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Do Job Destruction Shocks Matter in the Theory of Unemployment?†

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Because the data show that market tightness is not orthogonal to unemployment, this paper identifies the many empirical difficulties caused by adopting the free entry of vacancies assumption in the Diamond-Mortensen-Pissarides (DMP) framework. Relaxing the free entry assumption and using Simulated Method of Moments (SMM) finds the vacancy creation process is less than infinitely elastic. Because a recession-leading job separation shock then causes vacancies to fall as unemployment increases, the ad hoc restriction to zero job separation shocks (to generate Beveridge curve dynamics) becomes redundant. In contrast to standard arguments, the calibrated model finds the job separation process drives unemployment volatility over the cycle. (*JEL* E24, E32, J24, J63, J64)

This paper shows how the unemployment dynamics implied by the Diamond-Mortensen-Pissarides framework change fundamentally when the free entry of vacancies assumptions is relaxed. This is important because we show a key implication of the free entry approach—that conditional on productivity variables, market tightness is orthogonal to unemployment—is not consistent with the data. Furthermore, with a less than infinitely elastic vacancy creation process, we show why a recession-leading job separation shock then causes vacancies to fall as unemployment increases. This dynamic response is important because an ad hoc restriction to zero job separation shocks is not then necessary to generate Beveridge curve correlations. And once an exogenous, but data-relevant, job separation process is allowed, the relaxed framework further finds it is no longer necessary to make a small surplus assumption to generate sufficient unemployment volatility; see, e.g., Hagedorn and Manovskii (2008) and Ljungqvist and Sargent (2017). Several tests identify the much improved empirical properties of this relaxed approach relative to the free entry approach. And somewhat surprisingly, even though the calibrated model's reduced-form properties are fully consistent with the Shimer (2012) decomposition of the ins and outs of unemployment (which seemingly suggest job separation shocks play only a minor role in explaining unemployment volatility), the

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structural model finds it is the job separation process that drives the large variation in unemployment over the cycle.

The seminal contribution of Mortensen and Pissarides (1994)—henceforth, MP—was to identify an equilibrium model of unemployment consistent with three claimed properties of the business cycle; (MP1) job destruction flows and job creation flows covary negatively; (MP2) job destruction flows have greater variance than job creation flows; and (MP3) job destruction patterns are asymmetric in that job destruction increases rapidly at the start of recession (also see Davis and Haltiwanger 1992, the recent survey by Elsby, Michaels, and Ratner 2015 and Figures 4 and 5 regarding the Great Recession).[1] Shimer (2005), of course, identifies three difficulties with the MP framework: (S1) it generates too little unemployment persistence; (S2) with an appropriately calibrated productivity process, it yields insufficient unemployment volatility; and (S3) large job separation shocks generate a counterfactual positive correlation between unemployment and vacancies. Following Shimer (2005), Hall (2005), and Hagedorn and Manovskii (2008), the equilibrium unemployment literature typically assumes no aggregate job separation shocks and small surplus. Although this approach speaks to the Shimer criticisms (S1–S3), it is inconsistent with MP1–MP3, for it implies a much larger variance of job creation flows than of job separation flows. An important aim of our paper is to identify a fully consistent approach.

The free entry of vacancies assumption is very strong for it implies a penny increase in productivity causes an instantaneous jump in the number of vacancies.[2] Instead, we adopt a job creation process analogous to Diamond (1982) and Fujita and Ramey (2005): creating a new job here requires an initial investment in a new technology, where the sunk cost of any such investment is considered a random draw from an exogenous distribution. This "Diamond entry" process encompasses the free entry assumption as a special case but, with a finite measure of firms and heterogeneous investment costs, it also allows a vacancy creation process that is less than infinitely elastic. Because this elasticity is central to explaining equilibrium unemployment dynamics, we use Simulated Method of Moments (SMM) to identify it using target moments taken from Shimer (2005), which describes the cyclical behavior of unemployment, vacancies, and market tightness. Rather than being infinitely elastic, SMM instead finds the vacancy creation process is inelastic. This has important consequences. For example, unlike the free entry case, a steep increase in unemployment does not generate a correspondingly steep increase in vacancies. Indeed, an inelastic vacancy creation process generates the added unemployment persistence that is otherwise missing in the free entry approach; a more muted vacancy creation response to higher unemployment implies lower job finding rates and thus more persistent unemployment. It also fundamentally changes the impulse response of the economy to a job separation shock.

[1] Because we abstract from on-the-job search, our paper follows Shimer (2005) and refers instead to job separation shocks, which describe the outflow of employed workers into unemployment. Job destruction shocks are clearly related but are not the same: with on-the-job search, a job is also destroyed when an employee quits for alternative work and the firm does not hire a replacement.

[2] Free entry implies vacancies exhibit high frequency variations, which is also inconsistent with the data; see, e.g., Sniekers (2016).

With free entry, large job separation shocks generate a counterfactual positive correlation between unemployment and vacancies; see, e.g., Shimer (2005). This is not the case with Diamond entry. Following a single job separation shock, the calibrated model finds the stock of vacancies falls because oversampling by the pulse of laid-off workers depletes the existing vacancy stock. An inelastic vacancy creation process and a positively autocorrelated job separation process then generate an increasing unemployment stock, a declining vacancy stock which together imply worker job finding rates plummet. We show these unemployment dynamics, following a recessionary job separation shock, are fully consistent with the insights of Shimer (2005, 2012). But equally important, the approach is also consistent with MP1–MP3 and the US unemployment dynamics that followed the Great Recession.

The paper is structured as follows. Section I describes the model and Section II characterizes its (Markov) equilibrium. Section III describes the calibration exercise and considers various tests which compare the model's properties to the properties of the free entry/small surplus/no job separation shocks approach (also see Elsby, Michaels, and Ratner 2015 for a different test that supports our approach). Section IV examines the role played by the job separation process in explaining unemployment volatility, and Section V uses the calibrated model to consider the impact of the Great Recession on US labor market outcomes but using layoffs (taken from Job Openings and Labor Turnover Survey, or JOLTS) as the measure of job separation shocks. Section VI concludes and and is followed by the Data Appendix.

I. Model

We use a conventional equilibrium unemployment framework with discrete time and an infinite time horizon; e.g., Pissarides (2000). All firms and all workers are equally productive; all firms pay the same (Nash bargained) wage; each worker-firm match survives until it is hit by a job separation shock. The only difference is that vacancies evolve as a stock variable with a less than infinitely elastic vacancy creation process. Without free entry, the stocks of unemployment and vacancies become relevant aggregate state variables.

There is a finite, fixed measure $F > 0$ of firms who create vacancies. In every period, each firm has one new (independent) "business opportunity." Given that opportunity, the firm compares its investment cost x against its expected return. Its expected return depends on the state of the aggregate economy at time t, denoted Ω_t, which is described in detail below. We let $J_t = J(\Omega_t)$ denote the expected return of a business opportunity in state Ω_t. The investment cost x is an idiosyncratic random draw from an exogenous cost distribution H. For tractability, we assume this investment cost captures all of the idiosyncratic features associated with any given business venture—in other words, highly profitable opportunities correspond to low realized values of x. Should the firm decide to invest, it pays the sunk cost x and then holds an unfilled job with expected value J_t; i.e., each new investment generates one new vacancy.

Following Diamond (1982), each firm invests in its business opportunity if and only if it has positive value; i.e., when $x \leq J_t$. This requires no recall of a business opportunity should the firm not immediately invest in it. As investment occurs whenever $x \leq J_t$ then, at the aggregate level, $i_t = FH(J_t)$ describes total period t new vacancy creation.

To describe how a firm fills a vacancy, we adopt the standard matching framework (but without free entry). There is a unit measure of infinitely lived workers. All workers and firms are risk neutral and have the same discount factor $0 < \beta < 1$. Workers switch between being employed and unemployed depending on their realized labor market outcomes. $c \geq 0$ describes the per period cost of posting an unfilled vacancy.

Each period is characterized by the measure v_t of vacancies (currently unfilled jobs) and the measure u_t of unemployed workers (so that $1 - u_t$ describes the number employed). The hiring process is frictional: the measure m_t of new job-worker matches in period t is described by a matching function $m_t = m(u_t, v_t)$, where $m(\cdot)$ is positive, increasing, concave, and homogenous of degree one.

While unemployed, a job seeker enjoys per period payoff $z > 0$. In period t, each job-worker match produces the same market output $p = p_t$, where aggregate productivity p_t evolves according to an exogenous AR1 process (described below). Job separations are also an exogenous, stochastic process where δ_t describes the probability that any given job, either filled or unfilled, is destroyed. In the event of a filled job being destroyed, the worker separates from the firm and becomes unemployed, while the job's continuation payoff is zero.

We next describe the sequence of events within each period t. Each period has five stages:

Stage I [New Realizations]: Given (p_{t-1}, δ_{t-1}) from the previous period, new values of p_t, δ_t are realized according to

$$\ln p_t = \rho_p \ln p_{t-1} + \varepsilon_t,$$

$$\ln \delta_t = \rho_\delta \ln \delta_{t-1} + (1 - \rho_\delta) \ln \overline{\delta} + \eta_t,$$

where (ε_t, η_t) are white noise innovations drawn from the normal distribution with mean zero, covariance matrix Σ, $\overline{\delta} > 0$ is the long-run average job separation rate, while long-run productivity p is normalized to one;

Stage II [Bargaining and Production]: The wage w_t is determined by Nash bargaining. Production takes place so that a job match yields one period profit $p_t - w_t$, while the employed worker enjoys payoff w_t. Each unemployed worker enjoys payoff z;

Stage III [Vacancy Investment]: Firms invest in new vacancies i_t;

Stage IV [Matching]: Let u_t, v_t denote the stock of unemployed job seekers and vacancies at the start of this stage. Matching takes place so that $m_t = m(u_t, v_t)$ describes the total number of new matches;

Stage V [Job Separation]: Each vacancy and each filled job is independently destroyed with probability δ_t.

II. Markov Dynamics and Equilibrium

This section describes the (Markov) equilibrium dynamics. Because u_t is defined as the number unemployed in period t immediately prior to the matching stage (Stage IV), then u_t evolves according to

$$u_t = u_{t-1} + \delta_{t-1}(1 - u_{t-1}) - (1 - \delta_{t-1})\, m_{t-1}, \tag{1}$$

where $m_{t-1} = m(u_{t-1}, v_{t-1})$. The second term describes the stock of employed workers in period $t-1$ who become unemployed through a job separation shock. The last term describes the match outflow where such matches are also subject to the period $t-1$ job separation shock.

The vacancy stock dynamics are given by

$$v_t = (1 - \delta_{t-1})[v_{t-1} - m_{t-1}] + i_t, \tag{2}$$

where the first term describes those vacancies that survive (unfilled) from the previous matching event, while i_t describes new vacancy creation.

To determine equilibrium new vacancy creation i_t, we restrict attention to Markov equilibria. Once (p_t, δ_t) are realized, define the intermediate stock of vacancies

$$\tilde{v}_t = (1 - \delta_{t-1})[v_{t-1} - m_{t-1}],$$

which is the number of surviving vacancies carried over from the previous matching event. When bargaining occurs in Stage II, let $\Omega_t = \{p_t, \delta_t, u_t, \tilde{v}_t\}$ denote the corresponding state space. As described below, any standard Nash bargaining procedure yields a wage rule of the form $w_t = w^N(\Omega_t)$. Stage III then determines optimal investment $i_t = i(\Omega_t)$. As the matching and separation dynamics ensure Ω_t evolves as a first-order Markov process, then Ω_t is indeed a sufficient statistic for optimal decision making in period t.

We next characterize the Bellman equations describing optimal behavior. In period t and at the start of Stage II with state vector Ω_t (i.e., prior to production and matching but after new p_t, δ_t have been realized), let

$J_t = J(\Omega_t)$ denote the expected value of a vacancy;

$J_t^F = J^F(\Omega_t)$ denote the expected value of a filled job;

$V_t^U = V^U(\Omega_t)$ denote the worker's expected value of unemployment;

$V_t^E = V^E(\Omega_t)$ denote the worker's expected value of employment.

Let $E[\cdot \mid \Omega_t]$ denote the expectations operator given period t state vector Ω_t. The timing of the model implies the value functions J_t, J_t^F are defined recursively by

$$J_t = -c + \beta(1-\delta_t) E\left\{ \frac{m(u_t, v_t)}{v_t} J_{t+1}^F + \left[1 - \frac{m(u_t, v_t)}{v_t}\right] J_{t+1} \mid \Omega_t \right\}, \tag{3}$$

$$J_t^F = p_t - w_t + \beta(1-\delta_t) E\left\{J_{t+1}^F \mid \Omega_t\right\}. \tag{4}$$

The worker value functions are also defined recursively

$$V_t^U = z + \beta E\left[V_{t+1}^U + (1-\delta_t)\frac{m(u_t, v_t)}{u_t}\left[V_{t+1}^E - V_{t+1}^U\right] \mid \Omega_t\right], \tag{5}$$

$$V_t^E = w_t + \beta E\left[V_{t+1}^E + \delta_{t+1}\left[V_{t+1}^U - V_{t+1}^E\right] \mid \Omega_t\right]. \tag{6}$$

Because firms invest if and only if the business opportunity has cost $x \leq J_t$, equilibrium new vacancy creation $i_t = i(\Omega_t)$, where

$$i_t = FH(J_t), \tag{7}$$

and $J_t = J(\Omega_t)$.

Assuming workers have bargaining power $\phi \in [0,1]$, the axiomatic Nash bargaining approach closes the model with

$$(1-\phi)\left[V_t^E - V_t^U\right] = \phi\left[J_t^F - J_t\right].$$

Using the above equations, this condition determines the equilibrium wage $w_t = w(\Omega_t)$. The above thus yields a system of autonomous, first-order difference equations determining the evolution of Ω_t and the equilibrium value functions with corresponding investment rule $i_t = i(\Omega_t)$.

III. Calibration and Tests

The following calibrates the model to the data considered in Shimer (2005). As the framework is so standard, we adopt the calibration parameters as described in Mortensen and Nagypál (2007). Specifically, we assume each period corresponds to one month and a standard Cobb-Douglas matching function $m = Au^{\gamma}v^{1-\gamma}$. Table 1 describes the corresponding Mortensen/Nagypál parameter values. Note the Hosios condition is satisfied. As the productivity process for p_t implies its (long run) mean value equals one, surplus $(1-z)/z = 43$ percent is large. The monthly discount factor implies an annual discount rate of 4 percent.

Rather than impose zero job separation shocks, we calibrate the $\{p_t, \delta_t\}$ process to the data described in Shimer (2005). Figure 1 describes the magnitude of log deviations in job separation rates and labor productivity as computed for the Shimer (2005) data at business-cycle frequencies.[3]

[3] The Data Appendix describes how Shimer (2005) measures the job separation rate.

Table 1—Mortensen/Nagypál Parameters

Parameter		Value
γ	Elasticity parameter on matching function	0.6
ϕ	Worker bargaining power	0.6
z	Outside value of leisure	0.7
β	Monthly discount factor	0.9967

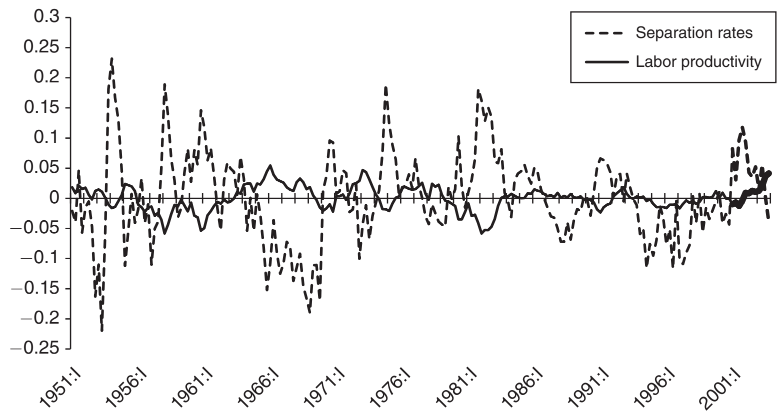

Figure 1. US Separation Rates and Labor Productivity (1951–2003)

Note: Both series are in logs as deviations from a HP trend with smoothing parameter 10^5.

Table 2—(p_t, δ_t) Stochastic Process (*monthly frequencies*)

Parameter		Value
ρ_p	Productivity autocorrelation	0.965
ρ_δ	Separation autocorrelation	0.875
σ_p	Standard deviation productivity shocks	0.0070
σ_δ	Standard deviation separation shocks	0.042
$\rho_{p\delta}$	Cross correlation	−0.63

As these data are only recorded quarterly while the model adopts a monthly time structure, we choose the autocorrelation parameters ρ_p, ρ_δ, and covariance matrix Σ so that the implied process (p_t, δ_t), when reported at quarterly intervals, matches the first-order autocorrelation and cross correlation implied by the data. Doing this yields the parameter values in Table 2.

As demonstrated in Figure 1 and consistent with the view expressed in MP, the job separation innovations are strongly negatively correlated with productivity innovations and have much greater variance. Of course MP described an endogenous job destruction margin and a single exogenous stochastic process for $\{p_t\}$.

When calibrating a DMP framework, it is often found that the vacancy posting cost c must be large. This is typically explained by arguing that it reflects previously sunk job creation investments. Here, we take the converse case: we instead presume small vacancy posting costs $(c = 0)$, and so all job creation costs are tied to the ex ante investment decision. Given the vacancy creation rule implies $i_t = FH(J_t)$, we adopt the simplest, most parsimonious functional form

$$i_t = FJ_t^{\xi} \tag{8}$$

so that ξ describes the elasticity of new vacancy creation with respect to vacancy value. Notice, $\xi = \infty$ describes infinitely elastic new vacancy creation (analogous to the free entry case), while $\xi = 0$ implies perfectly inelastic (fixed) new vacancy creation.

The framework is calibrated to fit the long-run turnover means. To ensure comparability of results, we follow Shimer (2005) who argues that the mean job separation probability should equal 3.4 percent per month, and that the average duration of an unemployment spell is 2.2 months; thus, the long-run unemployment rate equals $u = 7$ percent. We also note the average duration of vacancies is around three weeks (Blanchard and Diamond 1989). The first restriction ties down $\overline{\delta} = 0.034$ (mean monthly job separation). Depending on the choice of ξ, the latter two restrictions tie down A (the scale parameter on the matching function) and F (the scale parameter on the vacancy creation rule). For example, the choice $\xi = 1$ (the distribution of investment costs is uniform) requires $A = 0.594$ and $F = 0.0075$.

This leaves us with one free parameter ξ, the elasticity of the job creation process. We estimate ξ using simulated method of moments as described in Ruge-Murcia (2012) with a Newey-West diagonal weighting matrix. For each chosen value ξ we first update parameter values (A, F) so the generated data is consistent with the long-run turnover means. The target moments used to identify ξ are the standard deviations and correlations of unemployment, vacancies, and market tightness taken from table 1 in Shimer (2005).

A. *Results*

The first column in Table 3 records the data targets, where the Beveridge curve (BC) describes the negative correlation of vacancies with unemployment. The remaining columns describe the corresponding statistics using model generated data.

We begin with the final column, labeled H/M. This column instead assumes free entry, sets $z = 0.955$ (small surplus), $\phi = 0.052$ (low worker bargaining power), and $\delta_t = \overline{\delta}$ (no separation shocks), as considered in Hagedorn and Manovskii (2008).[4] This specification yields the BC and good volatility outcomes. The column "H/M with JD" augments the H/M specification with the above job separation process (and c appropriately recalibrated). Adding separation shocks yields greater unemployment volatility but, consistent with the arguments in Shimer (2005), reduces the strong negative correlation between unemployment and vacancies.[5]

[4] For comparability of results, we otherwise retain the Mortensen/Nagypál parameter values, set $x = 0$ and calibrate c to fit the same long-run turnover means. Doing this implies $c = 0.63$. Hagedorn and Manovskii (2008) instead specify $\gamma = 0.41$, $\overline{\delta} = 0.026$, $c = 0.58$.

[5] Fujita and Ramey (2012) also make this point and consider the role of on-the-job search in mitigating this problem.

Table 3—Simulation Results

	Data	$\xi = 0.265$	$\xi = 1$	H/M with JD	H/M
Panel A. Standard deviations					
σ_u	0.19	0.18	0.15	0.19	0.14
σ_v	0.20	0.20	0.14	0.24	0.27
σ_θ	0.38	0.38	0.28	0.40	0.40
Panel B. Cross correlations					
corr(v, u) [BC]	−0.89	−0.96	−0.93	−0.76	−0.87
corr(θ, u)	−0.97	−0.99	−0.99	−0.92	−0.95
corr(θ, v)	0.98	0.99	0.98	0.95	0.99

Notes: σ_x is the standard deviation of x, and corr(x, y) is the cross correlation between x and y. The first column contains the quarterly moments from Shimer's (2005) table 1. The second column contains the statistics from the estimated model. The third column contains a simulated model with $\xi = 1$, the fourth column contains free entry model with H/M calibration with separation shocks, and the last column contains H/M calibration without separation shocks. To calculate the quarterly moments, models are first simulated at monthly frequency and then aggregated.

The $\xi = 1$ column describes the results when the vacancy creation process is assumed unit elastic. For that choice, the model generates the right correlated behavior, but there is too little volatility. To fit the volatility targets, SMM infers the vacancy creation process must be less than unit elastic, where estimated $\xi = 0.265$. Although $\xi = 0.265$ slightly overstates the negative correlation of unemployment and vacancies, the fit to the chosen targets is otherwise perfect.

We now consider three tests that identify the very different dynamic properties of our relaxed approach relative to the free entry case. Section VI uses those insights to consider the dynamics of unemployment following the Great Recession. The Data Appendix reports the full set of data moments (corresponding to table 1, Shimer 2005) and the corresponding table for the case $\xi = 0.265$. Importantly for what follows, note table 1, Shimer (2005) finds that market tightness has an exceptionally high raw correlation of -0.97 with unemployment (also see Table 3), while the raw correlation of market tightness with productivity is only 0.40 and with job separation rates it is -0.71.

B. *Test 1: Market Tightness Dynamics*

Market tightness $\theta_t = V_t/U_t$ determines how worker job finding rates vary over the cycle. The free entry approach yields a particularly useful simplification: that equilibrium market tightness $\theta_t = \theta^*(p_t, \delta_t)$ is independent of unemployment U_t. But conditional on (p_t, δ_t), an obvious statistical test is whether market tightness θ_t is indeed orthogonal to unemployment. We thus ask whether the model-generated market tightness dynamics are consistent with the data.

The first column in Table 4 reports the results of estimating a reduced-form, log-linear statistical relationship

$$\log\theta_t = \alpha_0 + \alpha_1 \log p_t + \alpha_2 \log\delta_t + \alpha_3 \log U_{t-1}, \tag{9}$$

TABLE 4—REDUCED-FORM MARKET TIGHTNESS DYNAMICS

Parameters	Data	$\xi = 0.265$	$\xi = 1$	H/M with JD
$\widehat{\alpha}_1$ [productivity]	1.043	0.96	2.07	20.0
	(1.98)	(80.0)	(188)	(2,535)
$\widehat{\alpha}_2$ [JD δ_t]	−1.66	−0.65	−0.51	−0.26
	(−10.4)	(−240)	(196)	(−180)
$\widehat{\alpha}_2$ [unemployment]	−1.43	−1.94	−1.56	−0.001
	(−26.0)	(−1,620)	(−1,114)	(−1.4)

Notes: Estimation results of reduced-form equation (9), using Shimer (2005) data (second column) and models generated data (last three columns). t-statistics are reported in brackets.

on Shimer (2005) HP-filtered data where, because market tightness is measured as V_t/U_t, we mitigate simultaneity issues by using last period U_{t-1} as the conditioning variable.[6] Estimated t-statistics are reported in brackets.

According to the data (the first column of Table 4), market tightness is positively correlated with productivity and negatively correlated with job separation rates. But productivity shocks are barely significant (a t-statistic equal to 1.98), while market tightness is very strongly (negatively) correlated with unemployment (a t-statistic equal to -26). Figure 5 in Section V, which graphs how market tightness evolved following the 2008 Great Recession, fully supports this view of the data. The final column of Table 4 (H/M with JD) reports the corresponding results for the free entry/small surplus approach, augmented with the above job separation process. This approach yields the opposite scenario: small surplus and free entry imply market tightness is almost entirely driven by productivity shocks and, conditional on (p_t, δ_t), market tightness is orthogonal to unemployment.

Although not a perfect match, $\xi = 0.265$ yields parameter estimates that are broadly consistent with those identified on the data: market tightness is most highly (negatively) correlated with unemployment, though productivity and job separation shocks also play significant roles. Surprisingly given the insights that follow, the data suggest job separation shocks have an even greater impact on market tightness than that implied by the model.

C. *Test 2: Serial Persistence*

An important criticism due to Shimer (2005) is that the MP framework does not generate sufficient persistence. The first column in Table 5 describes the serial autocorrelation of unemployment, vacancies, and market tightness according to the (HP-filtered) data. The remaining columns describe the corresponding parameter estimates based on model-generated data. Measured at quarterly frequencies, the implied serial persistence parameters for productivity and job separation rates are $\rho_p = 0.88$ and $\rho_\delta = 0.73$, respectively. The first column in Table 5 reveals that unemployment, vacancies, and market tightness are much more persistent processes.

[6] Using $\log U_t$ as the conditioning variable finds estimated productivity effects ($\widehat{\alpha}_1$) become negative and insignificant, and there is an even stronger negative correlation between unemployment and measured market tightness.

TABLE 5—ESTIMATED SERIAL PERSISTENCE (*quarterly frequencies*)

	Data	$\xi = 0.265$	$\xi = 1$	H/M with JD
Unemployment	0.94	0.95	0.93	0.88
Vacancies	0.94	0.96	0.95	0.76
Market tightness	0.94	0.96	0.95	0.87

Notes: The data column is the autocorrelation of unemployment, vacancies, and market tightness from Shimer's (2005) table 1. The second column contains the autocorrelations of these variables from the estimated model (not targeted in estimation) and the rest are for the simulated model with $\xi = 1$ and H/M calibration with job destruction shock.

The column H/M with JD does not generate any added unemployment persistence beyond that of the underlying productivity process. The reason is very simple: a free entry specification implies $\theta = \theta^*(p_t, \delta_t)$ and, with no feedback from unemployment to market tightness, the small surplus assumption then implies unemployment has persistence $\rho_u = \rho_p = 0.88$, which is too low.

With $\xi = 0.265$, the second column demonstrates the serial persistence of (U_t, V_t, θ_t) is a near-perfect match to that implied by the data. This occurs because, as demonstrated in Table 4, market tightness is strongly, negatively correlated with unemployment. Thus, periods of high unemployment are characterized by below-trend job finding rates, which then increase the persistence of high unemployment. Of course the equilibrium degree of persistence ρ_u is an endogenous outcome that depends on the propagation mechanism implied by the model. Before examining that propagation mechanism in Section IV, we report our third test.

D. *Test 3: The Ins and Outs of Unemployment*

Shimer (2012) argues that the variation in unemployment is more highly correlated with variations in worker job finding rates than with job separation rates. The argument begins by noting that steady state unemployment

$$u = \frac{\overline{x}}{\overline{x} + \overline{f}},$$

where $\overline{x}$ is the (steady state) exit rate of employed workers into unemployment and $\overline{f}$ the rate unemployed workers become employed. It is then argued that the unemployment proxy

$$u_t^P = \frac{x_t}{x_t + f_t},$$

where x_t is the period t exit rate and f_t the job finding rate, is a reasonable approximation for actual unemployment u_t. This proxy variable u_t^P can then be further decomposed into job separation effects (variations in x_t) and job finding effects (variations in f_t). For example, putting $x_t = \overline{x}$, the sequence $\overline{x}/(\overline{x} + f_t)$ describes the variation in u_t^P due solely to variations in f_t. Similarly, $x_t/(x_t + \overline{f})$ describes the variation in u_t^P due to variations in x_t. Shimer (2012) defines the contribution of the job finding rate to variations in unemployment as the covariance of u_t and $\overline{x}/(\overline{x} + f_t)$ divided by the variance of u_t. Column 1, table 1, in

Shimer (2012) reports that variations in the job finding rate f_t contribute to 77 percent of the variation in unemployment, while variations in the job separation rate x_t only contribute to 24 percent.[7]

The small surplus/free entry approach is broadly consistent with this decomposition because large variations in job creation flows cause correspondingly large variations in unemployment and worker job finding rates. We now repeat the Shimer (2012) methodology on model-generated data with $\xi = 0.265$.[8] Computing those same statistics finds job finding variations, $\overline{x}/(\overline{x}+f_t)$, contribute 77 percent of the unemployment variation, while job separation variations, $x_t/(x_t+\overline{f})$, contribute a slightly smaller 21 percent. The (reduced-form) properties of the simulated data are thus fully consistent with the Shimer (2012) decomposition. Nevertheless, we now show that unemployment volatility in the structural model is driven by job separation shocks.

IV. How Important Are Job Separation Shocks in Explaining Unemployment Variation?

The above has established that our framework not only provides an excellent fit for the volatilities, cross correlations and persistences of market tightness, unemployment and vacancies, it is also entirely consistent with the Shimer (2012) decomposition of the ins and outs of unemployment. The interesting question then is how important are job separation shocks in explaining unemployment volatility? To answer this question we can instead assume zero job separation shocks $\delta_t = \overline{\delta}$, recalibrate the productivity process appropriately, and reestimate ξ. Doing this yields unemployment volatility $\sigma_u = 0.05$, which is only a quarter of that observed in the data.[9] This should not be surprising because Figure 1 demonstrates that productivity shocks are small and we have not specified small surplus. But how can this DMP framework, where unemployment volatility is driven by job separation shocks, be consistent with the Beveridge curve and the Shimer (2012) decomposition?

Consider Figures 2 and 3. Figure 2 describes the impulse response of unemployment to a single separation innovation at date zero (holding productivity fixed $p_t = 1$). It also plots the exogeneous AR1 job separation process δ_t.

The impulse response function labeled H/M with JD describes the impulse response of unemployment for the case of free entry and small surplus. That shock yields a relatively small increase in unemployment, and unemployment exhibits the same persistence as that of the underlying separation process. $\xi = 0.265$ instead generates a much higher unemployment peak and much greater persistence. Figure 3, which describes the corresponding impulse response of vacancies, reveals why.

[7] See figures 4 and 6 in Elsby, Michaels, and Solon (2009) and table 1 in Fujita and Ramey (2009) for alternative estimates.

[8] With $x_t \equiv \delta_t$ and $f_t \equiv (1-\delta_t)m(\theta_t)$.

[9] With no separation shocks, SMM maximizes unemployment volatility by setting ξ arbitrarily large; i.e., it rediscovers the free entry assumption.

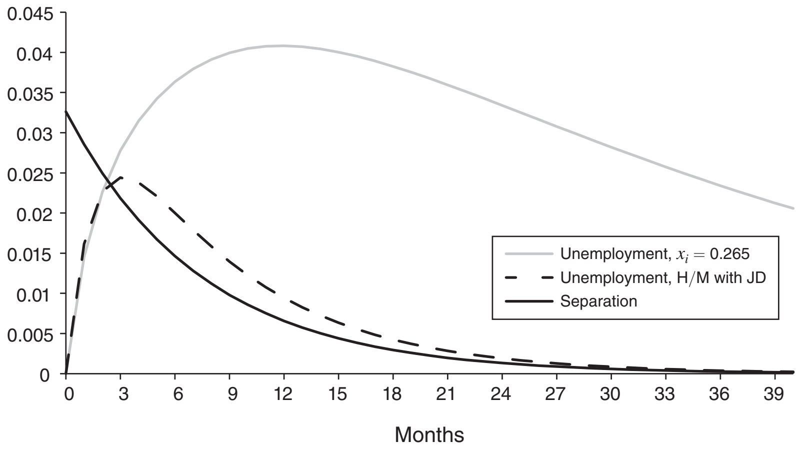

Figure 2. Impulse Response of Unemployment to a Separation Shock

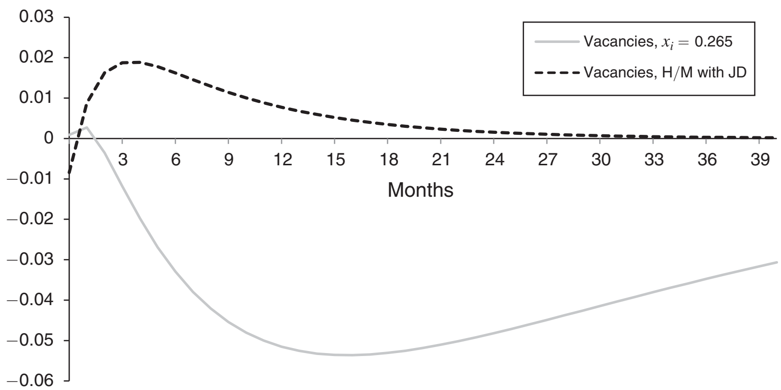

Figure 3. Impulse Response of Vacancies to a Separation Shock

Free entry with small surplus (H/M with JD implies) vacancies increase given a rise in unemployment. This vacancy response ensures unemployment quickly recovers to its long-run steady state. This adjustment process also implies unemployment and vacancies covary positively, which is inconsistent with the Beveridge curve.

In contrast with $\xi = 0.265$, Figure 3 demonstrates the vacancy stock falls as unemployment increases.[10] The job separation shock not only destroys some vacancies, it generates a rising tide of unemployed workers, some of whom quickly

[10] The initial iterations in Figure 3 are affected by the assumed timing of the model. For the free entry case, a higher job separation rate δ_t (which is known at Stage I but separations do not occur until Stage V) reduces Stage III market tightness. Because Stage III unemployment is on trend for the first iteration, lower market tightness then implies vacancies fall below trend for the first iteration (but subsequently increase as unemployment increases). Conversely for the case $\xi = 0.265$, new vacancy creation i_t is always above trend (which ensures the unemployment stock eventually returns to trend). For the first two iterations, the stock of vacancies (measured at Stage III prior to job destruction) is slightly above trend. But steeply increasing unemployment and oversampling then cause the vacancy stock to plummet, where the vacancy stock begins to recover only when unemployment falls below its peak.

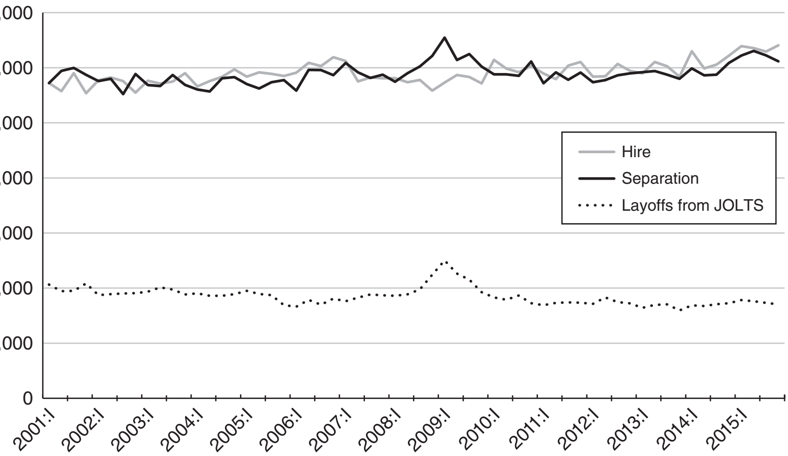

Figure 4. US Job Turnover (2000–2015)

Notes: Hires measure is the flow of workers from unemployment and nonlabor force to employment. Job separations is the flow of workers from employment to unemployment and nonlabor force (all in thousands).

rematch with the existing vacancy stock. With an inelastic vacancy creation process, oversampling of the vacancy stock by newly laid-off workers causes the vacancy stock to fall. Unemployed worker job finding rates then plummet as the increasing number of unemployed workers pursue ever scarcer vacancies. These dynamics thus generate results consistent with Shimer (2012), the reason being that a (recession-leading but short-lived) job separation shock causes (persistently) high unemployment and (persistently) low job finding rates. And by not imposing zero job separation shocks, the calibrated model is then free to find it is the job separation process that drives unemployment volatility.

V. The 2008–2009 Great Recession

The power of the approach is readily demonstrated by considering the aggregate labor market dynamics of the US economy following the 2008–2009 Great Recession. Using Current Population Survey (CPS) data, Figure 4 describes (seasonally adjusted) gross hires and gross job separations.[11] It also plots (nonfarm) layoffs taken from JOLTS (a time series which has been available since 2001).

Figure 4 reveals the unprecedentedly large spike in layoffs across the 2008–2009 Great Recession. Ceteris paribus, the free entry approach predicts vacancies increase and hires surge following such a shock. This did not happen. Instead, and consistent with our approach, this demonstrably large job separation shock generated Beveridge curve dynamics: the stock of vacancies fell steeply as unemployment increased.

[11] Series are constructed by the Bureau of Labor Statistics from the CPS and are available at https://www.bls.gov/cps/cps_flows.htm.

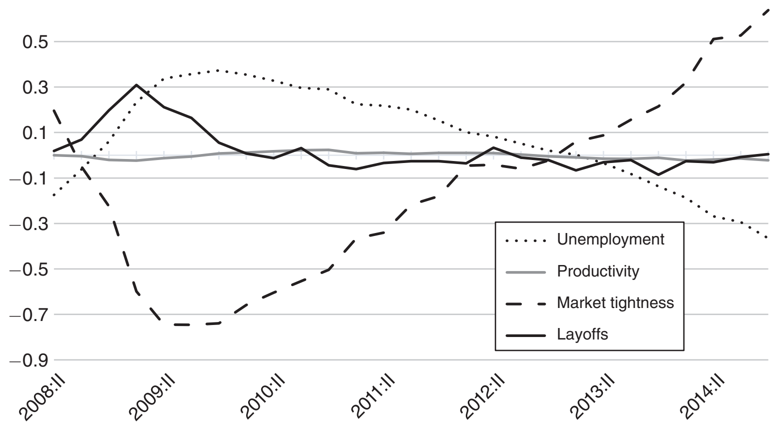

Figure 5. US Labor Market Indicators (2008–2015)

Notes: Series are quarterly deviations from HP trends ($\lambda = 10^5$). Productivity is the Bureau of Labor Statistics (BLS) output per worker from Major Sector Productivity and Costs; unemployment is BLS constructs from CPS; vacancies used in market tightness is job openings from JOLTS; and layoffs are also from JOLTS (nonfarm business).

Figure 5 describes in greater detail the evolution of the US labor market across and subsequent to the 2008–2009 layoff spike. Using the Shimer (2005) methodology, it describes unemployment, market tightness, productivity, and layoffs, each measured as log deviations from trend using an HP filter with smoothing parameter 10^5.

At the start of the layoff spike, market tightness was slightly above trend and unemployment slightly below. The surge in layoffs coincided with steeply increasing unemployment, a steep fall in vacancies (not graphed) and an even steeper fall in market tightness (graphed). Yet over this time period, 2008–2015, productivity was positively correlated with unemployment. Free entry and small surplus thus predict market tightness should have been positively correlated with unemployment. Consistent with Table 4, however, Figure 5 reveals that market tightness was instead strongly negatively correlated with unemployment. Furthermore, with high unemployment and above trend productivity from 2010 onward, free entry predicts the vacancy stock and gross hires should both have been well above trend. Figure 4 demonstrates hire flows merely reverted to trend. It is thus difficult to rationalize the post-2008 evolution of the US economy using the free entry approach. In contrast with $\xi = 0.265$, the impulse response functions (Figures 2 and 3) yield qualitatitively identical behavior following a job separation shock.

We identify the extent to which our framework is consistent with the data for the period 2001–2015 using the JOLTS layoff series as a more direct measure of the job separation process.[12] Although the 2008–2009 layoff spike is not consistent

[12] Though it should be noted that temporary layoffs are widespread in the United States; see, e.g., Feldstein (1976) and Fujita and Moscarini (2017).

Table 6—Simulation Results for JOLTS Calibration

	Data	$\xi = 0$	$\xi = 0.265$
Panel A. Standard deviations			
σ_u	0.203	0.128	0.113
σ_v	0.184	0.177	0.135
σ_θ	0.379	0.303	0.246
Panel B. Cross correlations			
corr(v, u) [BC]	−0.93	−0.98	−0.97
corr(θ, u)	−0.98	−0.99	−0.99
corr(θ, v)	0.98	0.99	0.99

Notes: In the data column, u is the unemployment constructed by BLS from CPS, v is the job openings from JOLTS, and $\theta = v/u$. The data is quarterly averaged over the period 2001–2015. All the statistics are calculated for HP-filtered (with $\lambda = 10^5$) series. σ_x is the standard deviation of x and corr(x, y) the cross correlation between x and y.

with a stationary AR1 process, we repeat the above methodology. For the period 2001–2015, (p_t, δ_t) are assumed to follow a joint AR1 process and we reset the autocorrelation parameters ρ_p, ρ_δ and covariance matrix Σ to match the data. Doing this implies $\rho_p = 0.95$, $\rho_\delta = 0.89$ with $\sigma_p = 0.0063, \sigma_\delta = 0.036$ and cross correlation $\rho_{p\delta} = -0.38$ at monthly frequencies. The first column in Table 6 reports the updated targets.

The third column in Table 6 records the corresponding statistics using model generated data with $\xi = 0.265$ as previously estimated. Not surprisingly given the close match of the impulse response functions (Figures 2 and 3) to the data (Figure 5), this specification continues to provide an excellent fit of the joint correlations of unemployment, vacancies, and market tightness. But this time $\xi = 0.265$ yields too little unemployment volatility. Because a more inelastic vacancy creation process deflates job finding rates following a large layoff shock, SMM this time estimates the polar case $\xi = 0$; i.e., perfectly inelastic vacancy creation rates. This in part reflects Figure 4, which shows that hires reverted to trend following the layoff spike—the so-called jobless recovery. Nevertheless, even with $\xi = 0$, this methodology yields too little unemployment volatility over this period.

VI. Conclusion

This paper has revealed the empirical difficulties caused by assuming the free entry of vacancies in the DMP framework. Specifically, a key implication of the free entry approach—that conditional on productivity variables, market tightness is orthogonal to unemployment—is not consistent with the data (e.g., Table 4 and Figure 5 for the Great Recession). By relaxing the free entry assumption in the DMP framework, estimation using SMM finds the vacancy creation process is instead inelastic. The resulting equilibrium framework is consistent both with the insights of Shimer (2005, 2012) and with the Mortensen and Pissarides (1994) view on job creation and job destruction (here job separation) patterns over the cycle. Results find an ad hoc restriction to zero job separation shocks is not appropriate. Indeed, when suitably relaxed, this DMP framework finds it is the job separation process that drives unemployment volatility over the cycle. The approach is particularly powerful for it provides a simple and coherent explanation for the observed unemployment and vacancy dynamics in the United States following the Great Recession.

Our approach suggests very different lines for future research. For example, what are the underlying economic factors that drive the job separation process? Mortensen and Pissarides (1994) identifies a mechanism whereby adverse aggregate productivity shocks cause pulses of job destruction. The Great Recession, however, suggests financial (or credit) shocks might also play an important role; see, e.g., Jermann and Quadrini (2012); Chodorow-Reich (2014); and Boeri, Garibaldi, and Moen (2015). For example, Bentolila et al. (2015) shows (for Spain) that firms with credit relationships tied to banks facing severe liquidity problems were much more likely to downsize or go out of business. Because the vacancy creation elasticity ξ plays a central role in determining the propagation properties of the economy, more direct evidence on its value is clearly desirable. Of course a major advantage of dropping the small surplus assumption is that the equilibrium DMP framework once more becomes relevant for policy analysis; see, e.g., Costain and Reiter (2008).

Data Appendix

A. *Job Separation Measures*

Given data on employment e_t (the number employed in month t), short-term unemployment u_t^0 (the number of workers unemployed with duration less than one month) and an estimate of worker job finding rate f_t, Shimer (2005) infers the job separation rate s_t using

$$u_{t+1}^0 = s_t e_t \left(1 - \frac{1}{2} f_t\right).$$

With the identifying assumption that f_t, s_t are constant within the month as first considered in Gregg and Petrongolo (2005), Shimer (2012) instead notes the condition

$$u_{t+1} = \frac{\left(1 - e^{-f_t - s_t}\right) s_t}{f_t + s_t} \left(u_t + e_t\right) + e^{-f_t - s_t} u_t$$

can be used to infer s_t. Elsby, Michaels, and Solon (2009) and Fujita and Ramey (2009) consider alternative approaches to measure s_t.

B. *Complete Results*

We report table 1 in Shimer (2005) and, for comparison, the equivalent table for our SMM results with $\xi = 0.265$.

Table B1—Summary Statistics, Quarterly US Data, 1951–2003, Table from Shimer (2005, 28)

	u	v	v/u	f	s	p
Standard deviations	0.190	0.202	0.382	0.118	0.075	0.020
Quarterly autocorrelation	0.936	0.940	0.941	0.908	0.733	0.878
Correlation matrix						
u	1	−0.894	−0.971	−0.949	0.709	−0.408
v		1	0.975	0.897	−0.684	0.364
v/u			1	0.948	−0.715	0.396
f				1	−0.574	0.396
s					1	−0.524
p						1

Table B2—SMM Results with $\xi = 0.265$

	u	v	v/u	f	s	p
Standard deviations	0.18	0.20	0.38	0.15	0.075	0.020
Quarterly autocorrelation	0.95	0.96	0.96	0.96	0.73	0.87
Correlation matrix						
u	1	−0.96	−0.99	−0.99	0.54	−0.63
v		1	0.99	0.99	−0.30	0.58
v/u			1	0.99	−0.42	0.61
f				1	−0.42	0.60
s					1	−0.52
p						1

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