows (that keep only one variable at steady state). The *total effect* is $(n_t + (1-\delta)\gamma(\sigma + (1-\sigma)\lambda f_{t-1})e_{t-1} + \varepsilon_1^{\tilde{v}} - \bar{v}^{\text{Inflow}})/\varepsilon_1^{\tilde{v}}$. We then decompose this total effect. The one-only decomposition features (i) the *only job creation n* effect $(n_t - \bar{n})/\varepsilon_1^{\tilde{v}}$, (ii) the only contact rate f effect $(1-\delta)\gamma(1-\sigma)\lambda(f_{t-1} - \bar{f})\bar{e}/\varepsilon_1^{\tilde{v}}$, (iii) the *only employment e* term, where we plot the sum of (iii.a) the mechanical employment rate effect $(1-\delta)\gamma(1-\sigma)\lambda\bar{f}(e_{t-1} - \bar{e})/\varepsilon_1^{\tilde{v}}$, (iii.b) the small effect of the employment change on quits through σ shocks $(1-\delta)\gamma\sigma(e_{t-1} - \bar{e})/\varepsilon_1^{\tilde{v}}$, as well as (iii.c) the small interaction between the two $(1-\delta)\gamma(1-\sigma)\lambda(f_{t-1} - \bar{f})(e_{t-1} - \bar{e})/\varepsilon_1^{\tilde{v}}$.

Figure F.2: Impulse Responses: Low-Crowd-Out Economy



Notes: Impulse response functions of new job creation, vacancy stock and unemployment to aggregate productivity, on-the-job search intensity and matching efficiency shocks. Y-axes measure percent deviations from steady state. The graphs arise from three model variants: the *full* model with reposting and imperfect crowd-out (green solid line), the *no-incremental-reposting* economy (blue dashed, where repostings are held at steady state yet the job creation cost mirrors the baseline model), and the *full-crowd-out* economy (red dash-dotted, where job creation costs depend on total inflows rather than new job creation, yet there is reposting).