Online Appendix of:

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

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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.

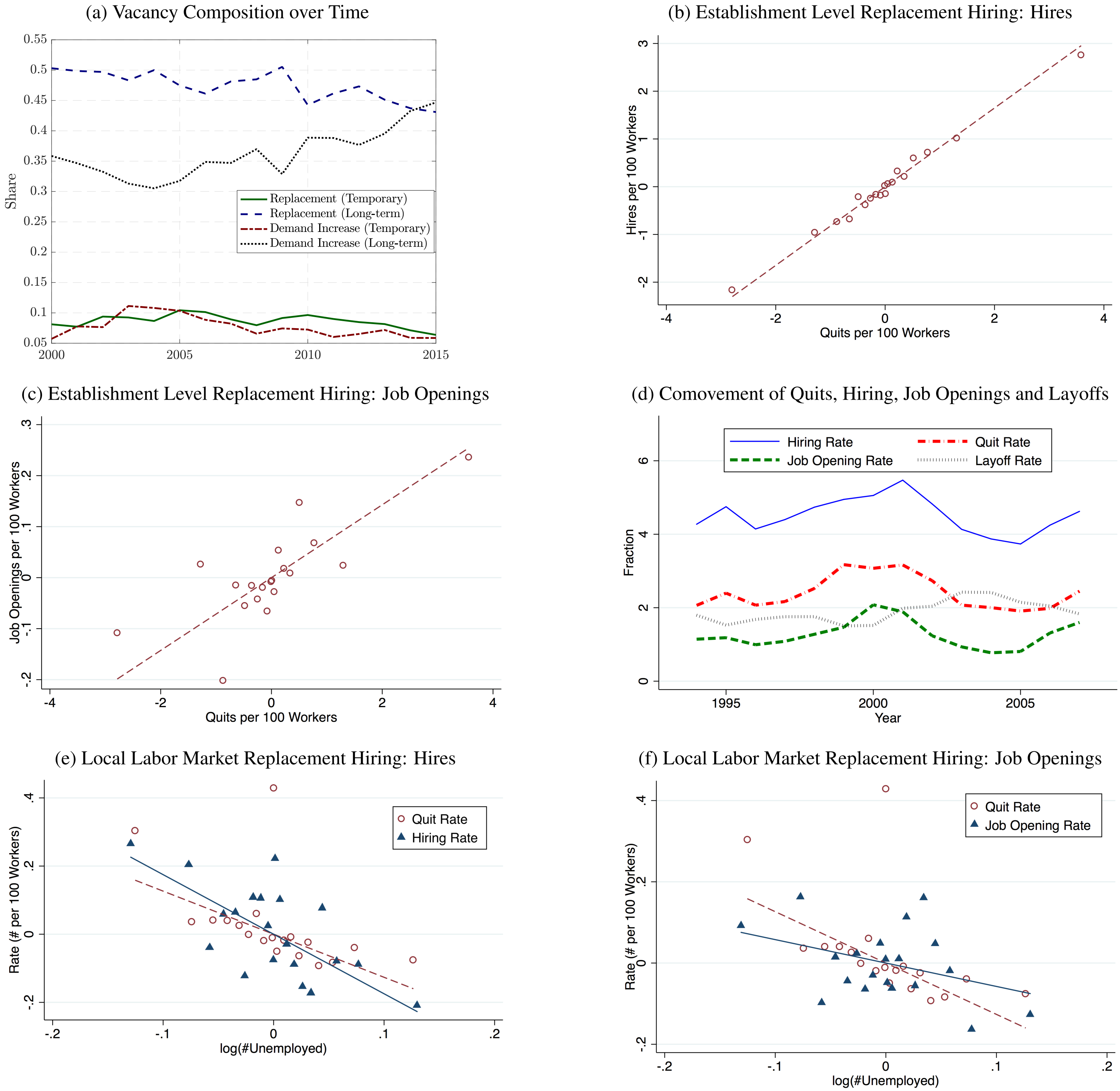
Table A.2: Event Study: Timing of Hires and Quits

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 $\{V_t\}_{t=1}^{T-1}$.

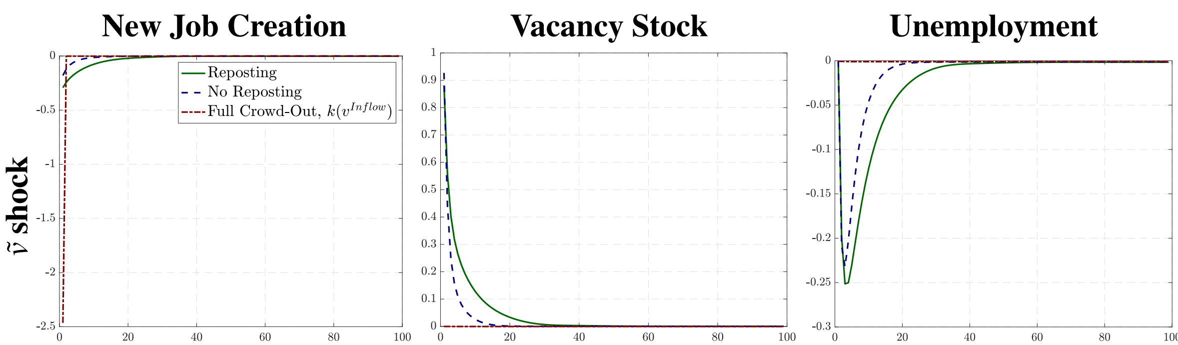
6. Check if $\max_{1 \le t < T} |\theta_t^1 - \theta_t^0|$ is less than a predetermined tolerance level. If yes, continue, if no update $\{\theta_t^0\}_{t=1}^{T-1}$ and go back to step 3.

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:

$$U(\mathbf{s}) = \max_{s_U \geq 0} \Big\{ b - c(s_U) + \beta(1-\delta)(1-\sigma)s_U f(\theta)\mathbb{E}[W(\underline{\xi}, \mathbf{s}')] + \beta(1-(1-\delta)(1-\sigma)s_U f(\theta))\mathbb{E}[U(\mathbf{s}')] \Big\}$$

$$\begin{aligned} W(\xi, \mathbf{s}) = \max_{s_E \geq 0} \Big\{ & w(\xi, \mathbf{s}) - \xi - c(s_E) + \beta\delta\mathbb{E}[U(\mathbf{s}')] + \beta(1-\delta)\sigma\mathbb{E}[U(\mathbf{s}')] \\ & + \beta(1-\delta)(1-\sigma)\Big[(1-s_E\lambda f(\theta))\mathbb{E}\big[\max\{W(\xi', \mathbf{s}'), U(\mathbf{s}')\}\big] + s_E\lambda f(\theta)\mathbb{E}[W(\underline{\xi}, \mathbf{s}')]\Big] \Big\} \end{aligned}$$

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

$$\begin{aligned} J(\xi, \mathbf{s}) = y - w(\xi, \mathbf{s}) + \beta(1-\delta)\Big[& \gamma s_E^* \lambda f(\theta)\mathbb{E}[V(\mathbf{s}')] + \gamma\sigma(1-s_E^*\lambda f(\theta))\mathbb{E}[V(\xi', \mathbf{s}')] \\ & + (1-\sigma)(1-s_E^*\lambda f(\theta))\Big\{\mathbb{E}\Big[\mathbb{I}\{W(\xi', \mathbf{s}') > U(\mathbf{s}')\}J(\xi', \mathbf{s}')\Big] + \gamma\mathbb{E}\Big[\mathbb{I}\{W(\xi', \mathbf{s}') \leq U(\mathbf{s}')\}V(\mathbf{s}')\Big]\Big\}\Big] \end{aligned}$$

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

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

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

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

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

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

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

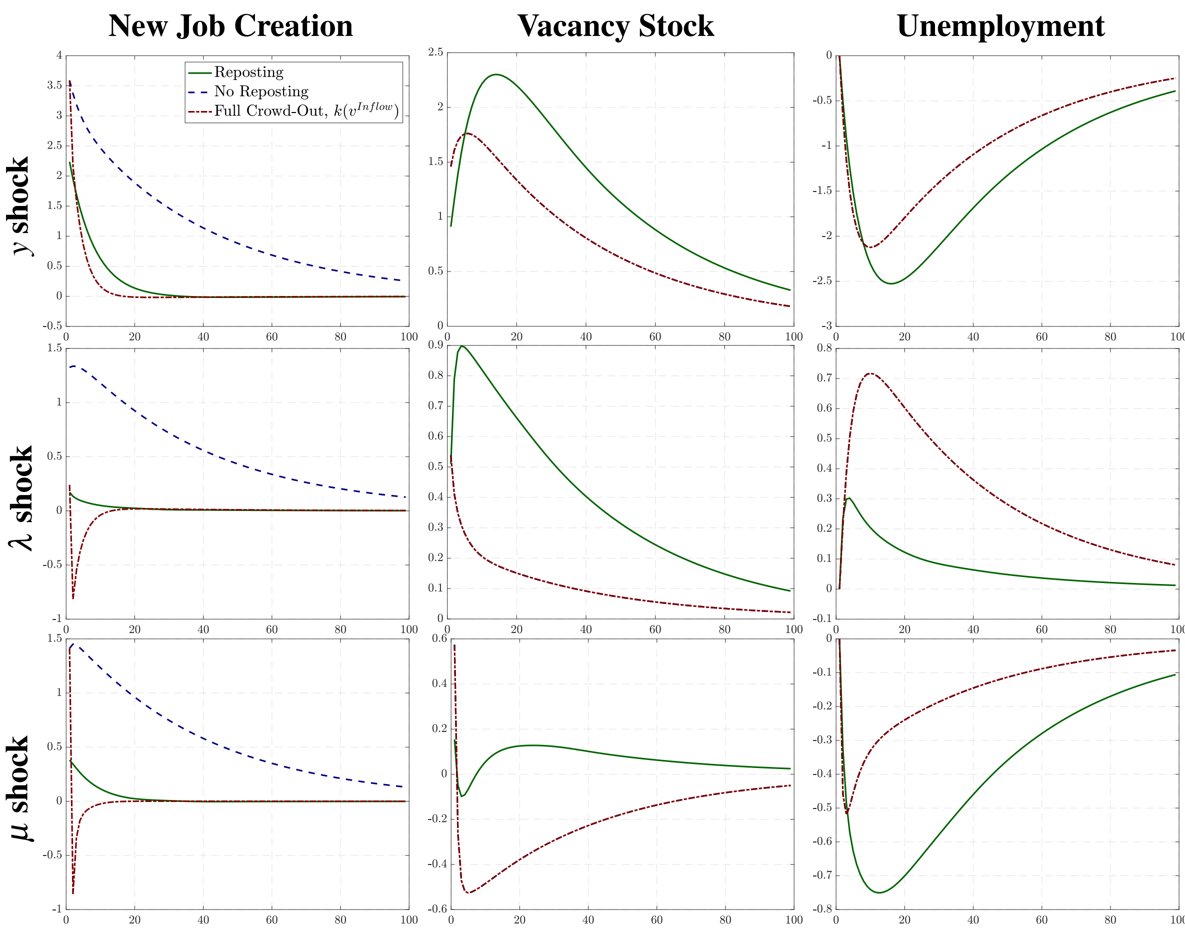
(a) Calibrated Parameters and Values

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

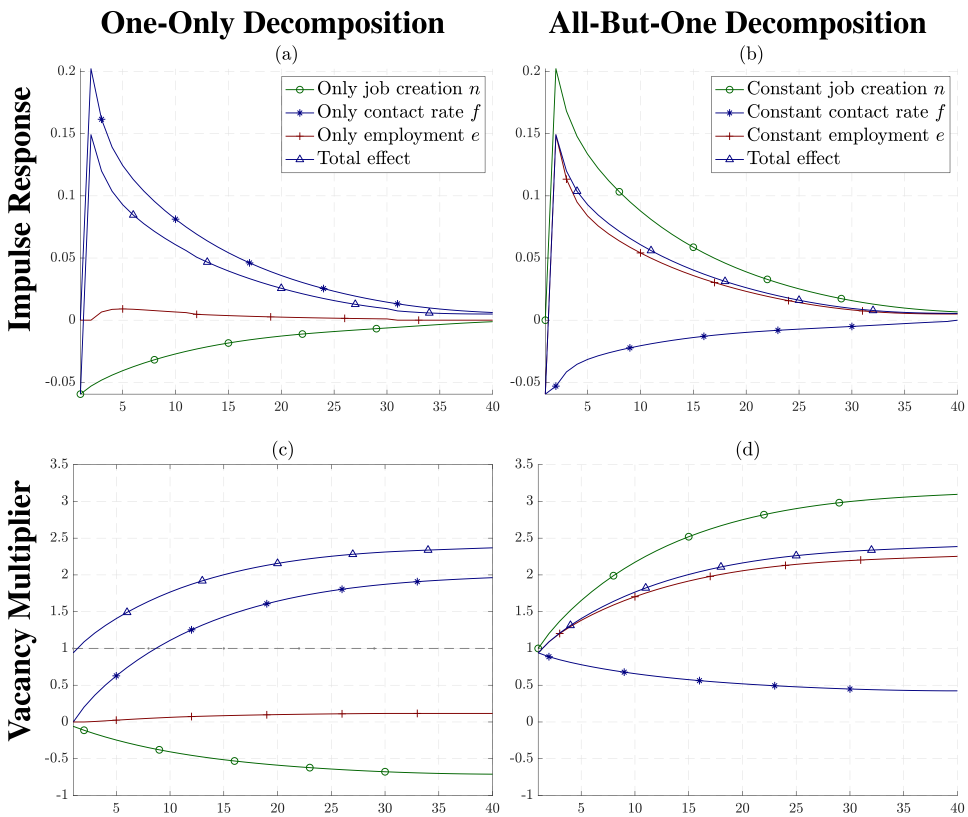
Figure E.1: Impulse Responses: Extended Model



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).

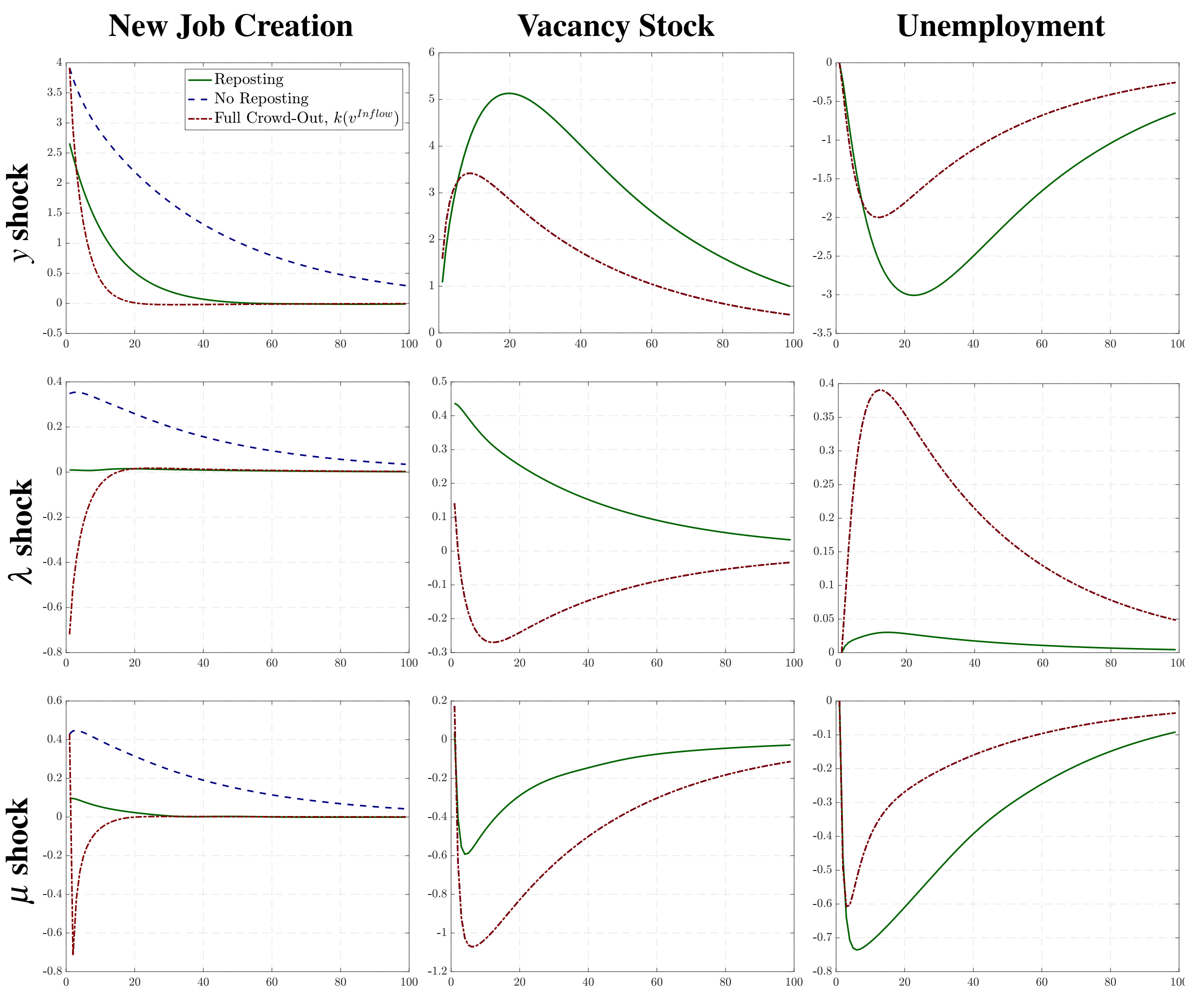
F Low Crowd-Out Economy

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).