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

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Abstract

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% of vacancy postings as quit-driven replacement hiring into old jobs, which evidently outlived their previous matches. Accordingly, aggregate and firm-level hiring tightly tracks 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.

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1 Introduction

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% of real-world job vacancies are for old jobs vacated by quits – rather than 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 also 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 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 et al. (2017)), 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 et al. (2018)). 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 et al. (1988): “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 counter-balanced 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 U.S. states, for which our model’s vacancy chain mechanism therefore suggests a novel rationalization.

One additional implication we explore is 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, may amplify labor market fluctuations, consistent with the correlations in Galí and Van Rens (2017) for the U.S. Similarly, while worker flow rates in Germany, the context of our vacancy survey, are comparable to many OECD countries (Elsby et al. (2013)), replacement hiring may play an even larger role in higher-churn labor markets such as the U.S.

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 et al. (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. Most closely related to our paper is ongoing work by Elsby et al. (2018), who study vacancy chains in a rich model featuring on-the-job search and large firms heterogeneous in productivity. 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 dur-

2 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 would be much smoother in a no-replacement-hiring counterfactual.

2.1 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% of job openings are posted in response to quits. Of these, 47ppt [9ppt] are permanent [temporary] quits. Around 35% of vacancies target permanent net job creation, and around 8% in response to temporary demand increases. The composition is quite stable between 2000 and 2015 (Appendix Figure A1 Panel (a)).

2.2 Establishment-Level Effects of Quits on Hiring

Next, 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”.1 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

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1We restrict our analysis to West Germany and establishments with at least 50 employees. We exclude extreme observations (|d ln Emp_{c,t}| > 40% employment growth and |Quit_{c,t}/Emp_{c,t-1}| > 20%).
for leads/lags $L \in \{0, 1, 2, 3\}$:

$$\frac{\{\text{Hires}_{e,t}, \text{Job Openings}_{e,t}\}}{\text{Emp}_{e,t-1}} = \beta_0 + \sum_{s=-L}^{+L} \nu_s \frac{\text{Quits}_{e,t+s}}{\text{Emp}_{e,(t+s)-1}} + \alpha_e + \alpha_t + \epsilon_{e,t} \quad (1)$$

$\nu_s$ measures the amount of (replacement) hires (or job openings) per quit at event time $s$. $\alpha_e$ [$\alpha_t$] is an establishment [year] fixed effect.

Figure 1 Panel (b) plots the estimates (complemented by regression results in Appendix Tables A1 and A2).\(^2\) One incremental quit is associated with between 0.74 and 1.0 additional hires ($p$-value < 0.1%). Cumulating across years would yield 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 Appendix Figure A1 Panel (b) [(c)] reveal a strikingly linear shape of the replacement hiring [job posting] relationship, consistent with job-level replacement hiring and motivating, in Section 3, our model of standard DMP atomistic firm-jobs rather than multi-worker firms.

### 2.3 Time Series Comovement

Figure 1 Panel (c) plots the U.S. 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 1600). 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. Appendix Figure A1 Panel (d) confirms similar aggregate cyclical patterns for Germany, Appendix Figure A1 Panel (e) [(f)] does so for quits and hires [job openings] in response to regional business cycles (municipalities).

### 2.4 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 – as in standard models. We study the \textit{equilibrium}

\(^2\)Appendix Table A1 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.
counterfactual in the cyclical analysis of the calibrated model in Section 4.4.

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 $\rho = \frac{r}{r + n} = 0.56$ in Germany. Percent deviations from trend in total vacancies are a $\rho$-weighted average of those in $r$ and $n$:

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

where in practice we study deviations from an HP trend with quarterly log time series (smoothing parameter of 1600).

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 2.2):

$$\frac{dv}{v} \bigg|_{dr=0} = (1 - \rho) \frac{dn}{n} = \frac{dv}{v} - \rho \frac{dr}{r} \approx \frac{dv}{v} - \rho \frac{dQuits}{Quits}$$

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 would have only dropped by 20% instead of 30%. 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.³

The Role of Churn $\rho$ The amplification potential naturally depends on $\rho$, 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 U.S. A back of the envelope extrapolation suggests a US ballpark $\rho^\text{US} \approx 0.9272$.⁴ Figure 2 Panels (a)-(c) therefore also plot this more speculative counterfactual, illustrating the potential range of amplification.

³To 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.

⁴Appendix Figure A1 Panel (d) highlights that German churn is an order of magnitude below the U.S. ones (since it represents annual hires while JOLTS is monthly), consistent with cross-country evidence on worker flows (Elsby et al. (2013)). Let $\rho^i = \frac{r^i}{r^i + n^i}$ denote the share of repostings in total job openings for country $i$. Under the approximation of one-to-one quit–replacement hiring, $\rho$ can be stated in terms of quit rate $Q^i$ and new-job-creation rate $N^i$: $\rho^i = \frac{Q^i}{Q^i + N^i}$, such that $N^i = Q^i [1/\rho^i - 1]$. Assuming $N^i = N^j = N$ technologically, we can express:

$$\rho^j = \frac{Q^j}{Q^j + N} = \frac{Q^j}{Q^j + Q^i [1/\rho^i - 1]} = \frac{1}{1 + Q^j/Q^i [1/\rho^i - 1]}.$$  For the US and Germany, $Q^\text{US}/Q^\text{DE} \approx 10$, and then $\rho^\text{DE} = 0.56$ implies $\rho^\text{US} = 0.9272$. 

5
3 A Model of Jobs, Matches and Replacement Hiring

We introduce longer-lived jobs and replacement hiring into the DMP model, and then study their equilibrium consequences quantitatively in Section 4.

Preview  We introduce longer-lived jobs and a distinction between jobs and matches with a one-time, sunk cost per new job created, \( k(n_t) \), with \( k'(n_t) \geq 0 \), for number \( n_t \) 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:

\[
V_t = k(n_t)
\]

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:

\[
v_t = n_t + (1 - q_{t-1})v_{t-1} + r_t
\]

closely track worker quits.

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

\[
\frac{dv_t}{dr_t} = \begin{cases} 
\epsilon & \text{if } \epsilon \in [0,1] \\
\frac{dn_t}{dr_t} + 1 & \text{if } \epsilon \in [-1,0] 
\end{cases}
\]

In our model, this “crowd-out” \( \frac{dn_t}{dr_t} \) is guided by the shape of job creation cost \( k(n_t) \). Since empirical crowd-out – we show – 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.

3.1 Environment

Time is discrete. There is a unit mass of workers, with risk neutral preferences and discount factor \( \beta \), 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 $\delta$: the worker becomes unemployed, the job disappears forever. Matches moreover dissolve with probability $\sigma$ (the worker becomes unemployed), or through a worker job-to-job quit (described below), but this vacant job remains intact with probability $\gamma$ (while $(1 - \gamma)$ of match dissolutions destroy the job).

**Job Creation**  One new job (aggregate count $n$) can be created at sunk cost $k(n)$. $k(n) = 0$ nests standard DMP.\(^5\) If $k(n) > 0$, firms will repost jobs vacated by quits. All vacancies also require the standard per-period maintenance cost $\kappa$.

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

**Timing**  The timing of events within period $t$ is:

1. $s_t$, the state of the economy, is realized, including unemployment $u_t$ and beginning-of-period (inherited) vacancies $\tilde{v}_t$.\(^6\)

2. Employed workers consume a bargained wage $w_t$ and produce $y_t$, unemployed workers receive unemployment benefit $b$.

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

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

5. Fraction $\delta$ of jobs are exogenously destroyed; these workers become unemployed.

6. Fraction $\sigma$ of matches are exogenously dissolved; these workers become unemployed.

Share $\gamma [1 - \gamma]$ of jobs hit by quits or $\sigma$-shocks can be reposted as vacancies [are destroyed].

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\(^5\)The model in Fujita and Ramey (2007) features a similar cost. They focus on smoothing out vacancy impulse responses, and do not feature quits or replacement hiring.

\(^6\)Our experiments will comprise perfect foresight transition dynamics, so we do not make $s_t$ explicit here.
The law of motion for unemployment is:

\[ u_t = \left(1 - (1 - \delta)(1 - \sigma)f(\theta_{t-1})\right)u_{t-1} + \delta(1 - u_{t-1}) + (1 - \delta)\sigma(1 - u_{t-1}) \]  

(7)

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

\[ v_t = n_t + (1 - \delta)\left(1 - (1 - \sigma)q(\theta_{t-1})\right)v_{t-1} + \gamma\left(\lambda f(\theta_{t-1})e_{t-1} + \sigma(1 - \lambda f(\theta_{t-1}))e_{t-1}\right) \]

\[ = \gamma\left(\sigma + (1 - \sigma)\lambda f(\theta_{t-1})\right)e_{t-1} \]

(8)

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

### 3.2 Value Functions

Value functions are expressed recursively, after the aggregate state is realized (i.e. after subperiod 1).

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

\[ U(s) = b + \beta(1 - \delta)(1 - \sigma)f(\theta)\mathbb{E}[W(s')] + \beta(1 - (1 - \delta)(1 - \sigma)f(\theta))\mathbb{E}[U(s')] \]  

(9)

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

\[ W(s) = w(s) + \beta(\delta + (1 - \delta)\sigma)\mathbb{E}[U(s')] + \beta(1 - \delta)(1 - \sigma)\left(1 - \lambda f(\theta) + \lambda f(\theta)\right)\mathbb{E}[W(s')] \]

\[ = 1 \]  

(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 (UE, \( f(\theta) \)) turns out to produce empirically realistic quits, as shown in Panel (d) of Figure 2, where we plot the log deviations from trend of 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, $R^2 = 0.77$). In Appendix Section B, we present a richer model that explicitly rationalizes job switching with heterogeneity in, and idiosyncratic shocks to, match quality (disamenity), and features endogenous job search effort.

**Firm Problem** Newly created jobs have value

$$N(s) = -k(n) + V(s) \quad (11)$$

Once created, a vacancy carries value

$$V(s) = -\kappa + \beta(1 - \delta) \left[ q(\theta)(1 - \sigma)\mathbb{E}[J(s')] + (1 - q(\theta)(1 - \sigma))\mathbb{E}[V(s')] \right] \quad (12)$$

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

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

$$J(s) = y - w(s) + \beta(1 - \delta) \left[ \gamma(\sigma + (1 - \sigma)\lambda f(\theta))\mathbb{E}[V(s')] + (1 - \sigma)(1 - \lambda f(\theta))\mathbb{E}[J(s')] \right] \quad (13)$$

**Free Entry** Free-entry in job creation drives new-job values $N(s) = -k(n) + V(s)$ to zero:

$$V(s) = k(n) \quad (14)$$

### 3.3 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) and Bagger et al. (2014), our simplification is also used in Fujita and Ramey (2012)). Joint match surplus $S(s)$ is

$$S(s) = J(s) - V(s) + W(s) - U(s) \quad (15)$$

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

$$\left( W(s) - U(s) \right)^\phi \left( J(s) - V(s) \right)^{1-\phi} \quad (16)$$

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7CPS job-to-job transition measures (with short/no nonemployment spell) are slightly smoother than quits but include layoffs/job destruction, not exclusively quits.
implying linear surplus sharing, worker [firm] capturing share $\phi [1 - \phi]$ of joint surplus $S$: \footnote{Using (9), (10), (12), (13), (15), (17) and (18), joint surplus is}

$$\phi S(s) = W(s) - U(s)$$

(17)

$$\quad (1 - \phi) S(s) = J(s) - V(s)$$

(18)

### 3.4 Stationary Equilibrium Definition

We solve the model in steady state. The stationary equilibrium of the model is a set of value functions $W(s)$, $U(s)$, $J(s)$ and $V(s)$, wage function $w(s)$, and new job creation $n$ such that: (i) Worker and firm values satisfy Bellman Equations (9), (10), (12), and (13). (ii) Wage $w(s)$ 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).

### 3.5 Calibration

Panel (a) of Appendix Table A3 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 Appendix C. We relegate the specification and calibration of job creation cost $k(n)$ to Section 4.

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%. Standard Cobb-Douglas matching function $M(s, v) = \mu s^{\eta} v^{1-\eta}$ features elasticity of matches with respect to total search effort $\eta$ and matching efficiency $\mu$. 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% (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 $\frac{EU}{EU + UE} = 5.7\%$ disciplines EU rate $\delta + (1 - \delta)\sigma = 2.72\%$. Targeting job filling rate $(1 - \delta)(1 - \sigma)q(\theta) = 0.9$ (Fujita and Ramey (2007)) normalizes steady state market tightness $\frac{(1-\delta)(1-\sigma)f(\theta)}{(1-\delta)(1-\sigma)q(\theta)} = \theta = \frac{0.45}{0.9} = 0.5$. 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 $\lambda = \frac{EE\text{ rate}}{UE\text{ rate}} = 0.056$, targeting an average monthly quit rate of 2.5% (CPS EE, Fujita and Nakajima (2016), and JOLTS quit rate). To separately identify match-separation $\sigma = 0.0051$ and job-destruction $\delta = 0.0222$ shocks, we target a vacancy reposting share $\rho = \gamma(1-\delta)[1-\lambda f + \sigma (1-\lambda f)] e^{\frac{\gamma}{n+\gamma(1-\delta)[1-\lambda f]}} = 56\%$ (Section 2.1).

## 4 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 $\bar{n}$:

$$k(n) = k_1 + k_2 \times \frac{n - \bar{n}}{\bar{n}}$$  \hspace{1cm} (19)

$k_1$ 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.

### 4.1 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:

$$\kappa + (1 - \beta(1 - \delta))k_1 + \left(1 - \beta(1 - \delta)\mathbb{E}\left[\frac{n' - \bar{n}}{n - \bar{n}}\right]\right)\frac{n - \bar{n}}{\bar{n}}k_2 = \beta(1 - \delta)q(\theta)(1 - \phi)\mathbb{E}[S(s')]$$  \hspace{1cm} (20)

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 (20) clarifies that $\kappa$ 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 ~ 1.0 (cumulative) estimate from Section 2.2.

### 4.2 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 $\Upsilon = \frac{\mu}{\mu + \lambda(1-u)}$, or is destroyed by a $\delta$-shock. The chain
length $C$ counts these vacancies, obtained recursively:\footnote{If $\delta = 0$ and $\gamma = 1$, we obtain}

$$
\mathbb{E}[C] = 1 \cdot [\delta + (1 - \delta)q\gamma] + (1 - \delta)q(1 - \gamma)(\mathbb{E}[C] + \gamma) + (1 - \delta)(1 - q)\mathbb{E}[C]
$$

$$
= \frac{\delta + (1 - \delta)q(\gamma + (1 - \gamma))}{1 - (1 - \delta)(1 - q\gamma)}
$$

(23)

In our calibrated model, the length is 1.88: one vacancy entails 0.88 vacancies in excess of itself.

### 4.3 Aggregate Equilibrium Effects

The vacancy chain is a microeconomic concept tracking the lifecycle of a single vacancy and its “offsprings”. Whether and how much such a vacancy injection actually adds to the total vacancy stock on net (and on other quantities) depends on equilibrium adjustment.

**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 beginning-of-period vacancy shifts $d\bar{v}$, one additional vacancy is crowded out by $\frac{dn}{dt} \in [-1, 0]$, and on net raise the vacancy stock only by $\left( 1 + \frac{dn}{dt} \right) \leq 1$. Crowd-out $\frac{dn}{dt}$ is an equilibrium outcome and depends on $k_2$, the coefficient on the increasing degree of hiring cost. In Panel (a) of Figure 3 we plot $\frac{dn}{dt}$ for various values of $k_2$, along with total-vacancy response $\frac{dv}{dt} = 1 - \frac{dn}{dt}$, 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” $\epsilon^0_s$ shock:\footnote{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% 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.}

$$
v_t = n_t + (1 - \delta)\left( (1 - (1 - \sigma)q(\theta_{t-1}))v_{t-1} + \gamma\left( \sigma + (1 - \sigma)\lambda f(\theta_{t-1}) \right) e_{t-1} \right) + \epsilon^0_s
$$

In calculating the impulse responses (and additional business cycle dynamics in Section 4.4), we focus on perfect foresight transition dynamics following one-time, unanticipated shocks out

Calibrated as $0.057 + 0.056(1 - 0.057) = 0.057$ to 1.92, close to the 1.88 value since $\delta \ll \gamma$. The full length can be calculated analogously by iso-length paths:

$$
\mathbb{E}[C] = \sum_{c=1}^{\infty} c \cdot \Pr(C = c) = \sum_{c=1}^{\infty} c \cdot \left[ (1 - \gamma)^c - 1 \right]
$$

(21)

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

(22)
of steady state, using a shooting algorithm (details in Appendix C.3).

\( k_2 = 0 \) provides an extreme benchmark of perfect neutrality of vacancy inflows such as from replacement hiring: full crowd-out \( \left( \frac{dn}{\partial \bar{\theta}} = -1 \right) \) and no pass-through into total vacancies \( \left( \frac{dv}{\partial \bar{\theta}} = 0 \right) \), since \( n \) adjusts such that \( v^* = \theta^* \cdot u \), and \( \theta \) 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 for 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 \( \theta \)), 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 towards 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 et al. (2017)), and sharp hiring (employment) reductions do not lead unaffected employers in the same local labor market to expand in the short run (e.g. Mian and Sufi (2014), Gathmann et al. (2018)). Some caveats apply to our extrapolation from local to aggregate crowd-out.\(^\text{11}\) Based on the preponderance of the evidence, we set \( k_2 = 1 \), still implying some crowd-out, \( \frac{dn}{\partial \bar{\theta}} = -0.1187 \).

**Equilibrium Effects of Reposting: the Vacancy Multiplier** To investigate the dynamic equilibrium effects of a (one-time, perfectly transitory) vacancy injection \( \varepsilon \varepsilon \) such as arising from reposting, we define a vacancy multiplier, which cumulates the vacancy inflows generated by the

---

\(^\text{11}\)First, most studies do not differentiate between employment and hiring (although Cahuc et al. (2017) 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 \( \frac{1}{\text{Share Tradable}} \)), which would further increase the positive estimates. Third, agglomeration forces may mask crowd-out (Moretti (2010), Gathmann et al. (2018)). Fourth, non-local other markets (capital,...) 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.
shock (as deviations from steady state $\bar{v}^{\text{inflow}}$):\(^{12}\)

$$M(h) = \frac{\sum_{s=1}^{h} (v_s^{\text{inflow}} - \bar{v}^{\text{inflow}})}{\epsilon_1}$$

(24)

for horizon $h$, where $v^\text{inflow}_s = n_s + (1 - \delta)\gamma(\sigma + (1 - \sigma)\lambda f(\theta_{s-1}))e_{s-1} + \epsilon^\delta_s$ captures the total inflow of newly created and reposted vacancies (with $\epsilon^\delta_s = 0 \forall s \neq 1$).

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 $0.88 = 1 + \frac{dn}{dt}$, 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 4.4 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.

### 4.4 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 2.4.

Figure 5 presents the impulse responses from the various 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 same steady state and adjustment costs. (While $k_2 = 0$ would generate neutrality, it would also shut off adjustment cost

\(^{12}\)We again increase the vacancy stock by 1% from its steady state level at time $t = 1$. We have checked that the multiplier is nearly invariant for different shock sizes.
$k'(n)$, 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. Second, we add a “full crowd-out economy” (red dash-dotted lines), where vacancy creation costs $k(.)$ depend on total vacancy inflows rather than only newly created job openings $n$, generating full crowd-out as new and reposted inflows are perfect substitutes therein.\(^{13}\)

**Vacancy Injection** We complete the discussion of the equilibrium multiplier from Section 4.3, in the first row of Figure 5, presenting the IRFs following the vacancy injection shock – perhaps capturing cyclical shifts in public employment (e.g., Baily and Tobin (1977), Holmlund and Linden (1993), Quadrini and Trigari (2007)) or sectoral shocks (e.g., Lilien (1982), Abraham and Katz (1986), Chodorow-Reich and Wieland (2016)).

In the full 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. Lastly, in the full-crowd-out economy $n$ fully neutralizes the injection.

**Aggregate Productivity** The second row of Figure 5 presents IRFs to productivity shocks (Shimer (2005), Hagedorn and Manovskii (2008); similar results for discount factor shocks (Hall (2017)), where $y$ increases exogenously by 1.5% 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.

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

\(^{13}\)Here perhaps an unmodelled actor neutralizes reposting fluctuations by adding and subtracting to $\tilde{v}_t$ (but not to $n_t$) to obtain: $v_t = n_t + (1 - \delta) \left[ (1 - (1 - \sigma)q(\theta_{t-1}))v_{t-1} + \gamma (\sigma + (1 - \sigma)\lambda f(\bar{\theta}))\tilde{v}_{t-1} \right] + \varepsilon_t$.

\(^{14}\)Specifically, creation costs become $k(t) = k_1 + k_2 \frac{\bar{\nu} - 1}{n}$, where inflows $\nu_t = n_t + \gamma (\sigma + (1 - \sigma)\lambda f(\bar{\theta}_{t-1}))\varepsilon_{t-1}$.
Vacancies increase through a conventional “labor supply” channel by facilitating vacancy filling (lowering labor market tightness $\theta = \frac{\text{Job Openings}}{\text{Unemployed} + \text{On-the-job Searchers}}$, 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. $n$ is stable in the full model on net, balancing limited crowd-out with the labor supply channel. Interestingly, due 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 $\mu$ by 1% (persistence $\rho_{\mu} = 0.975$), discussed as a potential cyclical driver in e.g. Barnichon and Figura (2011), Davis et al. (2013), Cheremukhin and Restrepo-Echavarria (2014), and Furlanetto and Groshenny (2016).

Higher matching efficiency stimulates job creation and – unlike the asymmetric $\lambda$ 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.

In conclusion, with new empirical evidence and a calibrated parsimonious model with longer-lived jobs, our paper has painted a picture of recessions as times when 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, amplifying business cycles.
References


Cahuc, Pierre, Carcillo, Stéphane, and Barbanchon, Thomas Le (2017). “The Effectiveness of Hiring Credits”.

Cerqua, Augusto and Pellegrini, Guido (2018). “Local Multipliers at Work”.


Figure 1: Replacement Hiring in the Data

(a) Composition of Job Openings in Germany

(b) Event Study of Hires following Quits

(c) U.S. Time Series of Job Openings, Hires and Quits

(d) Cyclicality of Job Openings and Quits

(e) Cyclicality of New Hires and Quits

Notes: Panel (a): Composition of job openings (last filled job at establishment) by reason, 2000-15 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. Source: IAB Job Vacancy Survey. Panel (b): Establishment level event study of hires (per year) on quits (per year). We plot 95% confidence bands for the 3-lag/lead specification, estimating regression model (1), detailed in text. Source: IAB LIAB. 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 1600). Sources: BLS Labor Turnover Survey and JOLTS.
Figure 2: Counterfactual Time Series, and Quit Cyclicality

Notes: All time series are quarterly, logged and HP-filtered with smoothing parameter $\lambda = 1600$. 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 ($R^2 = 0.77$).
Notes: Panel (a) presents the simulated model’s 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 $\kappa_2$. Panel (b) presents a meta study of empirical estimates speaking to employment crowd-out underlying our calibration of $\kappa_2$. Some sensitivities are back 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, 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), Giupponi and Landais (2018)), we could construct SEs with the Delta method as follows (i.e. be forced to assume a zero covariance term): \[
\text{SE} = \text{SE}^2 + \left(1 + \frac{\beta^2}{\beta_0^2} \right)^2 \cdot \left(\text{SE}^2 + \text{SE}^2 \right) = \text{SE}^2 + \left(1 + \frac{1}{\beta^2} \right)^2 \cdot \left(1 + \frac{1}{\beta_0^2} \right)^2 \cdot \text{SE}^2. \]
In practice, since spillover effects are small compared to direct effects, and since direct effects are precisely estimated, these SEs are close to SE\text{Direct}/\beta_\text{Spillover}, which we therefore report for this subset. Below we describe the papers and calculations, ordered by effect size. Blasco and Menon (2011) replicate Moretti (2010) (described below) and estimate a tradable-on-tradeable jobs multiplier, from 1991 to 2001, and 2007, in the US. 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 elig. workers in LLM on inel. firm emp. growth \((d\mu_{\text{non}}/d\mu_{\text{elig}})/(d\mu_{\text{elig}}/\mu_{\text{tot}})\)) is reported as \(\beta^2 = -0.00937\) (T.3 C.3, divided by 100); i.e. the market-level sensitivity, norm. by total emp., is \((d\mu_{\text{non}})/(d\mu_{\text{elig}}/\mu_{\text{tot}}) = -\beta^2 \cdot (\mu_{\text{elig}}/\mu_{\text{tot}})\), where \(\mu_{\text{tot}}/\mu_{\text{elig}} = 0.75\) (source: correspond. with authors). The market-level direct effect traced out is \(\beta D \cdot (d\mu_{\text{elig}}/\mu_{\text{tot}})\), where \(\beta D = 0.284\) (T.2 C.1) is the direct firm-level emp. effect of subsidy eligibility \((d\mu_{\text{elig}}/\mu_{\text{tot}})\). Hence, the implied market job-for-job crowd-out of inel. emp. in response to policy-induced direct emp. effect, \(d\mu_{\text{non}}/d\mu_{\text{elig}} = \left(\left(d\mu_{\text{non}}/\mu_{\text{elig}}\right)/\left(d\mu_{\text{elig}}/\mu_{\text{tot}}\right)\right) \times (\mu_{\text{tot}}/\mu_{\text{elig}})\), is given by \(\beta^2 \cdot \beta_0^2 / \beta_0^2 = (0.00937)/0.75/0.284 = 0.025\). 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 0.002161/0.75/0.284 = 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 -0.072 effect employment 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 manuf. emp. sensitivity to energy emp. (T.6 C.1, “All Years”, “Traded sector” reports the local job multipliers for tradable on other tradables (we report the least positive among the two industry variants). We construct clustered by state SE with an IV strategy (as the dep. var., exposed tradable as endog. var., 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 multipliers for tradable on other tradables (we report the least positive among the two industry variants). We construct clustered by state SE with an IV strategy (as the dep. var., exposed tradable as endog. var., 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 multipliers for tradable on other tradables (we report the least positive among the two industry variants).
Figure 4: The Vacancy Multiplier: Impulse Responses and Decompositions

(a) Impulse Responses: Vacancy Inflows in “One-Only” Decompositions

(b) Impulse Responses: Vacancy Inflows in “All-But-One” Decompositions

(c) Vacancy Multiplier (Cumulative Impulse Responses) and “One-Only” Decompositions

(d) Vacancy Multiplier (Cumulative Impulse Responses) and “All-But-One” Decompositions

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%, for simulated time series and its components. The variables are normalized by the size of vacancy injection. 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).
Notes: Impulse response functions of new job creation, vacancy stock and unemployment to exogenous vacancy injection, 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).
A Supplementary Evidence on Replacement Hiring

Table A1: Establishment-level Regressions

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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% absolute employment change. Data are annual covering 1993-2008. Source: LIAB sample of the IAB Establishment Survey.
### Table A2: Event Study: Timing of Hires and Quits

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| Establishment FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Year FE          | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

| N     | 24509 | 11414 | 5732 | 2832 | 18015 | 6433 | 2912 | 1385 |
| R²    | .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% absolute employment change. Data are annual covering 1993-2008. Source: LIAB sample of the IAB Establishment Survey.
Figure A1: Further Evidence on Quits, Hiring, Job Openings and Layoffs from Germany

(a) Vacancy Composition over Time

(b) Establishment Level Replacement Hiring: Hires

(c) Establishment Level Replacement Hiring: Job Openings

(d) Comovement of Quits, Hiring, Job Openings and Layoffs

(e) Local Labor Market Replacement Hiring: Hires

(f) Local Labor Market Replacement Hiring: Job Openings

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/reirement-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 A1 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)): $\text{Outcome}_{e,l,t} = \beta_0 + \beta_1 \ln(\text{Unemp}_{l(e),t}) + \alpha_e + \alpha_t + \varepsilon_{e,t}$ 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 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 C.2, and IRFs can be generated using the algorithm in C.3. Once calibrated to realistic quit levels and cyclicality, it behaves very similarly to our parsimonious model presented in the main text.

Let $\xi \in [\xi, \bar{\xi}]$ 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:

$$U(s) = \max_{s_{t} \geq 0} \left\{ b - c(s_{t}) + \beta(1 - \delta)(1 - \sigma)s_{t}f(\theta)\mathbb{E}[W(\xi, s')] + \beta(1 - (1 - \delta)(1 - \sigma)s_{t}f(\theta)]\mathbb{E}[U(s')] \right\}$$

$$W(\xi, s) = \max_{s_{t} \geq 0} \left\{ w(\xi, s) - \xi - c(s_{t}) + \beta\delta\mathbb{E}[U(s')] + \beta(1 - \delta)\sigma\mathbb{E}[U(s')] \right\}$$

$$V(s) = -\kappa + \beta(1 - \delta)\left[ q(\theta)(1 - \sigma)\mathbb{E}[J(\xi, s')] + (1 - q(\theta)(1 - \sigma))\mathbb{E}[V(s')] \right]$$

$$J(\xi, s) = y - w(\xi, s) + \beta(1 - \delta)\left[ \gamma s_{t}^{\xi}\lambda f(\theta)\mathbb{E}[V(s')] + \gamma \sigma(1 - s_{t}^{\xi}\lambda f(\theta)]\mathbb{E}[V(\xi', s')] \right]$$

$$+ (1 - \sigma)(1 - s_{t}^{\xi}\lambda f(\theta)] \left[ \mathbb{E}\{W(\xi', s') > U(s') \} J(\xi', s') \right] + \gamma \mathbb{E}\{W(\xi', s') \leq U(s') \} V(s') \right\} \right\}$$

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

$$v_t = n_t + (1 - \delta)\left[ (1 - (1 - \sigma)q(\theta_{t-1}))v_{t-1} + \gamma (\lambda f(\theta_{t-1}) \int_{\tilde{\xi}} s_{t}^{\xi} e_{t-1}(\tilde{\xi})d\tilde{\xi} \right]$$

$$+ \int_{\tilde{\xi}} (\sigma + (1 - \sigma)P(\xi > \xi^c|\tilde{\xi})) (1 - \lambda f(\theta_{t-1})s_{t}^{\xi}(\tilde{\xi}) e_{t-1}(\tilde{\xi})d\tilde{\xi}) \right)$$

$$u_t = (1 - (1 - \delta)(1 - \sigma)s_{u}f(\theta_{t-1}))u_{t-1} + \delta(1 - u_{t-1})$$

$$+ (1 - \delta)(1 - \sigma)\int_{\tilde{\xi}} P(\xi > \xi^c|\tilde{\xi}) (1 - \lambda f(\theta_{t-1})s_{t}^{\xi}(\tilde{\xi}) e_{t-1}(\tilde{\xi})d\tilde{\xi}) + (1 - \delta)\sigma(1 - u_{t-1})$$

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

$$e_t(\xi) = (1 - \delta)(1 - \sigma)\left( \int_{\tilde{\xi}} P(\xi|\tilde{\xi}) (1 - \lambda f(\theta_{t-1})s_{t}^{\xi}(\tilde{\xi}) e_{t-1}(\tilde{\xi})d\tilde{\xi}) + s_{u}f(\theta_{t-1})u_{t-1} + \lambda f(\theta_{t-1}) \int_{\tilde{\xi}} s_{t}^{\xi}(\tilde{\xi}) e_{t-1}(\tilde{\xi})d\tilde{\xi} \right)$$

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

where $\xi^c(s)$ denotes the endogenous separation cutoff implicitly defined by $W(\xi^c, s) = U(s)$.
C Computational Details

C.1 Calibration

Table A3: Calibration and Model Fit

(a) Calibrated Parameters and Values

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<tr>
<th>Parameter Description</th>
<th>Symbol</th>
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<td>Discount factor</td>
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<td>Elasticity of matching function</td>
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<td>Reposting rate</td>
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<td>Fixed cost of vacancy creation</td>
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(b) Estimated Parameters and Values

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<td>Vacancy posting cost</td>
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(b) Target Moments and Model Fit

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<td>Job-to-job rate</td>
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<td>CPS - Fujita and Nakajima (2016)</td>
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<td>Unemployed job finding rate</td>
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<td>CPS - Shimer (2005)</td>
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<td>Reposted vacancy share</td>
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<td>IAB German Job Vacancy Survey</td>
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<td>Job filling rate</td>
<td>0.9</td>
<td>0.9</td>
<td>Fujita and Ramey (2007)</td>
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C.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 $\theta_0$.

2. For each guess of $\theta_n$ in iteration $n$:
   
   (a) Iterate on $S(s)$ given in Footnote 8 to solve for match surplus.
   
   (b) Iterate on the laws of motion in equations (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 percent deviation from $\theta_n$.
   
   (d) If the percent 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 $\omega < 1$.

C.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 C.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, $\{\theta^0_t\}_{t=1}^{T-1}$.

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 $\{\theta^0_t\}_{t=1}^{T-1}$, the shock, and the terminal values of $S_T$ and $V_T$.

5. Compute the sequence of market tightness $\{\theta^1_t\}_{t=1}^{T-1}$ 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 $\max_{1 \leq t < T} |\theta^1_t - \theta^0_t|$ is less than a predetermined tolerance level. If yes, continue, if no update $\{\theta^0_t\}_{t=1}^{T-1}$ and go back to step 3.

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