Two-State Duration Dependence and the Persistence of the Unemployment Rate

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Abstract

In US data, the unemployment rate is highly persistent over the business cycle, but standard calibrated search models predict little persistence after shocks. I show that incorporating duration dependence in job finding and separation rates significantly increases the persistence of the unemployment rate. To do so, I embed two-state duration dependence into an otherwise-standard Diamond-Mortensen-Pissarides search model. Intuitively, after recessions, the composition of the labor force shifts toward the long-term unemployed and the short-term employed, decreasing the aggregate job finding rate, increasing the aggregate job separation rate, and prolonging the effects of shocks. In my empirical calibration, duration dependence increases the persistence of the unemployment rate by 90%, measured in half-lives. The model is flexible enough to match the tenure profiles of job-finding and separation rates for infinitely many combinations of pure duration dependence and permanent heterogeneity, and the extent to which duration dependence increases persistence depends on the share of observed duration dependence that is driven by pure duration dependence rather than permanent heterogeneity.

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In US data, the unemployment rate is persistent over the business cycle, especially in its slow decline after recessions. However, the canonical Diamond-Mortensen-Pissarides (DMP) frictional search model fails to generate this persistence (Pries, 2004; Shimer, 2005). Instead, the model predicts that the unemployment rate quickly returns to its steady state after shocks. Simultaneously, job finding and separation rates exhibit clear duration dependence: unemployed workers with long unemployment spells are less likely to find jobs, and employed workers with short employment spells are more likely to lose jobs.

In this paper, I show that introducing a simple form of duration dependence significantly increases unemployment persistence in an otherwise-standard DMP model. I embed "two-state duration dependence" in the model, meaning that both unemployed and employed workers are subject to duration dependence. I then calibrate the model using US microdata, simulate it under different levels and sources of duration dependence, and show that duration dependence substantially helps reconcile the model with the data.

Before proceeding, it is useful to define precisely what is meant by duration dependence. For unemployed workers, it refers to the fact that workers with longer unemployment spells are less likely to find a job. On average, a worker unemployed for less than a month has a 50% probability of finding a job, whereas a worker unemployed for over eight months has only a 20% probability.[1]

Observed duration dependence in job-finding rates has two possible explanations. The first is "pure" duration dependence, a causal mechanism in which longer unemployment duration decreases a worker's probability of finding a job. Kroft et al. (2013) documents pure duration dependence in a resume audit study, finding that job applicants unemployed for less than one month are 45% more likely to receive a callback than otherwise identical applicants who have been unemployed for eight months.[2] The reason for pure duration dependence is unclear, but a definitive theory for why it exists is not necessary for the

[1] Technically, I am referring to *negative* duration dependence. As is common, I use the terms "duration dependence" and "negative duration dependence" interchangeably in this paper.

[2] For more experimental evidence, see Eriksson and Rooth (2014), Farber et al. (2019), and Oberholzer-Gee (2008).

purposes of this paper.[3]

The second explanation for observed duration dependence is permanent heterogeneity. If workers are permanently heterogeneous in job finding rates, then those with higher job finding rates will, on average, exit unemployment earlier in their unemployment spells. Consequently, as unemployment duration increases, the remaining pool of unemployed workers is more likely to consist of workers with lower job finding rates, thereby generating duration dependence in the aggregate.

Analogously, duration dependence for employed workers refers to the fact that employed workers with longer employment spells are less likely to separate from their jobs. As with finding-rate duration dependence, it may be caused by pure duration dependence or permanent heterogeneity in separation rates.

I model two-state duration dependence in a parsimonious yet flexible framework. There are two job finding rates and two separation rates, high and low. Workers are either high or low finding type and high or low separation type. Low-type workers always find (or separate from) jobs at the low rate. High-type workers begin unemployment (or employment) spells at the high rate but may randomly transition to the low rate as their spells progress.

Thus, the model accounts for both sources of duration dependence in finding rates. First, the longer a worker is unemployed, the more likely they are to face the low finding rate, generating pure duration dependence. Second, since workers begin their unemployment spells with heterogeneous finding rates, the model also includes permanent heterogeneity. The same applies to the separation side of the model.

In addition to standard moments, I calibrate the model to match the job finding rate by

[3]One theory is that workers lose skills while unemployed, reducing productivity upon re-employment (Ljungqvist and Sargent, 1998; Edin and Gustavsson, 2008). Another is that firms interpret long duration as a signal of inefficiency and statistically discriminate against such workers (Blanchard and Diamond, 1994; Lockwood, 1991). My model assumes workers are homogeneous in productivity, ruling out both of these theories.

One theory that is compatible with my model involves recall hiring: over 40% of unemployed workers who separate into unemployment return to their previous employer, and recall probability declines sharply over the unemployment spell (Fujita and Moscarini, 2017). A second theory is that long-term unemployed workers gradually exhaust the job opportunities in their social network. Finally, long unemployment duration is associated with discouragement and lower search intensity (Faberman and Kudlyak, 2019; Krueger and Mueller, 2011).

unemployment duration and the separation rate by employment duration. Thus, the model matches the observed duration dependence in the data. However, calibration presents a familiar identification challenge: the data does not readily disentangle pure duration dependence from permanent heterogeneity. Indeed, the model can reproduce observed duration dependence using only pure duration dependence, only permanent heterogeneity, or a mix of both. I exploit this ambiguity by comparing model predictions under extreme specifications with only pure duration dependence or permanent heterogeneity.

For my main empirical results, I attempt to match the "true" mix of pure duration dependence and permanent heterogeneity. To do so, I estimate a mixed proportional hazard model, a well-known duration model that generates an estimate of pure duration dependence, and target the implied counterfactual decrease in finding (and separation) rates in the absence of permanent heterogeneity. The mixed proportional hazard models imply that finding-rate duration dependence reflects both pure duration dependence and permanent heterogeneity, whereas separation duration dependence is driven mainly by pure duration dependence.

I analyze the effects of duration dependence by comparing model simulations across my suite of calibrations. For illustrative purposes, I first feed the model productivity shocks, followed by separation rate shocks. Then, for empirical results, I shock both simultaneously.

The main result of this paper is that duration dependence—particularly pure duration dependence—increases the persistence of the unemployment rate over the business cycle. Intuitively, on the finding side of the model, recessions decrease job finding rates, shifting the composition of the unemployment pool toward the long-term unemployed. Due to pure duration dependence, the long-term unemployed are less likely to find jobs. Thus, duration dependence further decreases the average job finding rate and slows the recovery of the unemployment rate.

On the separation side, for the unemployment rate to recover after a recession, unemployed workers must find jobs. As they do, the employment pool shifts toward short-term employed workers, who—due to pure duration dependence—are more likely to become unemployed again. Therefore, the average job separation rate increases further, and the unemployment rate recovers more slowly.

My main empirical result is that both types of duration dependence increase the autocorrelation of the unemployment rate from 0.87 to 0.93, a 90% increase in the half-lives. The increase is 54% under finding-rate duration dependence and 24% under separation-rate duration dependence, indicating that finding-rate duration dependence generates more persistence. If all observed duration dependence is assumed to be pure duration dependence, persistence increases by 117%; if permanent heterogeneity explains all duration dependence, then persistence increases by only 16%. Thus, the extent to which duration dependence increases persistence depends on the share of observed duration dependence that is driven by pure duration dependence rather than by permanent heterogeneity. About 30% of the increase in persistence from duration dependence is attributable to feedback with the free-entry condition.

Policymakers have expressed concern about the aggregate effects of duration dependence. A 2014 White House report titled "Addressing the Negative Cycle of Long-Term Unemployment" claimed that "the cycle of long-term unemployment hampers the economy at large, depressing aggregate demand and resulting in the underutilization of productive resources" (White House, 2014). In 2012, the Congressional Budget Office estimated that duration dependence "currently accounts for about a quarter of a percentage point of the increase in unemployment during and following the recession" (Congressional Budget Office, 2012). In this paper, I show that such claims can be backed by theory only if there is sufficient pure duration dependence, which I observe in the data.

The remainder of this paper is as follows. I contextualize the paper within the literature in Section 1. The model is described and calibrated in Sections 2 and 3. Section 4 presents my results. I conclude in Section 5.

1 Related Literature

Pries (2004) and Shimer (2005) established that DMP models fail to generate realistic persistence of the unemployment rate due to the lack of internal propagation. Similar to this paper, Pries (2004) and Gorry et al. (2020) address the lack of persistence in the DMP model by adding new elements. Gorry et al. (2020) shows that changes in the skill composition of the labor force over the business cycle amplify shocks and increase persistence. My theory also emphasizes changes in the composition of the labor force, but instead of heterogeneity in skill, my model incorporates heterogeneity and duration dependence in finding and separation rates. Pries (2004) emphasizes the high risk of job loss for newly-employed workers. Though my implementation is more abstract, I incorporate this feature. I also include finding-rate duration dependence and allow for permanent heterogeneity.

Another well-known problem with DMP models is that they struggle to match business-cycle volatility in matching efficiency (Barnichon and Figura, 2015; Lubik, 2009). In my model, unemployment composition is an endogenous channel through which matching efficiency decreases during recessions.

I also contribute to a strand of literature that links finding-rate duration dependence to aggregate labor market dynamics. For example, Kroft et al. (2016) shows that duration dependence decreased the aggregate job finding rate during the Great Recession, slowing recovery.[4] Ahn and Hamilton (2020) and Hornstein (2012) account for duration dependence in analyzing the unemployment rate over the business cycle, but these papers do not use duration dependence as an explanation for unemployment persistence and do not account for separation-rate duration dependence.[5] In a different model, Pissarides (1992) showed that the loss of skills during unemployment generates more persistence in unemployment. Separation-rate duration dependence has received less attention in the literature, though Pries and Rogerson (2022) and Krolikowski (2017) are notable exceptions.

In general, the driving force behind my results is that the composition of the labor force shifts during recessions. The same force is explored in Ferraro (2018), Ravenna and Walsh (2012), Wiczer (2015), and Donovan et al. (2024), but duration dependence is not a key

[4] *During* the Great Recession, Elsby et al. (2010) and Aaronson et al. (2010) conjectured that duration dependence would slow the recovery of the unemployment rate.

[5] Also see Jarosch and Pilossoph (2019), which provides a counter-argument that duration dependence in callback rates is irrelevant in the aggregate.

mechanism in these papers.[6]

2 Model

2.1 Environment

The starting point for the model is the canonical DMP search model in discrete time.[7] Workers and firms are risk neutral and discount the future at discount factor β. At time t, employed workers produce A_t of the numeraire good in exchange for the wage w_t, unemployed workers receive unemployment benefits b, and firms post v_t job vacancies to maximize expected future profit. There is one job per firm.

The unemployment rate is u_t and the employment rate is e_t with $u_t + e_t = 1$. Unemployed workers find jobs and become employed with some probability, which I refer to as the job finding rate. Similarly, the job separation rate is the probability that employed workers separate from their jobs and become unemployed.

My model departs from the canonical model by introducing two-state duration dependence, heterogeneity in finding and separation rates that depends on how long the worker has been unemployed or employed. There are two finding rates, high, f_t^h, and low, f_t^ℓ, where the low finding rate is a constant fraction $\gamma \in (0, 1]$ of the high finding rate, $f_t^\ell = \gamma f_t^h$. Symmetrically, there are two separation rates, high, s_t^h, and low, s_t^ℓ, where the low separation rate is a fraction $\delta \in (0, 1]$ of the high separation rate, $s_t^\ell = \delta s_t^h$.

Workers are one of four permanent types, high-high, high-low, low-high, and low-low, where the first term refers to the worker's finding type and the second to the worker's separation type. I denote the fraction of the labor force of each type as π^{hh}, $\pi^{h\ell}$, $\pi^{\ell h}$, and $\pi^{\ell\ell}$, where $\pi^{hh} + \pi^{h\ell} + \pi^{\ell h} + \pi^{\ell\ell} = 1$. The convention in this paper is that the first letter in a superscript refers to finding while the second letter refers to separation.

[6] Though I discuss recessions, in principle, my analysis could include positive shocks. In a model where shocks are only recessionary (Dupraz et al., 2019), an analysis of unemployment persistence is simultaneously an analysis of slow recoveries.

[7] See Pissarides (2000), Chapter 1 and Mortensen and Pissarides (1994).

I refer to a worker's current finding and separation rates as its *state*. Let F denote a worker's finding rate and S the worker's separation rate. The stock of unemployed workers in state FS is u_t^{FS}, and the stock of employed workers in state FS is e_t^{FS}.

Low finding-type workers (in $\pi^{\ell h}$ or $\pi^{\ell\ell}$) always find jobs at the low rate f_t^{ℓ}. High finding-type workers (in π^{hh} or $\pi^{h\ell}$) begin unemployment spells with the high finding rate f_t^h, but with probability ϕ, they transition to the low finding rate for the remainder of their unemployment spell. Below, I denote this finding rate with $\bar{\ell}$, where the bar designates a "temporarily low" finding rate. When they find a job, their finding rate returns to the high rate.

Thus, the model includes both pure duration dependence and permanent heterogeneity in finding rates. Pure duration dependence arises because the longer a high finding-type worker remains unemployed, the more likely they are to switch to the low finding rate. Since ϕ is the probability of switching to the low finding rate, ϕ determines the level of pure duration dependence. Permanent heterogeneity arises because workers begin unemployment spells with different finding rates, and the π parameters determine the level of permanent heterogeneity.

The structure of job separation rates mirrors that of job finding rates. Low separation-type workers (in $\pi^{h\ell}$ or $\pi^{\ell\ell}$) always separate from jobs at the low separation rate s_t^{ℓ}. High separation-type workers begin employment spells with the high separation rate s_t^h, but with probability η, they transition to the low separation rate for the remainder of the employment spell. Again, I denote workers with temporarily low separation rates with $\bar{\ell}$. And like the finding side, the separation side of the model allows for both pure duration dependence and permanent heterogeneity where η determines the level of pure duration dependence while the π parameters determine permanent heterogeneity.

Altogether, unemployed workers have finding rates $F \in \{h, \ell, \bar{\ell}\}$ and separation rates $S \in \{h, \ell\}$, while employed workers have finding rates $F \in \{h, \ell\}$ and separation rates

$S \in \{h, \ell, \bar{\ell}\}$. The stocks of workers satisfy

$$\pi^{\ell\ell} = e_t^{\ell\ell} + u_t^{\ell\ell} \tag{1}$$

$$\pi^{h\ell} = e_t^{h\ell} + u_t^{h\ell} + u_t^{\bar{\ell}\ell} \tag{2}$$

$$\pi^{\ell h} = e_t^{\ell h} + e_t^{\ell\bar{\ell}} + u_t^{\ell h} \tag{3}$$

$$\pi^{hh} = e_t^{hh} + e_t^{h\bar{\ell}} + u_t^{hh} + u_t^{\bar{\ell}h} \tag{4}$$

and

$$u_t = u_t^{\ell\ell} + u_t^{h\ell} + u_t^{\bar{\ell}h} + u_t^{\ell h} + u_t^{hh} + u_t^{\bar{\ell}h} \tag{5}$$

$$e_t = e_t^{\ell\ell} + e_t^{h\ell} + e_t^{\ell h} + e_t^{\ell\bar{\ell}} + e_t^{hh} + e_t^{h\bar{\ell}}. \tag{6}$$

The model perfectly nests standard DMP if $\phi = \eta = 0$ and $\pi^{hh} = 1$, in which case all workers always have the high finding and separation rates. I use this case as the benchmark for analyzing the effects of duration dependence.

2.2 Dynamics

There are 12 worker states, so the model includes 12 laws of motion and 12 value functions. For the sake of brevity and intuition, I will illustrate the model's dynamics using six of the value functions. The rest of the value functions and all of the laws of motion are in Appendix B.

For low-low type workers, who make up a fraction $\pi^{\ell\ell}$ of the labor force, the value of employment is

$$E_t^{\ell\ell} = w_t + \beta[s_t^{\ell} U_{t+1}^{\ell\ell} + (1 - s_t^{\ell}) E_{t+1}^{\ell\ell}]. \tag{7}$$

In time t, the worker earns the wage w_t. In the next period, they become unemployed with probability s_t^{ℓ}; otherwise, they remain employed. The value of unemployment is

$$U_t^{\ell\ell} = b + \beta[f_t^{\ell} E_{t+1}^{\ell\ell} + (1 - f_t^{\ell}) U_{t+1}^{\ell\ell}]. \tag{8}$$

Unemployed workers receive benefits b and find jobs at rate f_t^ℓ. Therefore, low-low type workers always find jobs at rate f_t^ℓ and separate from jobs at rate s_t^ℓ.

Next, consider high-high type workers, who make up a fraction π^{hh} of the labor force. These workers are subject to duration dependence in both finding and separation rates. For a worker with high finding and separation rates, the value of employment is

$$E_t^{hh} = w_t + \beta \left[s_t^h U_{t+1}^{hh} + (1 - s_t^h) \left(\eta E_{t+1}^{h\bar{\ell}} + (1 - \eta) E_{t+1}^{hh} \right) \right]. \tag{9}$$

In time t, the worker earns the wage w_t. With probability s_t^h, they separate from their job and become unemployed; otherwise, they remain employed. Conditional on remaining employed, with probability η, they transition to the low separation rate, $E_{t+1}^{h\bar{\ell}}$. Otherwise, they retain the high separation rate, E_{t+1}^{hh}.

If the worker transitions to the low separation rate, they separate from their job with probability s_t^ℓ for the remainder of the employment spell. The value of employment is then

$$E_t^{h\bar{\ell}} = w_t + \beta \left[s_t^\ell U_{t+1}^{hh} + (1 - s_t^\ell) E_{t+1}^{h\bar{\ell}} \right]. \tag{10}$$

Upon separation, the value of unemployment is

$$U_t^{hh} = b + \beta \left[f_t^h E_{t+1}^{hh} + (1 - f_t^h) \left(\phi U_{t+1}^{\bar{\ell}h} + (1 - \phi) U_{t+1}^{hh} \right) \right]. \tag{11}$$

The worker receives unemployment benefits b and finds a job with probability f_t^h. Conditional on not finding a job, with probability ϕ, the worker transitions to the low finding rate, $U_{t+1}^{\bar{\ell}h}$. Otherwise, the worker keeps the high finding rate, U_{t+1}^{hh}

If the worker transitions to the low finding rate, the value of unemployment is

$$U_t^{\bar{\ell}h} = b + \beta \left[f_t^\ell E_{t+1}^{hh} + (1 - f_t^\ell) U_{t+1}^{\bar{\ell}h} \right]. \tag{12}$$

Thus, the worker faces the low finding rate f_t^ℓ for the remainder of the unemployment spell. Note that the high-high type worker always begins unemployment with the high finding rate and employment with the high separation rate.

High-low and low-high workers follow a similar pattern, but these workers only experience one type of duration dependence. The remaining value functions, as well as all of the model's laws of motion, are written in Appendix B.

2.3 Job Finding Rates

I adopt a frictional matching technology that generates $f_t^\ell = \gamma f_t^h$ and nests the standard Cobb-Douglas matching function.

At time t, the number of unemployed workers with the high finding rate is $u_t^{h\ell} + u_t^{hh}$. The number of matches between open job vacancies and unemployed workers with the high finding rate is

$$m_t^h = \mu \frac{u_t^{h\ell} + u_t^{hh}}{u_t} \left[u_t^{h\ell} + u_t^{hh} + \gamma \left(u_t^{\ell\ell} + u_t^{\bar{\ell}\ell} + u_t^{\ell h} + u_t^{\bar{\ell}h} \right) \right]^\alpha v_t^{1-\alpha} \tag{13}$$

where μ is match efficiency and α is an elasticity parameter. For intuition, contrast Equation (13) with the standard Cobb-Douglas matching function, $m_t = \mu u_t^\alpha v_t^{1-\alpha}$. My function differs in two ways. First, $(u_t^{h\ell} + u_t^{hh})/u_t$ is the share of the unemployment pool to which this matching function applies, a necessary element because search is random and firms post vacancies for the unemployment pool as a whole. Second, $\left[u_t^{h\ell} + u_t^{hh} + \gamma \left(u_t^{\ell\ell} + u_t^{\bar{\ell}\ell} + u_t^{\ell h} + u_t^{\bar{\ell}h} \right) \right]$ replaces u_t and represents the weighted "matchability" of the unemployment pool.

Similarly, the number of matches between open job vacancies and unemployed workers with the low finding rate is

$$m_t^\ell = \gamma\mu \frac{u_t^{\ell\ell} + u_t^{\bar{\ell}\ell} + u_t^{\ell h} + u_t^{\bar{\ell}h}}{u_t} \left[u_t^{h\ell} + u_t^{hh} + \gamma \left(u_t^{\ell\ell} + u_t^{\bar{\ell}\ell} + u_t^{\ell h} + u_t^{\bar{\ell}h} \right) \right]^\alpha v_t^{1-\alpha}. \tag{14}$$

Compared to Equation (13), Equation (14) is scaled down by γ and applies to unemployed workers with the low finding rate, $u_t^{\ell\ell} + u_t^{\bar{\ell}\ell} + u_t^{\ell h} + u_t^{\bar{\ell}h}$.

Let $\theta_t = v_t/u_t$ denote labor market tightness and $x_t = (u_t^{h\ell} + u_t^{hh})/u_t$ denote the fraction of the unemployment pool with the high finding rate. I refer to x_t as "unemployment composition." Mathematically, the high finding rate is

$$f_t^h = \frac{m_t^h}{u_t^{h\ell} + u_t^{hh}} = \mu[x_t(1-\gamma) + \gamma]^\alpha \theta_t^{1-\alpha}, \tag{15}$$

and the low job finding rate is

$$f_t^\ell = \frac{m_t^\ell}{u_t^{\ell\ell} + u_t^{\bar{\ell}\ell} + u_t^{\ell h} + u_t^{\bar{\ell}h}} = \gamma\mu[x_t(1-\gamma) + \gamma]^\alpha \theta_t^{1-\alpha}. \tag{16}$$

Hence, my matching function successfully generates $f_t^\ell = \gamma f_t^h$ and nests the standard matching function when $x_t = 1$.

Unemployment composition x_t is the key source of additional persistence on the finding side of my model. The aggregate (or average) job finding rate is

$$f_t = x_t f_t^h + (1 - x_t) f_t^\ell = \mu[x_t(1-\gamma) + \gamma]^{\alpha+1} \theta_t^{1-\alpha}. \tag{17}$$

Note that f_t is increasing in x_t as well as θ_t.[8] Later in the paper, I show that x_t decreases during recessions because unemployment spells become longer, which further decreases the aggregate job finding rate and slows recovery.

From the firm's perspective, the probability that an open job vacancy is filled by an unemployed worker from the high state is $h_t^h = m_t^h / v_t$, and the probability that an open position is filled by a worker from the low state is $h_t^\ell = m_t^\ell / v_t$. The aggregate hiring rate is

$$h_t = h_t^\ell + h_t^h = \mu[x_t(1-\gamma) + \gamma]^{\alpha+1} \theta_t^{-\alpha}. \tag{18}$$

Like the aggregate job finding rate in Equation (17), the aggregate hiring rate is increasing in x_t.[9]

[8] In the DMP model, $f_t = \mu\theta_t^{1-\alpha}$.
[9] In the DMP model, $h_t = \mu\theta_t^{-\alpha}$.

2.4 Job Separation Rates

The high separation rate s_t^h is determined by an exogenous shock process, and $s_t^\ell = \delta s_t^h$ directly follows. Let $y_t = (e_t^{\ell h} + e_t^{hh})/e_t$ denote the fraction of the employment pool with the high separation rate. The aggregate (or average) job separation rate is

$$s_t = y_t s_t^h + (1 - y_t) s_t^\ell. \tag{19}$$

Even though s_t^h is exogenous, s_t is endogenous because it depends on y_t. Like the finding side of the model, y_t generates persistence in s_t beyond the persistence of s_t^h.

2.5 Free Entry Condition and Wage

Wages are determined by Nash bargaining. For simplicity, I assume that all workers are paid the same wage.[10] To reconcile a homogeneous wage with heterogeneous workers, I assume that firms cannot observe individual workers' finding and separation rates. Thus, firms know the composition of the labor force, but cannot direct vacancies to certain types of unemployed workers, and do not know the finding and separation rates of the workers they employ.

From the firm's perspective, the value of a filled job is

$$J_t = A_t - w_t + \beta \left[s_t V_{t+1} + (1 - s_t) J_{t+1} \right].$$

where V_t is the value of an open job vacancy. In the current period, the firm earns the value of the worker's production, A_t, minus the wage w_t. With probability s_t, the match is destroyed, and the job becomes an open vacancy; otherwise, the job remains intact for another period. Note that s_t is the separation rate for the average worker, not an individual worker.

[10] I experimented with heterogeneous wages and found little of interest.

The value of an open job vacancy is

$$V_t = -\kappa + \beta \left[h_t J_{t+1} + (1 - h_t) V_{t+1} \right].$$

where κ is the cost of posting a vacancy each period. With probability h_t, the vacancy is converted into a filled job; otherwise, the vacancy remains. Similarly, h_t is the average hiring rate for the unemployment pool as a whole.

I assume that firms can freely enter the labor market and post vacancies. Under free entry, profit maximization requires that the total discounted value of a vacancy equals zero, $V_t = 0$, in equilibrium. Therefore, the previous two equations become

$$J_t = A - w_t + \beta(1 - s_t) J_{t+1} \tag{20}$$

and

$$\kappa = \beta h_t J_{t+1}. \tag{21}$$

Equation (21), the free entry condition, determines the number of vacancies posted in equilibrium.

The wage bargaining problem can thus be characterized as Nash bargaining under incomplete information. Following Harsanyi and Selten (1972), the equilibrium wage is given by the solution to

Suppose that workers have Nash bargaining weight ψ. Therefore, in equilibrium, workers earn a fraction ψ of the total match surplus, worker surplus plus firm surplus. Firm surplus is the value of a filled job minus the value of a vacancy, $J_t - V_t = J_t$. Worker surplus is the value of employment minus the value of unemployment. However, both depend on the worker's current state. The firm does not observe the worker's state, so it must negotiate on expectations over possible states.

Thus, the wage bargaining problem can be characterized as Nash bargaining under incomplete information. Following Harsanyi and Selten (1972), the equilibrium wage solves

$$\arg\max_{w_t} \left[\left(E_t^{\ell\ell} - U_t^{\ell\ell}\right)^{e_t^{\ell\ell}/e_t} \left(E_t^{h\ell} - U_t^{h\ell}\right)^{e_t^{h\ell}/e_t} \left(E_t^{\ell h} - U_t^{\ell h}\right)^{e_t^{\ell h}/e_t} \left(E_t^{\ell\bar{\ell}} - U_t^{\ell h}\right)^{e_t^{\ell\bar{\ell}}/e_t} \right.$$
$$\left. \times \left(E_t^{hh} - U_t^{hh}\right)^{e_t^{hh}/e_t} \left(E_t^{h\bar{\ell}} - U_t^{hh}\right)^{e_t^{h\bar{\ell}}/e_t} \right]^{\psi} J_t^{1-\psi}$$

The large bracketed term is the incomplete-information version of worker surplus.[11] Each multiplied term is the worker surplus for a worker in a certain state, and the exponent for each is the probability that the employed worker is in that state.

Taking logs and maximizing, the equilibrium wage solves

$$\frac{\psi}{e_t}\left(\frac{e_t^{\ell\ell}}{E_t^{\ell\ell} - U_t^{\ell\ell}} + \frac{e_t^{h\ell}}{E_t^{h\ell} - U_t^{h\ell}} + \frac{e_t^{\ell h}}{E_t^{\ell h} - U_t^{\ell h}} + \frac{e_t^{\ell\bar{\ell}}}{E_t^{\ell\bar{\ell}} - U_t^{\ell h}} + \frac{e_t^{hh}}{E_t^{hh} - U_t^{hh}} + \frac{e_t^{h\bar{\ell}}}{E_t^{h\bar{\ell}} - U_t^{hh}}\right) = \frac{1-\psi}{J_t} \tag{22}$$

Again, the model nests DMP with standard Nash bargaining if $\phi = \eta = 0$ and $\pi^{hh} = 1$.

2.6 Shocks

I simulate the model's response to exogenous shocks to productivity and the high separation rate. For illustrative results, I shock one variable at a time. In that case, the log of $z_t \in \left\{A_t, s_t^h\right\}$ follows an AR(1) process in deviations from the steady state,

$$\log(z_{t+1}) - \log(z) = \rho_z(\log(z_t) - \log(z)) + \varepsilon_z, \quad \varepsilon_z \sim \mathcal{N}(0, \sigma_z^2) \tag{23}$$

where ρ_z is the persistence parameter, σ_z^2 is the variance of innovations, and z is the variable's steady state value.

For my empirical results, I shock productivity and separation rates simultaneously using

[11] For reference, in the DMP model, the wage solves $\arg\max_{w_t} \left(E_t - U_t\right)^{\psi} J_t^{1-\psi}$.

Table 1: External parameters

Parameter	Meaning	Value	Explanation/source
β	Discount factor	0.9967	4% annual risk-free rate
b	Unemployment benefits	0.7	Mortensen and Nagypal (2007)
α	Matching function elasticity	0.6	Petrongolo and Pissarides (2001), Lange and Papageorgiou (2020)
ψ	Worker bargaining weight	0.6	Jäger et al. (2020)
A	Steady state productivity	1	Normalization

External parameter choices.

the VAR process

$$\begin{gathered}\begin{bmatrix}\log(A_{t+1})-\log(A)\\ \log(s^h_{t+1})-\log(s^h)\end{bmatrix}=\begin{bmatrix}\omega_{AA} & \omega_{As^h}\\ \omega_{s^hA} & \omega_{s^hs^h}\end{bmatrix}\begin{bmatrix}\log(A_t)-\log(A)\\ \log(s^h_t)-\log(s^h)\end{bmatrix}+\begin{bmatrix}\varepsilon_A\\ \varepsilon_{s^h}\end{bmatrix},\\ \begin{bmatrix}\varepsilon_A\\ \varepsilon_{s^h}\end{bmatrix}\sim\mathcal{N}\left(\begin{bmatrix}0\\0\end{bmatrix},\begin{bmatrix}\Sigma_A^2 & \Sigma_{As^h}\\ \Sigma_{As^h} & \Sigma_{s^h}^2\end{bmatrix}\right).\end{gathered}\tag{24}$$

3 Calibration

3.1 External Calibration

I adopt the conventional external parameter values listed in Table 1. The model period is one month. For exogenous shocks, I use the parameters in Table 2. Univariate shocks are mostly illustrative, so I set $\rho_A = \rho_{s^h} = 0.95$ for consistency. I estimate the other parameters in the data.[12]

My primary data source is the CPS, though I construct monthly productivity data using the monthly GDP data maintained by Koop et al. (2023). See Appendix A for details.

[12] s^h_t is not observable in the data, but s_t is, so I estimate Equation (24) by looping over the model. See Appendix C for details.

Table 2: Estimated shock parameters

Parameter	Value
ρ_A	0.95
σ_A	0.006
ρ_{s^h}	0.95
σ_{s^h}	0.124
ω_{AA}	0.947
ω_{As^h}	-0.011
ω_{s^hA}	-1.395
$\omega_{s^hs^h}$	0.499
Σ_A	0.006
Σ_{s^h}	0.119
$\Sigma_{As^h}/(\Sigma_A\Sigma_{s^h})$	-0.154

Data source: CPS. The bottom entry is written as the correlation coefficient.

3.2 Internal Calibration

I calibrate the remaining parameters so that the steady state of the model matches the unemployment rate, the average job finding rate, the job finding rate as a function of unemployment duration, and the job separation rate as a function of employment duration. Letting $\tau = 0, 1, 2, \ldots$ denote the number of continuous periods a worker has been unemployed or employed, I write the latter two functions as $f(\tau)$ and $s(\tau)$.

To match $f(\tau)$ and $s(\tau)$, I leverage the fact that the model implies closed-form functions for both. In particular, the job finding rate as a function of unemployment duration is

$$f(\tau) = f^\ell + x(0)(f^h - f^\ell)\frac{(1-\phi)^\tau(1-f^h)^\tau}{\prod_{i=0}^{\tau-1}(1-f(i))}. \tag{25}$$

See Appendix B for the derivation. Here, $\tau = 0$ denotes newly unemployed workers, and $x(0)$ is the share of these workers who start unemployment with the high job-finding rate. Similarly,

$$s(\tau) = s^\ell + y(0)(s^h - s^\ell)\frac{(1-\eta)^\tau(1-s^h)^\tau}{\prod_{i=0}^{\tau-1}(1-s(i))} \tag{26}$$

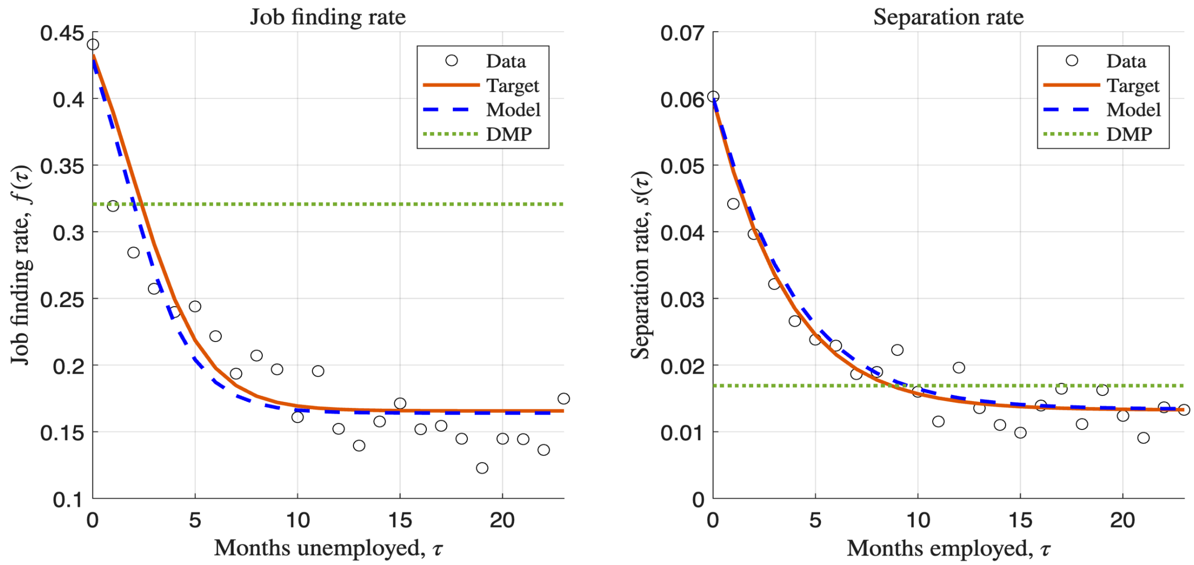

Figure 1: Finding and separation rate curves

Data source: CPS. The target curves fit Equations (27) and (28) to the data. The model curve fits the model to the parameters of the target curve. Besides DMP, every calibration generates the same model curve. The DMP curve calibrates the model without any duration dependence.

where $y(0)$ is the share of newly employed workers who start with the high separation rate.[13]

Equations (25) and (26) can be written as functions of three parameters each,

$$f(\tau) = \lambda_1 + \lambda_2 \frac{\lambda_3^\tau}{\prod_{i=0}^{\tau-1}(1 - f(i))} \tag{27}$$

$$s(\tau) = \xi_1 + \xi_2 \frac{\xi_3^\tau}{\prod_{i=0}^{\tau-1}(1 - s(i))}. \tag{28}$$

I estimate λ_1, λ_2, λ_3, ξ_1, ξ_2, and ξ_3 in the data, then target these estimates in calibration. Figure 1 plots the data, target functions, and model fits for $f(\tau)$ and $s(\tau)$. The target functions fit the data well, and the model fits the targets almost perfectly. In contrast, the standard DMP model implicitly assumes that the functions are flat.

However, given these moments, the model parameters are merely jointly identified, not separately identified. Just as it is difficult to discern whether the downward-sloping $f(\tau)$ curve is caused by pure duration dependence or permanent heterogeneity, the ambiguity

[13]The product in the denominator equals one if $\tau \leq 1$.

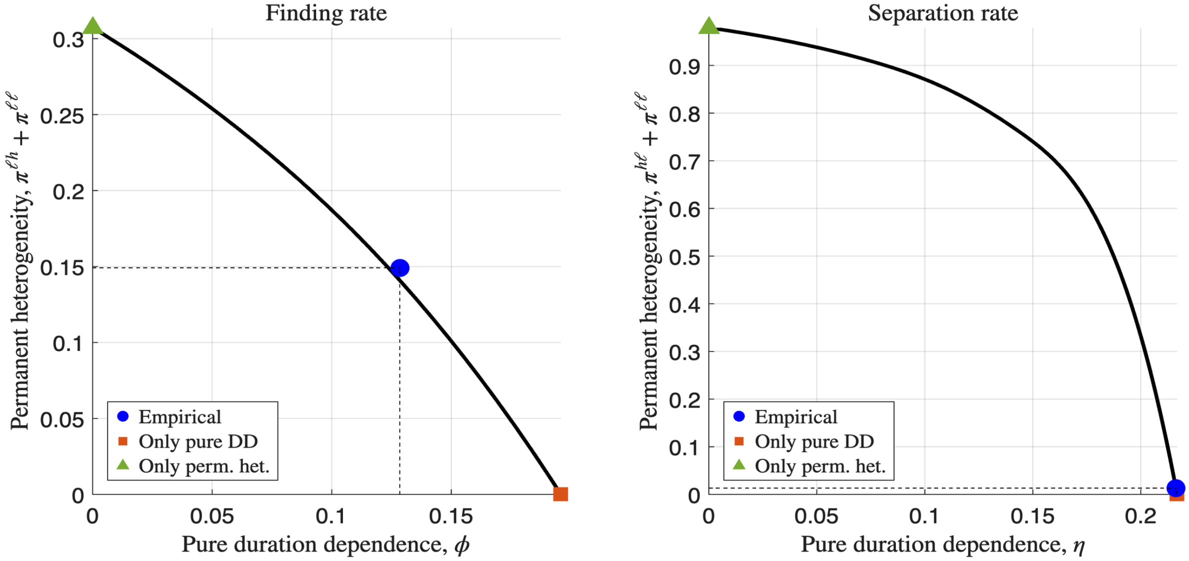

Figure 2: Equal-fit curves

Curves show loci of model parameter values that fit the data equally well. Labeled points refer to specific calibrations that I use to generate results.

holds in my model. Whether the downward slope in $f(\tau)$ reflects pure duration dependence, permanent heterogeneity, or a combination of both, parameters exist such that $f(\tau)$ in the model matches $f(\tau)$ in the data, and likewise for $s(\tau)$.[14]

Figure 2 illustrates the identification problem. Consider the left-hand panel with ϕ on the horizontal axis and $\pi^{\ell h} + \pi^{\ell\ell}$ on the vertical axis. Since ϕ is the probability that an unemployed worker with the high finding rate transitions to the low finding rate, ϕ represents the level of pure duration dependence for job finding rates. If there is no pure duration dependence, then $\phi = 0$. Conversely, since $\pi^{\ell h} + \pi^{\ell\ell}$ is the fraction of the labor force with permanently low job finding rates, it represents the level of permanent heterogeneity; if there is none, then $\pi^{\ell h} + \pi^{\ell\ell} = 0$. The curve in Figure 2 plots a locus of parameter values that fit $f(\tau)$ equally well. In fact, the model successfully fits the data even under the extreme

[14]Distinguishing pure duration dependence from heterogeneity is classic econometric puzzle (Heckman and Singer, 1984; Heckman, 1991). In response, the literature has developed a wide variety of approaches for distinguishing the two as well as a broad range of findings (Castro et al., 2025; Alvarez et al., 2023; Zuchuat et al., 2023; Lyshol et al., 2021; Mueller et al., 2021; Abbring et al., 2002; Machin and Manning, 1999; van den Berg and van Ours, 1996).

assumptions of no pure duration dependence or no permanent heterogeneity. Note that it slopes downward; if the level of pure duration dependence decreases, the level of permanent heterogeneity must increase to compensate.

The right-hand panel of Figure 2 shows the same for separation rates. Again, there are infinite combinations of pure duration dependence, η, and permanent heterogeneity, $\pi^{h\ell}+\pi^{\ell\ell}$, that successfully match $s(\tau)$.

I exploit the identification problem to demonstrate how pure duration dependence and permanent heterogeneity generate different predictions in the model. In particular, I consider three calibrations for both finding and separation rates. For ease of exposition, I will describe the calibrations using the finding side of the model; the separation side is analogous.

I call the first calibration the "pure duration dependence" calibration. In this calibration, there is no permanent heterogeneity in job finding rates ($\pi^{\ell h} + \pi^{\ell\ell} = 0$), so the downward-sloping $f(\tau)$ curve is entirely generated by pure duration dependence. I denote this calibration in Figure 2 with an orange square on the horizontal axis. Second, in the "permanent heterogeneity" calibration, I assume that there is no pure duration dependence, $\phi = 0$. In this case, the downward-sloping $f(\tau)$ curve is entirely generated by permanent heterogeneity in finding rates. It is denoted with a green triangle on the vertical axis in Figure 2.

Third, in the "empirical" calibration, I aim to match the "true" mix of pure duration dependence and permanent heterogeneity in the data. To do so, I estimate a mixed proportional hazard (MPH) model on my data to obtain an estimate of pure duration dependence, which I add to my calibration targets.

In a mixed proportional hazard model, the instantaneous hazard rate of an unemployed worker transitioning to employment is

$$\Psi(X, \tau, v) = \Phi(\tau) \exp(\beta' X) v \tag{29}$$

where X a vector of observable characteristics and v is unobserved heterogeneity, drawn from a gamma distribution.[15] Thus, the hazard rate is a multiplicative function of unemployment

[15]See **?** and Jenkins (2005) for overviews of the MPH model.

duration, observable characteristics[16], and unobservable type.[17] I estimate the model in discrete time.

My object of interest is $\Phi(\tau)$, the baseline hazard, which measures how unemployment duration affects the individual hazard rate. In my model, $\Phi(\tau)$ corresponds to a counterfactual where $f(\tau)$ decreases only because of pure duration dependence. Take $f(0)$ as given. In Appendix B, I show that the corresponding counterfactual job finding rate is

$$f(\tau|\text{pure DD}) = f^{\ell} + (f^h - f^{\ell}) \left[1 + \phi \sum_{i=1}^{\tau} \frac{1}{(1-\phi)^i} \left(\frac{1-f^{\ell}}{1-f^h} \right)^{i-1} + \frac{1-x(0)}{x(0)} \right]^{-1}. \tag{30}$$

for $\tau \geq 1$. In the empirical calibration, I calibrate the model so that $f(\tau|\text{pure DD})$ matches $\Phi(\tau)$ for the first six months of unemployment. See Appendix C for details.

I plot the resulting empirical calibration in Figure 2 using blue circles. For finding rates, the empirical calibration roughly bisects the equal-fit curve, reflecting significant roles for both pure duration dependence and permanent heterogeneity. In contrast, for separation rates, the empirical calibration is practically indistinguishable from the pure duration dependence calibration. Parameter values are presented in the next section. To address concerns about the separation rate result, Appendix D shows that this empirical calibration produces roughly the same unemployment persistence as a calibration that bisects the equal-fit curve.

Before proceeding to the calibration results, I add two minor notes about the calibration strategy. First, for each calibration, I normalize κ such that steady-state labor market tightness θ equals 1. Second, in the empirical calibration for both sides, one π parameter is unidentifiable, so I normalize $\pi^{\ell\ell} = 0$, which does not affect the results.

Table 3: Calibration results

Finding duration dependence					
Parameter	Meaning	DMP	Pure DD	Empirical	Perm. het.
μ	Match efficiency	0.321	0.507	0.596	0.717
γ	Finding rate penalty	1.000	0.383	0.347	0.308
ϕ	High-low transition rate	0.000	0.183	0.128	0.000
$\pi^{\ell\ell} + \pi^{\ell h}$	Permanently low finding rate share	0.000	0.000	0.149	0.295
Separation duration dependence					
Parameter	Meaning	DMP	Pure DD	Empirical	Perm. het.
s^h	High separation rate	0.017	0.060	0.061	0.270
δ	Separation rate penalty	1.000	0.222	0.221	0.049
η	High-low transition rate	0.000	0.224	0.216	0.000
$\pi^{\ell\ell} + \pi^{h\ell}$	Permanently low separation rate share	0.000	0.000	0.013	0.981

Estimated parameter values given different calibration assumptions. DMP refers to a calibration where there is no duration dependence in finding or separation rates. "Pure DD" refers to the pure duration dependence calibration, where all of the observed duration dependence is caused by pure duration dependence. "Perm. het." refers to the permanent heterogeneity calibration, where all of the observed duration dependence is caused by permanent heterogeneity. The "empirical" calibration additionally targets the results of a mixed proportional hazards model.

3.3 Calibration Results

Table 3 lists the resulting internal parameters. To present the results concisely, I take advantage of the fact that in the steady state, the finding and separation sides of the model are independent. That is, parameters on one side do not affect the other. Appendix C includes a table with all parameter values for all calibrations.

The values in Table 3 quantify the "trade-off" illustrated in Figure 2: as the level of pure duration dependence decreases, the level of permanent heterogeneity must increase to compensate. Additionally, the penalties for finding and separation rates are substantial. In the empirical calibration, the low finding rate is 35% of the high finding rate, and the low

[16] In my estimation, X consists of age, sex, race, marital status, and education.

[17] The inclusion of unobserved heterogeneity makes Equation (29) a *mixed* proportional hazard model. Since estimation methods tend to overestimate the effects of pure duration dependence, my goal is to account for as much heterogeneity as possible to generate a conservative estimate of pure duration dependence. Thus, I include unobserved heterogeneity in addition to observed heterogeneity. In fact, in my estimation, unobserved heterogeneity accounts for much more observed duration dependence than observed heterogeneity.

separation rate is 22% of the high separation rate.

My calibration reflects how the unemployment pool in the US is characterized by the rapid churn of short-term unemployed workers coupled with a relatively stable group of long-term unemployed workers. In the empirical calibration, $1-(\pi^{\ell\ell}+\pi^{\ell h})\approx 0.85$, meaning 85% of workers start unemployment with the high finding rate, $f^h = 0.44$, and thus typically find jobs within a few months. However, since $x \approx 0.5$, 50% of unemployed workers face the low finding rate, $f^\ell = 0.19$.[18]

On the separation side, $1-(\pi^{\ell\ell}+\pi^{h\ell})\approx 0.98$ and $y \approx 0.06$. So, 98% of employed workers begin employment with the high finding rate, $s^h = 0.061$. However, the separation rate is much lower than the finding rate, and at a given point in time, 94% of employed workers have the low finding rate, $s^\ell = 0.013$.

In words, most unemployed workers find jobs early in their unemployment spells, while most employed workers do not separate until later in their employment spells. Thus, the calibration suggests that unemployed workers rarely experience pure duration dependence, whereas employed workers usually do. Consequently, the two groups that generate the persistent dynamics in my model—the short-term employed and the long-term unemployed—are relatively small.

4 Results

4.1 Finding-rate Duration Dependence and Productivity Shocks

To establish the intuition for how pure duration dependence increases the persistence of the unemployment rate, consider the effects of a negative productivity shock when only job finding rates exhibit duration dependence.[19] Figure 3 displays impulse response functions (IRF) and succinctly illustrates the model's main mechanisms. Each panel compares the DMP benchmark with three calibrations for finding-rate duration dependence: pure duration

[18] This result is empirically compatible with Morchio (2020), which finds that 2/3 of prime-age unemployment is accounted for by only 10% of the labor force.

[19] Duration dependence in separation rates has a negligible impact after productivity shocks.

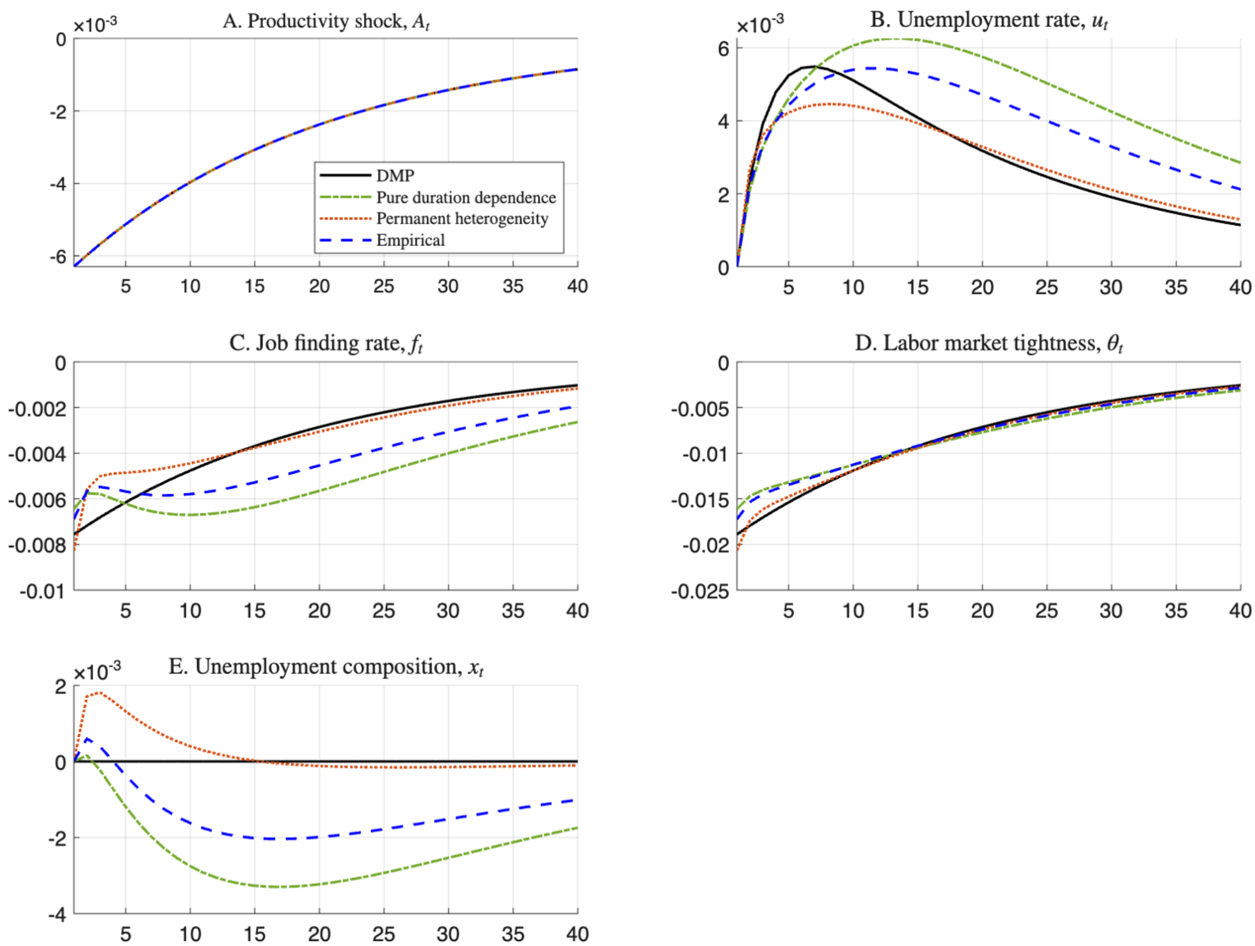

Figure 3: Impulse response functions after productivity shock with finding-rate duration dependence

Variables are in logs, and the vertical axes show deviations from the steady state. Panel A shows the exogenous shock; other panels show endogenous responses.

dependence, permanent heterogeneity, and empirical. In Figure 3 and the future IRFs in this paper, the variables are in logs, the vertical axis displays deviation from the steady state, and the size of the shock is one standard deviation.[20]

The productivity shock in Panel A decreases the value of a filled job, which induces firms to post fewer jobs, thereby decreasing θ_t and job finding rates. As a result, the decrease in outflow from unemployment increases the unemployment rate in Panel B. However, the increase in the unemployment rate is significantly more persistent in the empirical calibration than DMP, as reflected by the more hump-shaped blue line, and is even more persistent under pure duration dependence. In contrast, the persistence of unemployment under the permanent heterogeneity calibration is similar to the DMP calibration. The remaining panels explain these findings.

Since the separation rate is fixed, the shape of the aggregate job finding rate in Panel C fully determines the shape of the unemployment rate. The aggregate job finding rate is then a function of unemployment composition, x_t (Panel D), and labor market tightness, θ_t (Panel E). The response of θ_t is similar across calibrations, so the difference in the aggregate finding rate is driven by unemployment composition.

Compared to DMP, the empirical calibration allows for pure duration dependence, and workers who do not find jobs flow to the low finding rate. These flows accumulate over the recession, generating the negative hump shape of x_t, which is then reflected in a second, slow-developing decrease in the aggregate finding rate. As a result, the finding rate is low for a longer period of time, and the unemployment rate is slower to recover. Once the deviation of x_t drops below zero, it recovers slowly. At that point, a larger share of the unemployment pool is less likely to find a job, and x_t can recover only as these workers gradually find jobs, a process that is inherently slow.

In the pure duration dependence calibration, the decrease in x_t is greater, generating a larger, more persistent decrease in f_t and more persistence in the unemployment rate. On the other hand, under permanent heterogeneity, x_t instead slightly increases after the shock, and unemployment persistence is similar to DMP. Therefore, the extent to which duration

[20] I generate simulation results using Dynare (Adjemian et al., 2011).

dependence increases persistence depends on the level of pure duration dependence. More pure duration dependence causes larger changes in unemployment composition, generating more persistence.

Returning to the DMP calibration, note how f_t mirrors the path of A_t. Herein lies the reason why the DMP model fails to generate persistence in unemployment. Because vacancies v_t is a jump variable, θ_t adjusts to A_t every period via the free entry condition. So, θ_t follows the path of A_t, and since f_t is only a function of θ_t, it follows the same path as A_t as well. The result is that the finding rate recovers as quickly as the shock.[21] With duration dependence, f_t is also a function of x_t. Although θ_t recovers at roughly the same speed, the composition effect drags down the aggregate finding rate, and unemployment recovers more slowly.

Finally, why does x_t initially increase after the shock in all non-DMP calibrations? In the steady state, the inflow rate equals the outflow rate for all types of unemployed workers. Then, the shock decreases high and low finding rates proportionally. Since workers with high finding rates flow into unemployment at a higher rate, the proportional fall in outflows produces more build-up for unemployed workers with high finding rates, and the fraction of unemployed workers with high finding rates initially increases.[22] In the empirical and pure duration dependence calibrations, the initial spike in x_t is quickly reversed as unemployed workers flow to the low finding rate.

4.2 Separation Shocks

Similarly, pure duration dependence in separation rates increases the persistence of the unemployment rate after separation shocks. Intuitively, the shock shifts the composition of the employment pool toward the short-term employed, who are more likely to separate. In other words, pure duration dependence in separation rates generates recurring job loss.

First, consider a separation shock in a model with duration dependence only in separa-

[21] Table **??** in the Appendix shows that the correlation between A_t and f_t is 0.999 in the DMP model.

[22] Mathematically, x_t will initially jump as long as $1-\phi > f/f^h$. This inequality holds for every calibration, and it is guaranteed to hold if there is no pure duration dependence.

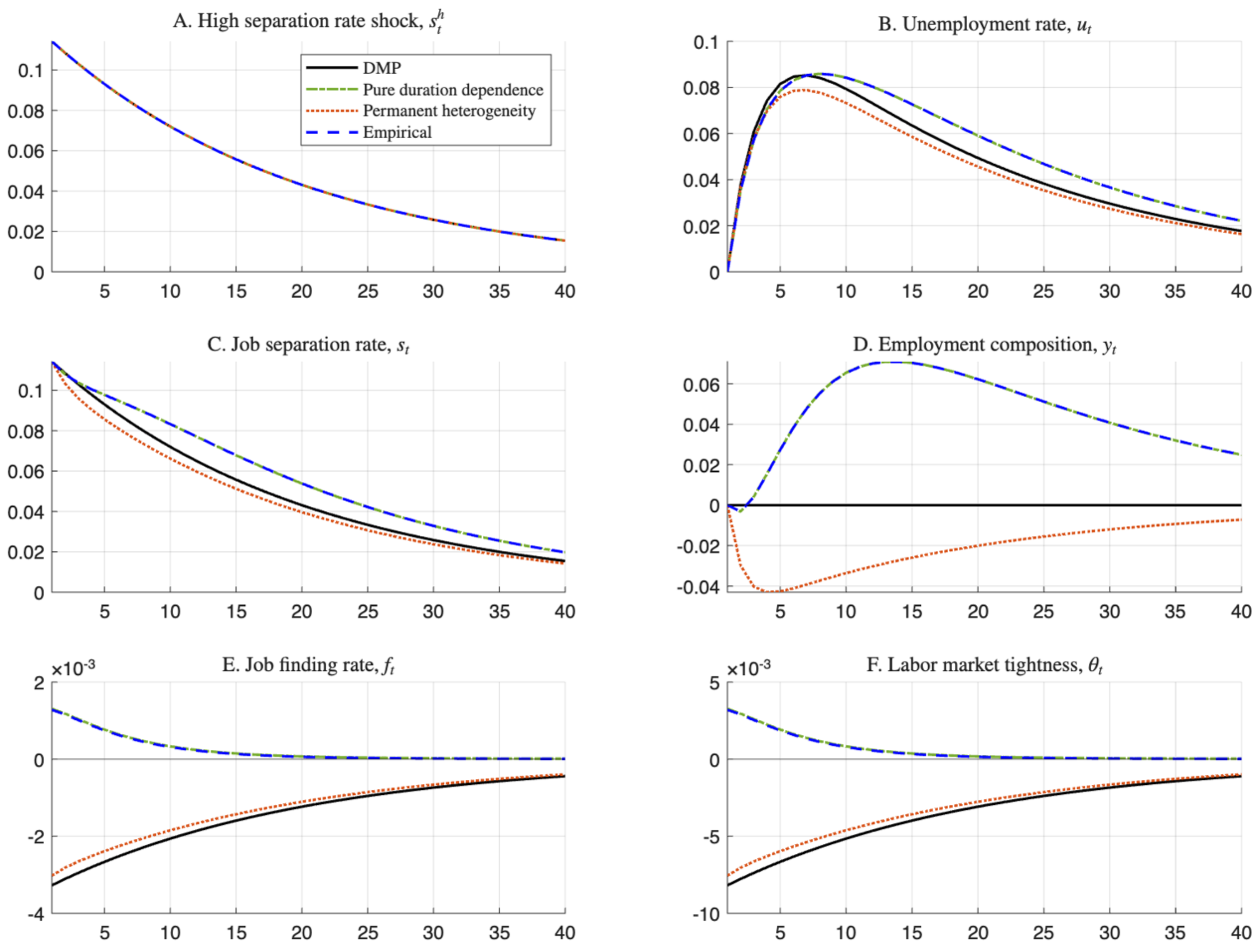

Figure 4: Impulse response functions of separation shock with only separation duration dependence

Variables are in logs, and the vertical axes show deviations from the steady state. Panel A shows the exogenous shock; other panels show endogenous responses. In all panels, the empirical calibration is essentially identical to the pure duration dependence calibration. Each line refers to a different calibration of the model.

tion rates. The shock to s_t^h appears in Panel A of Figure 4. Unsurprisingly, the IRFs for the empirical calibration are essentially identical to the pure duration dependence calibration. The unemployment rate in Panel B is clearly more hump-shaped with the empirical calibration than DMP, which is more hump-shaped than with the permanent heterogeneity calibration.

Thus, the main finding regarding finding-rate duration dependence also holds for separation rates: pure duration dependence increases the persistence of the unemployment rate. The intuition is similar, too. In DMP, $s_t^h = s_t$. In non-DMP calibrations, s_t is also a function of the composition of the employment pool, y_t, in Panel D.

Whether y_t rises or falls depends on whether observed duration dependence in separation rates reflects pure duration dependence or permanent heterogeneity. In both cases, y_t initially decreases for the same reason that productivity shocks initially increased x_t above.[23] However, under the empirical calibration, y_t soon increases. Intuitively, as the unemployment rate recovers, unemployed workers must find jobs. The employment pool then shifts toward the short-term employed, and because of pure duration dependence, the short-term employed have a higher separation rate. Therefore, y_t increases, which further increases s_t. Thus, pure duration dependence slows the recovery of s_t, which slows the recovery of u_t. Under pure heterogeneity, the opposite occurs; y_t continues to decrease, the increase in s_t is reduced, and the unemployment rate recovers faster.[24]

Unlike productivity shocks, both finding-rate and separation-rate duration dependence matter after separation shocks. Figure 5 shows the response of the model to a separation shock under four specifications: no duration dependence (the DMP benchmark), both types of duration dependence, and each type individually. Whenever the model includes duration dependence, I use the empirically calibrated parameters for that side.

With finding-rate duration dependence, the separation shock increases the aggregate finding rate—an odd result—and reduces the effect of the shock. In the first period of the

[23]Mathematically, y_t will increase in $t = 1$ if $1 - \eta > s/s^h$, which is always true in the data.

[24]For completeness, Figure 4 also includes the responses to the job finding rate, labor market tightness, and unemployment composition, but these effects are relatively insignificant.

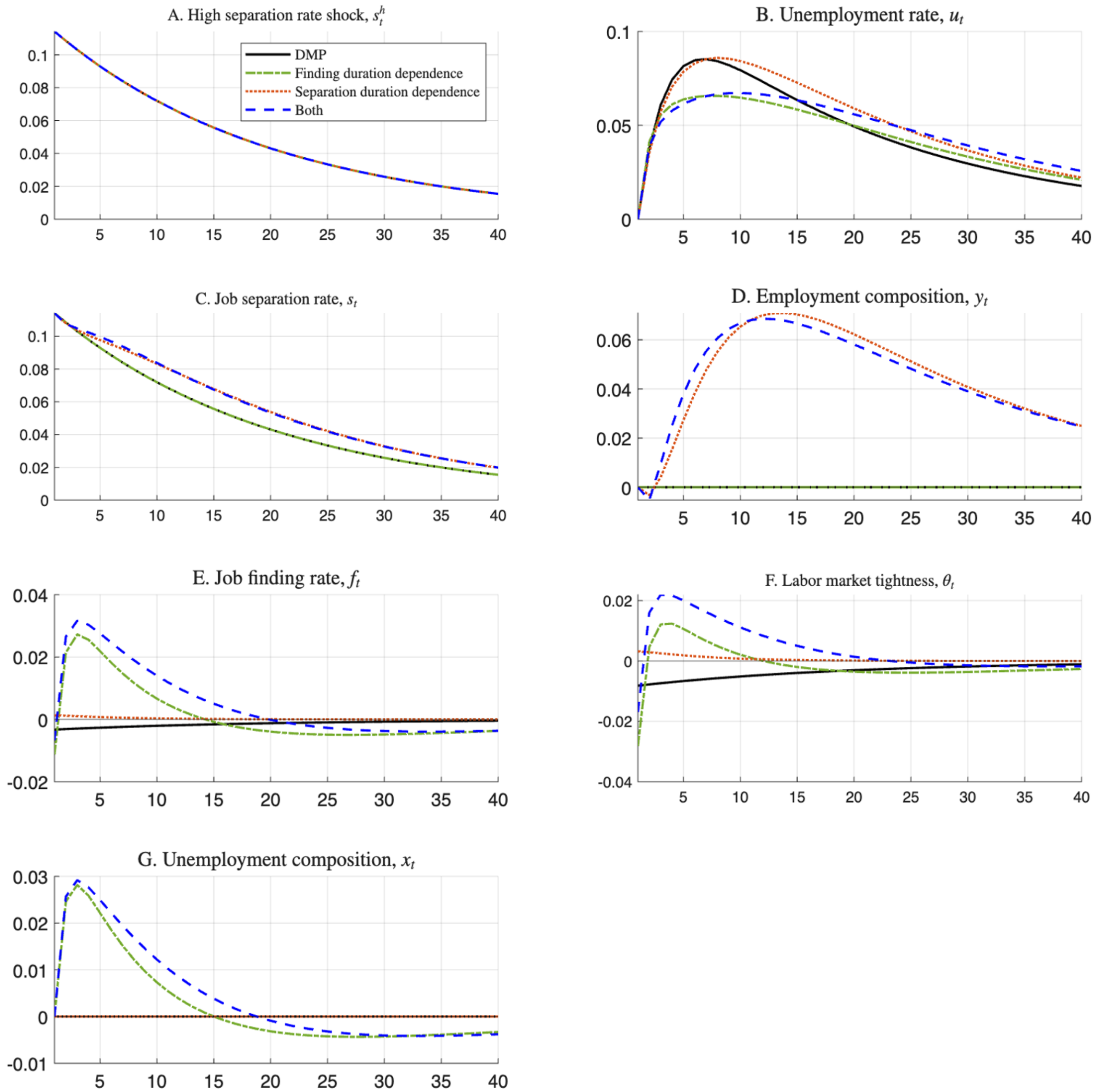

Figure 5: Impulse response functions of separation shock with finding and separation duration dependence

Variables are in logs, and the vertical axes show deviations from the steady state. Panel A shows the exogenous shock; other panels show endogenous responses. Both finding and separation duration dependence rely on their empirical calibration. Each line refers to a different calibration of the model.

shock ($t = 0$ in Figure 5), higher separation rates decrease the value of a filled job, so θ_t and f_t decrease. However, since newly unemployed workers are, by definition, short-term unemployed, they tend to have high finding rates, so the sudden inflow of workers improves the composition of the unemployment pool, increasing x_t and putting upward pressure on f_t. Furthermore, the improvement of the unemployment pool incentivizes firms to post more vacancies, so θ_t increases as well.

Altogether, duration dependence in finding rates attenuates the effect of a separation shock on the unemployment rate in the short to medium run. In the long run, pure duration dependence eventually pushes x_t and f_t below the steady state, and the unemployment rate recovers more slowly. Compared to the effect on the separation rate, the effect on the finding rate is minor. However, given that separation shocks are larger than productivity shocks for simultaneous shocks, the effect is not insignificant.[25]

4.3 Simultaneous Shocks and Empirical Results

I generate my empirical results using simultaneous shocks to productivity and the separation rate. Figure 6 shows the impulse responses, and the top two panels display the exogenous shocks. As in Figure 5, Figure 6 plots the responses of the model without duration dependence (DMP), with both types of duration dependence, and with each type individually. When the model includes duration dependence, I use the empirically calibrated parameters for that side of the model.

The main variable of interest is the unemployment rate in Panel C. Both finding and separation duration dependence significantly increase persistence. Although finding-rate duration dependence has a stronger effect, the impact is greatest when both types are present.

The other variables in Figure 6 resemble previous IRFs. In response to the negative productivity shock, θ_t and f_t immediately decrease. If there is duration dependence in finding rates, then x_t increases in the next period, pushing θ_t and f_t upward in the medium run, though not above the steady state. In the long run, x_t drops below zero, f_t decreases for a

[25]Numerically, duration dependence in finding rates increases the persistence of the unemployment rate after separation rate shocks because of this long-run effect.

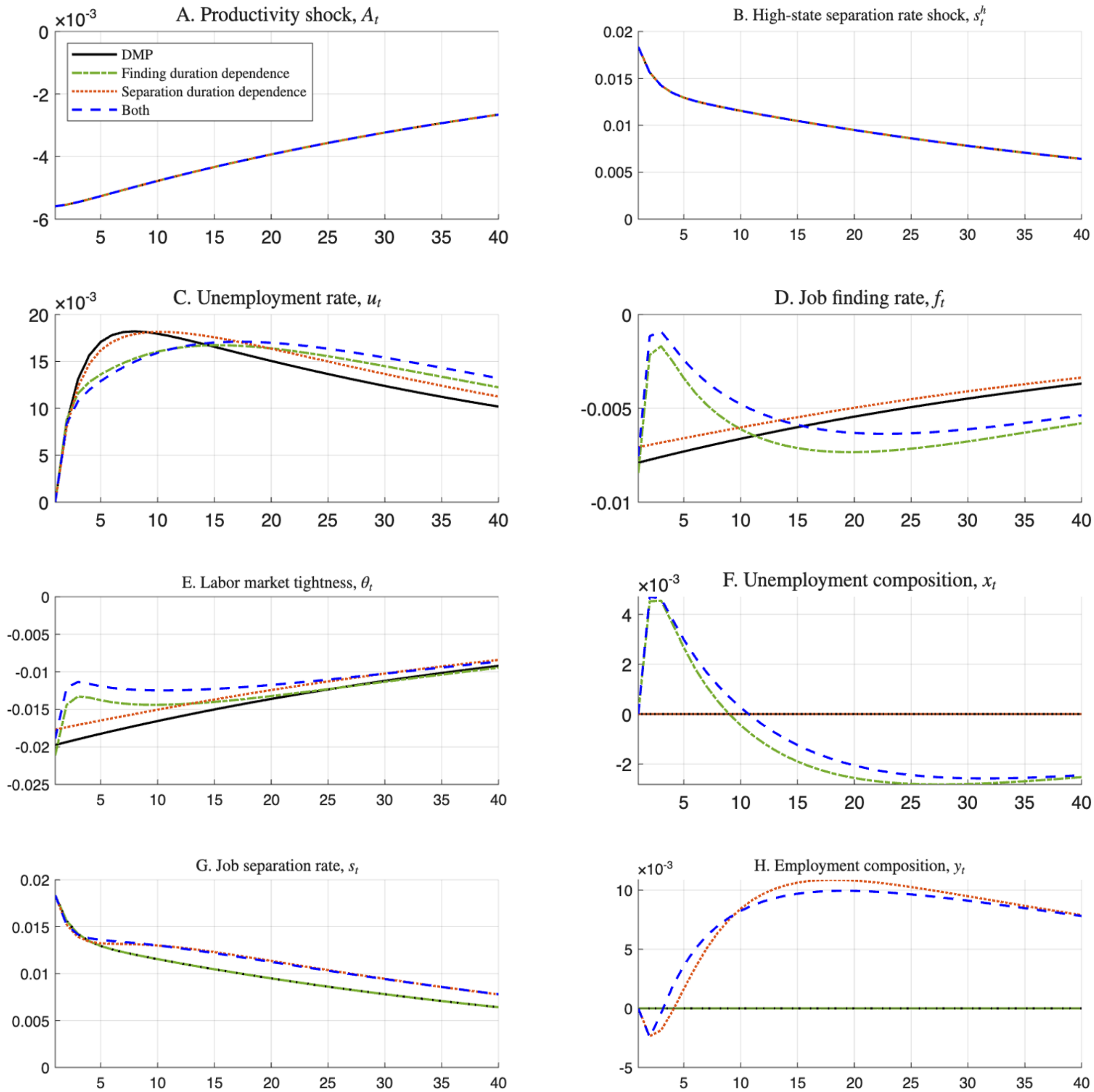

Figure 6: Impulse response functions of simultaneous shock

Variables are in logs, and the vertical axes show deviations from the steady state. Panels A and B show the exogenous shock; other panels show endogenous responses. Both finding and separation duration dependence rely on their empirical calibration. Each line refers to a different calibration of the model.

second time, and f_t slowly returns to the steady state. Simultaneously, duration dependence in separation rates generates a small decrease in y_t followed by a long, persistent increase, and s_t recovers slowly as well.

In Figure 6, the aggregate finding rate responds by about half as much as the separation rate. Since the separation shock outweighs the productivity shock, its upward pressure on x_t dominates the downward pressure on x_t from the productivity shock in the short run. Thus, duration dependence does not slow the recovery of the finding rate until a year after the shock. As in Shimer (2005), standard productivity data implies that productivity shocks alone generate little volatility in finding rates. I address the problem in Appendix D by following Hagedorn and Manovskii (2008) and choosing values for b and ψ that amplify productivity shocks. With this recalibration, the finding shock dominates the separation shock, x_t increases only slightly before decreasing, and the unemployment rate becomes even more persistent.

I quantify persistence using autocorrelations and, for the unemployment rate, half-lives in Table 4.[26] See Table 4's counterpart with standard deviations in Appendix D.

Table 4 shows that duration dependence in both finding and separation rates increases the autocorrelation of the unemployment rate from 0.869 to 0.928, a 90% increase when measured in half-lives. Duration dependence in finding rates boosts persistence by 54%, compared with just 24% from duration dependence in separation rates, implying that most of the increase in persistence is driven by duration dependence on the finding side. Since $54\% + 24\% < 90\%$, the interaction between finding and separation duration dependence is positive, generating further persistence. If we assume that all duration dependence is caused only by pure duration dependence, the effect is larger and persistence increases by 117%. In contrast, if duration dependence is caused only by permanent heterogeneity, then the persistence of the unemployment rate increases by 16%.

[26]Half-lives are calculated as $\ln(0.5)/\ln(\rho)$ where ρ is the autocorrelation of the variable. Assume that the variable z_t follows an AR(1) process in log deviations from the steady state, $\tilde{z}_{t+1} = \rho\tilde{z}_t + \varepsilon_t$, where $\tilde{z}_t = \ln(z_t) - \ln(z)$. Let $t = 0$ be the period of a shock. The half-life calculates how many periods it will take to recover to $0.5\tilde{z}_0$ in the absence of further shocks. Thus, the half-life T solves $\tilde{z}_T = 0.5\tilde{z}_0$. Plugging in $\tilde{z}_T = \rho^T\tilde{z}_0$, one obtains $T = \ln(0.5)/\ln(\rho)$.

Table 4: Autocorrelation of model variables in simulations

	DMP	Empirical			Extremes			
f duration dependence	None	Emp.	Emp.	None	Pure DD	Pure DD	Perm. het.	Perm. het.
s duration dependence	None	Emp.	None	Emp.	Pure DD	Perm. het.	Pure DD	Perm het.
$AC(u_t)$	0.869	0.929	0.913	0.893	0.937	0.922	0.917	0.886
$HL(u_t)$	4.9	9.4	7.6	6.1	10.7	8.5	8.0	5.7
$\%\Delta HL(u_t)$	0.0	89.9	53.5	24.3	117.4	73.0	61.2	16.3
$AC(\theta_t)$	0.959	0.925	0.933	0.960	0.930	0.937	0.925	0.930
$AC(f_t)$	0.959	0.774	0.806	0.960	0.843	0.865	0.618	0.607
$AC(x_t)$		0.516	0.509		0.704	0.720	0.325	0.279
$AC(s_t)$	0.539	0.622	0.539	0.616	0.622	0.495	0.622	0.503
$AC(y_t)$		0.913		0.934	0.910	0.853	0.918	0.788

AC refers to autocorrelation, HL to half-lives, and $\%\Delta HL$ to percent change in half-lives relative to DMP. Half-lives are calculated as $\ln(0.5)/\ln\rho$, where ρ is the autocorrelation. All variables are quarterly. “Emp.”, “pure DD,” and “perm. het.” refer to the empirical, pure duration dependence, and permanent heterogeneity calibrations. Each column refers to a different calibration of the model. The model is simulated for 50,000 periods.

In summary, duration dependence increases the persistence of the unemployment rate, the effect increases with the level of pure duration dependence, and finding-rate duration dependence is more responsible for the increase in persistence than separation-rate duration dependence.

4.4 The Effects of Free Entry and Equilibrium

In this section, I explore the extent to which the free entry condition affects my results. The model requires substantial machinery to allow for endogenous job posting in equilibrium, and perhaps a simpler model would generate similar results.[27] Nevertheless, it turns out that free entry significantly amplifies the effects of duration dependence in the model.

To isolate the effects of free entry, I consider an "intermediate" version of the model where there is no feedback between duration dependence and the number of jobs posted in equilibrium. The exercise is not straightforward for productivity shocks since they only affect unemployment through the free entry condition. My solution is to fix x_t to its steady state value in the aggregate hiring rate, Equation (18), which only affects the free entry condition, Equation (21). Firms still respond to productivity shocks as usual, but not to changes in the composition of unemployment.

For the separation side, I simply assume that separation rates do not affect job posting. To do so, I fix s_t in Equation (20) to its steady state value. Therefore, the separation rate will change over the business cycle, but job-posting decisions will not be affected by it.

I quantitatively evaluate the interaction between duration dependence and free entry in Table 5 by comparing my main empirical object of interest, the autocorrelation of u_t, under different assumptions and by feeding the model productivity, separation rate, and simultaneous shocks. For each type of shock, I first simulate the model under the DMP benchmark. In this case, free entry will not interact with duration dependence in any case. I then use the empirical calibration with both types of duration dependence, turning off interactions between duration dependence and free entry as described above, before I allow

[27]For example, one could write a model with exogenous shocks to finding rates.

Table 5: Effect of free entry condition on persistence of unemployment rate

	Productivity shock			Separation shock			Simultaneous shock		
Calibration	DMP	Emp.	Emp.	DMP	Emp.	Emp.	DMP	Emp.	Emp.
FEC interactions	No	No	Yes	No	No	Yes	No	No	Yes
$AC(u_t)$	0.941	0.966	0.974	0.941	0.962	0.964	0.869	0.917	0.929
$HL(u_t)$	11.4	19.8	25.9	11.4	17.8	19.1	4.9	8.0	9.4
$\%\Delta HL(u_t)$	0.0	73.8	127.1	0.0	56.0	67.2	0.0	61.9	89.9

"Emp." refers to empirical calibration and "FEC" to the free entry condition. The columns with the DMP calibration will generate identical results when allowing for FEC interactions.

for interactions as usual.

For productivity shocks, about 40% of the increase in half-lives comes from interactions between duration dependence and free entry. When x_t decreases during a recession, firms are less likely to find new workers, so they post fewer jobs, further decreasing θ_t and the aggregate finding rate. See Figure 12 in Appendix D for a visualization using impulse responses. In contrast, free entry makes little difference after separation rate shocks. All else equal, an increase in separation rates will induce firms to post fewer jobs, but separation shocks also increase x_t, as explained above, which has the opposite effect. Quantitatively, the effects roughly offset.

Predictably, under simultaneous shocks to productivity and separation rates, the effect of the free entry condition lies in the middle. The right three columns in Table 5 show that about 30% of the increase in the persistence of the unemployment rate due to duration dependence is due to feedback between duration dependence and free entry.

5 Conclusion

The canonical DMP search model fails to generate realistic persistence in the unemployment rate over the business cycle (Shimer, 2005; Pries, 2004). In this paper, I show that accounting for two-state duration dependence (duration dependence in both job finding and separation rates) significantly increases the persistence of the unemployment rate, reconciling the theory with the data.

I incorporate two-state duration dependence in an otherwise-standard DMP model by allowing for two job finding rates and two job separation rates. Due to pure duration dependence, workers may transition from the high rate to the low rate. Due to permanent heterogeneity, they begin unemployment and employment spells with different rates.

Taking the model to the data is not straightforward. The model is relatively parsimonious, but identifying pure duration dependence from permanent heterogeneity remains an enduring challenge. I exploit the ambiguity in the calibration to show how the model's predictions differ sharply depending on the extent to which observed duration dependence is caused by pure duration dependence versus permanent heterogeneity. In my headline empirical results, I target additional moments generated by a mixed proportional hazard model.

I show that *pure* duration dependence increases the persistence of the unemployment rate over the business cycle. During recessions, job finding rates decrease and job separation rates increase. As the unemployment rate returns to its steady state, there will be a higher incidence of long-term unemployment and short-term employment. Due to pure duration dependence, the long-term unemployed are less likely to find a job, and the short-term unemployed are more likely to become unemployed again. Thus, pure duration dependence pushes the aggregate job finding rate down and the aggregate job separation rate up, prolonging the effects of the shock and slowing the recovery of unemployment.

Empirically, duration dependence increases the persistence of the unemployment rate by 90%, measured in half-lives. Alone, finding-rate duration dependence increases persistence by 54% while separation-rate duration dependence increases persistence by 24%. The effect is larger if all observed duration dependence is assumed to be pure, and it nearly disappears if it instead reflects only permanent heterogeneity. Among other lessons, these results suggest that the challenge of identifying pure duration dependence from permanent heterogeneity is of some interest to macroeconomists.

Appendix

A Data

To construct the moments used for calibration, I primarily use the Current Population Survey (CPS) for January 1978-March 2020. The Basic Monthly CPS includes data on unemployment duration. For employment duration, I use the annual Job Tenure Supplement, in which workers disclose how long they have held their current job. However, since my model incorporates employment spell duration, not job duration, there is a discrepancy between the model and the data.

To validate my usage of job tenure data, I conducted an experiment using the SIPP (Survey of Income and Program Participation), which follows individuals for about four years. Using the SIPP, I generated job separation rates as a function of job tenure for workers who were unemployed before their current job. For such workers, job tenure is equivalent to the length of their employment spell. In that data, $s(\tau)$ has a similar shape to that in this paper. Although the scale differs—and SIPP monthly transition rates diverge substantially from CPS rates anyway (Engbom, 2022)—the shape is what matters for my analysis.

The model period is monthly, so I estimate monthly AR(1) and VAR models for productivity and separation rates. Because monthly productivity data for the US does not exist, I construct monthly productivity by dividing monthly GDP estimates from Koop et al. (2023) by monthly employment from the Current Employment Statistics. I detrend the productivity series data using the Hodrick-Prescott filter.

B Model Details

B.1 Remaining Value Functions

Consider high-low type workers, who always have the low separation rate but may have the high or low finding rate. Their value of employment is

$$E_t^{h\ell} = w_t + \beta \left[s_t^{\ell} U_{t+1}^{h\ell} + (1 - s_t^{\ell}) E_{t+1}^{h\ell} \right]. \tag{31}$$

Upon losing their job, these workers begin unemployment spells with the high finding rate in $U_t^{h\ell}$. With probability ϕ, they flow to the lower finding rate in $U_t^{\bar{\ell}\ell}$. Thus,

$$U_t^{h\ell} = b + \beta \left[f_t^h E_{t+1}^{h\ell} + (1 - f_t^h) \left(\phi U_{t+1}^{\bar{\ell}\ell} + (1 - \phi) U_{t+1}^{h\ell} \right) \right] \tag{32}$$

and

$$U_t^{\bar{\ell}\ell} = b + \beta \left[f_t^{\ell} E_{t+1}^{h\ell} + (1 - f_t^h) U_{t+1}^{\bar{\ell}\ell} \right]. \tag{33}$$

Finally, consider low-high type workers, who always have the low finding rate but may have the high or low separation rate. The value of employment with the high separation rate is

$$E_t^{\ell h} = w_t + \beta \left[s_t^h U_{t+1}^{\ell h} + (1 - s_t^h) \left(\eta E_{t+1}^{\ell\bar{\ell}} + (1 - \eta) E_{t+1}^{\ell h} \right) \right]. \tag{34}$$

If the worker does not separate, with probability η, they flow to the low separation rate, where the value of employment is

$$E_t^{\ell\bar{\ell}} = w_t + \beta [s_t^{\ell} U_{t+1}^{\ell h} + (1 - s_t^{\ell}) E_{t+1}^{\ell\bar{\ell}}]. \tag{35}$$

Whenever a worker in this group is unemployed, they have the low finding rate. So,

$$U_t^{\ell h} = b + \beta [f_t^{\ell} E_{t+1}^{\ell h} + (1 - f_t^{\ell}) U_{t+1}^{\ell h}]. \tag{36}$$

B.2 Laws of Motion

The laws of motion follow from the value functions. For low-low type workers,

$$e^{\ell\ell}_{t+1} = (1 - s^{\ell}_t)e^{\ell\ell}_t + f^{\ell}_t u^{\ell\ell}_t \tag{37}$$

$$u^{\ell\ell}_{t+1} = (1 - f^{\ell}_t)u^{\ell\ell}_t + s^{\ell}_t e^{\ell\ell}_t. \tag{38}$$

For high-low type workers,

$$e^{h\ell}_{t+1} = (1 - s^{\ell}_t)e^{h\ell}_t + f^{\ell}_t u^{h\ell}_t + f^{\ell}_t u^{\bar{\ell}\ell}_t \tag{39}$$

$$u^{h\ell}_{t+1} = (1 - f^{\ell}_t)(1 - \phi)u^{h\ell}_t + s^{\ell}_t e^{h\ell}_t \tag{40}$$

$$u^{\bar{\ell}\ell}_{t+1} = (1 - f^{\ell}_t)u^{\bar{\ell}\ell}_t + \phi(1 - f^{\ell}_t)u^{h\ell}_t. \tag{41}$$

For low-high type workers,

$$e^{\ell h}_{t+1} = (1 - s^{h}_t)(1 - \eta)e^{\ell h}_t + f^{\ell}_t u^{\ell h}_t \tag{42}$$

$$e^{\ell\bar{\ell}}_{t+1} = (1 - s^{\ell}_t)e^{\ell\ell}_t + (1 - s^{h}_t)e^{\ell h}_t \tag{43}$$

$$u^{\ell h}_{t+1} = (1 - f^{\ell}_t)u^{\ell h}_t + s^{h}_t e^{\ell h}_t + s^{\ell}_t e^{\ell\bar{\ell}}_t. \tag{44}$$

Finally, for high-high type workers,

$$e^{hh}_{t+1} = (1 - s^{h}_t)(1 - \eta)e^{hh}_t + f^{h}_t u^{hh}_t + f^{\ell}_t u^{\bar{\ell}h}_t \tag{45}$$

$$e^{h\bar{\ell}}_{t+1} = (1 - s^{\ell}_t)e^{h\ell}_t + \eta(1 - s^{h}_t)e^{hh}_t \tag{46}$$

$$u^{hh}_{t+1} = (1 - f^{h}_t)(1 - \phi)u^{hh}_t + s^{h}_t e^{hh}_t + s^{\ell}_t e^{h\bar{\ell}}_t \tag{47}$$

$$u^{\bar{\ell}h}_{t+1} = (1 - f^{l}_t)u^{\bar{\ell}h}_t + \phi(1 - f^{h}_t)u^{hh}_t. \tag{48}$$

B.3 Deriving $f(\tau)$ and $s(\tau)$

In this section, I derive $f(\tau)$; the process for $s(\tau)$ is symmetric. In the next two sections, I only deal with the steady state, so I remove all t subscripts.

Let $u(\tau)$ denote the number of unemployed workers who have been unemployed for τ continuous periods. Similarly, let $u^{h\ell}(\tau)$ denote the number of high-low type unemployed workers, and $u^{\ell h}(\tau)$ the number of high-high type unemployed workers, who have been unemployed for τ continuous periods. $u^{h\ell}(\tau)+u^{hh}(\tau)$ is the number of unemployed workers who have been unemployed for τ periods who have the high finding rate. Thus, $x(\tau) = [u^{h\ell}(\tau)+u^{hh}(\tau)]/u(\tau)$ is the fraction of unemployed workers who have been unemployed for τ periods with the high job finding rate.

For each τ,

$$f(\tau) = x(\tau)f^h + [1-x(\tau)]f^\ell = f^\ell + x(\tau)(f^h - f^\ell). \tag{49}$$

Thus, to derive $f(\tau)$, we must derive $x(\tau)$.

First, solve for $x(0) = [u^{h\ell}(0)+u^{hh}(0)]/u(0)$. The number of unemployed workers with $\tau = 0$ is the number of employed workers who just separated from their jobs. Therefore, $u(0) = \delta e$. Using similar logic, the laws of motion above generate

$$u^{hl}(0) = \delta^\ell e^{h\ell}$$

and

$$u^{hh}(0) = \delta^h e^{hh} + \delta^\ell e^{h\bar{\ell}}.$$

Thus,

$$x(0) = \frac{u^{h\ell}(0)+u^{hh}(0)}{u(0)} = \frac{\delta^\ell e^{h\ell} + \delta^h e^{hh} + \delta^\ell e^{h\bar{\ell}}}{\delta e}. \tag{50}$$

I can algebraically solve for each element in $x(0)$ as a function of model parameters.

Next, solve for $x(1)$. The number of workers who have been unemployed for one period equals the number of workers who lost their jobs one period ago and did not find work during that period. So,

$$u(1) = u(0)[1-f(0)] = \delta e[1-f(0)].$$

The number of workers unemployed for one period with the high finding rate equals the number of workers who were separated one period ago, did not find a job at the high finding rate, and did not flow to the low finding rate. So,

$$u^{h\ell}(1) = u^{h\ell}(0)(1 - f^h)(1 - \phi)$$

and

$$u^{hh}(1) = u^{hh}(0)(1 - f^h)(1 - \phi).$$

Altogether,

$$x(1) = \frac{u^{h\ell}(1) + u^{hh}(1)}{u(1)} = \frac{[u^{h\ell}(0) + u^{hh}(0)](1 - f^h)(1 - \phi)}{u(0)[1 - f(0)]} = x(0)\frac{(1 - f^h)(1 - \phi)}{1 - f(0)}.$$

Using the same procedure for $x(2)$, we find

$$x(2) = \frac{u^{h\ell}(2) + u^{hh}(2)}{u(2)} = x(0)\frac{(1 - f^h)^2(1 - \phi)^2}{[1 - f(0)][1 - f(1)]}.$$

In general,

$$x(\tau) = x(0)\frac{(1 - f^h)^\tau(1 - \phi)^\tau}{\prod_{i=0}^{\tau-1}(1 - f(i))}. \tag{51}$$

Plug Equation (51) into Equation (49) to obtain Equation (25).

The same procedure is used to derive $s(\tau)$. Let $y(\tau)$ denote the fraction of employed workers with τ continuous periods employed who have the high separation rate. In general,

$$s(\tau) = y(\tau)s^h + [1 - y(\tau)]s^\ell = s^\ell + y(\tau)[s^h - s^\ell]. \tag{52}$$

An analogous procedure generates

$$y(\tau) = y(0)\frac{(1 - s^h)^\tau(1 - \eta)^\tau}{\prod_{i=0}^{\tau-1}(1 - s(i))}, \tag{53}$$

and one can plug Equation (53) into Equation (52) to obtain Equation (26).

B.4 Deriving $f(\tau|\textbf{pure DD})$

Take all $\tau = 0$ values as given. In the counterfactual model where the decrease in $f(\tau)$ is caused only by pure duration dependence,

$$f(\tau|\text{pure DD}) = f^{\ell} + x(\tau|\text{pure DD})(f^{h} - f^{\ell}), \tag{54}$$

where $x(0|\text{pure DD}) = x(0)$. For $\tau > 0$, $x(\tau|\text{pure DD})$ reflects changes in $x(\tau)$ that would occur without the effects of permanent heterogeneity.

Recall that $x(\tau) = [u^{hh}(\tau) + u^{h\ell}(\tau)]/u(\tau)$. For $\tau = 1$,

$$x(1) = \frac{u^{hh}(1) + u^{h\ell}(1)}{u(1)} = \frac{u^{hh}(1) + u^{h\ell}(1)}{u^{hh}(1) + u^{h\ell}(1) + u^{\tilde{\ell}h}(1) + u^{\tilde{\ell}\ell}(1) + u^{\ell h}(1) + u^{\ell\ell}(1)}$$

We can break the denominator into three groups,

$$u^{hh}(1) + u^{h\ell}(1) = [u^{hh}(0) + u^{h\ell}(0)](1 - f^{h})(1 - \phi) \tag{55}$$

$$u^{\tilde{\ell}h}(1) + u^{\tilde{\ell}\ell}(1) = [u^{hh}(0) + u^{h\ell}(0)](1 - f^{h})\phi \tag{56}$$

$$u^{\ell h}(1) + u^{\ell\ell}(1) = [u^{\ell h}(0) + u^{\ell\ell}(0)](1 - f^{\ell}). \tag{57}$$

Notice that $x(1) < x(0)$ for two reasons. First, because of pure duration dependence, workers with high finding rates who fail to find jobs flow to the low finding rate. These workers leave the numerator but stay in the denominator in Equation (56).

Second, because of permanent heterogeneity, workers who start with low finding rates are less likely to exit unemployment. Mathematically, the denominator begins with workers in Equation (57), and the size of this group decreases more slowly than the numerator. To write a counterfactual job finding rate where these workers do not affect $x(\tau)$ for $\tau > 1$, I assume that the outflow rate of this group is the same as the outflow rate of the numerator, $(1 - f^{h})(1 - \phi)$. Thus, define

$$[u^{\ell h}(1) + u^{\ell\ell}(1)|\text{pure DD}] = [u^{\ell h}(0) + u^{\ell\ell}(0)](1 - f^{h})(1 - \phi), \tag{58}$$

and let

$$x(1|\text{pure DD}) = \frac{u^{hh}(1) + u^{h\ell}(1)}{u^{hh}(1) + u^{h\ell}(1) + u^{\tilde{\ell}h}(1) + u^{\tilde{\ell}\ell}(1) + [u^{\ell h}(1) + u^{\ell\ell}(1)|\text{pure DD}]}.$$

After Plugging in Equations (55), (56), and (58),

$$x(1|\text{pure DD}) = \left[1 + \frac{\phi}{1-\phi} + \frac{1-x(0)}{x(0)}\right]^{-1}. \tag{59}$$

In the next period,

$$\begin{aligned} x(2|\text{pure DD}) &= \frac{u^{hh}(2) + u^{h\ell}(2)}{u(2)} \\ &= \frac{u^{hh}(2) + u^{h\ell}(2)}{u^{hh}(2) + u^{h\ell}(2) + u^{\tilde{\ell}h}(2) + u^{\tilde{\ell}\ell}(2) + [u^{\ell h}(2) + u^{\ell\ell}(2)|\text{pure DD}]} \end{aligned}$$

where

$$\begin{aligned} u^{hh}(2) + u^{h\ell}(2) &= [u^{hh}(1) + u^{h\ell}(1)](1-f^h)(1-\phi) \\ u^{\tilde{\ell}h}(2) + u^{\tilde{\ell}\ell}(2) &= [u^{\tilde{\ell}h}(1) + u^{\tilde{\ell}\ell}(1)](1-f^\ell) + [u^{hh}(1) + u^{h\ell}(1)](1-f^h)\phi \\ [u^{\ell h}(2) + u^{\ell\ell}(2)|\text{pure DD}] &= [u^{\ell h}(1) + u^{\ell\ell}(1)](1-f^h)(1-\phi). \end{aligned}$$

After some algebra,

$$x(2|\text{pure DD}) = \left[1 + \phi\left(\frac{1}{1-\phi} + \frac{1}{(1-\phi)^2}\frac{1-f^\ell}{1-f^h}\right) + \frac{1-x(0)}{x(0)}\right]^{-1}$$

If we continue to iterate forward, we find

$$x(\tau|\text{pure DD}) = \left[1 + \phi\sum_{i=1}^{\tau}\frac{1}{(1-\phi)^i}\left(\frac{1-f^\ell}{1-f^h}\right)^{i-1} + \frac{1-x(0)}{x(0)}\right]^{-1} \tag{60}$$

for $\tau \geq 1$. Plug Equation (60) into Equation (54) to obtain Equation (30).

I numerically verified the counterfactual expressions for $f(\tau)$ without permanent heterogeneity and without pure duration dependence.

C Calibration Details

C.1 Empirical Calibration

I estimate the mixed proportional hazard (MPH) model in discrete time. Given the continuous-time hazard rate in Equation (29), the discrete-time hazard rate, analogous to the job-finding rate in my model, is

$$\Psi(X,\tau,v) = 1 - \exp\left\{ - \exp\left[\ln \int_{\tau-1}^{\tau} \Phi(s) ds + \beta' X + \ln(v) \right] \right\}. \tag{61}$$

My main object of interest is $\ln(q_\tau) \equiv \ln \int_{\tau-1}^{\tau} \Phi(s) ds$, the effect of pure duration dependence on the finding rate after τ periods. I estimate q_τ for each τ by using dummy variables for each unemployment duration. The vector of observable characteristics X includes age, age squared, sex, race, marital status, and education.

After estimating Equation (61), I choose β_0 so that the predicted discrete-time hazard at $\tau = 0$ is $f(0) = 1 - \exp[-\exp(\beta_0)]$. Then, the counterfactual job-finding rate at higher τ driven only by pure duration dependence is

$$f(\tau|\text{pure DD}) = 1 - \exp[-\exp(\beta_0 + \ln q_\tau)]. \tag{62}$$

Estimates for Equation (62) appear in Figure 7.

My empirical calibration matches the share of the decline in the job-finding rate that comes from pure duration dependence. Each line in Figure 8 shows the percentage of the decrease in the job finding rate attributable to pure duration dependence. The solid blue line is the MPH estimate for the first six months, and the solid orange line comes from the model calibration that matches this moment. For example, the MPH estimates imply that 65% of the decline in the job finding rate from $\tau = 0$ to $\tau = 1$ is due to pure duration dependence. The dotted lines show the corresponding curves for alternative model fits along the equal-fit

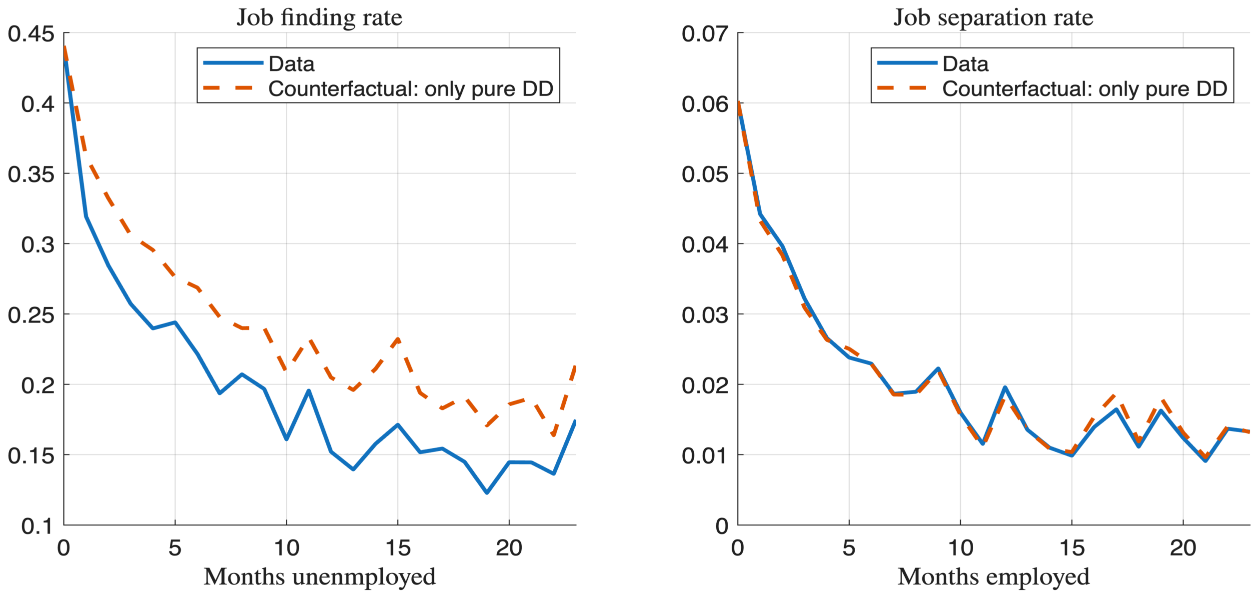

Figure 7: Counterfactual transition rates with only pure duration dependence as implied by the mixed proportional hazard model

Data source: CPS. The counterfactual curves are generated by applying estimates from the mixed proportional hazard model to Equation (62).

curves in Figure 2.

In the model, both pure duration dependence and unobserved heterogeneity can eventually explain the entire decline in the job-finding rate. Because this may not hold in the data, I restrict the calibration target to the first six months.

C.2 s_t^h Shock Estimation

I feed the model shocks to productivity, A_t, and the high separation rate, s_t^h. While A_t is observable in the data, s_t^h is not; I only observe the overall job separation rate, s_t. Since I only use univariate separation shocks for illustration, I assign the s_t^h AR(1) process the same persistence as productivity and set its volatility equal to that of an AR(1) estimated on s_t. To estimate Equation (24), I first estimate the VAR for monthly A_t and s_t. Then, I loop over my empirical model to find the VAR parameters for (A_t, s_t^h) that reproduce the empirical VAR parameters for (A_t, s_t).

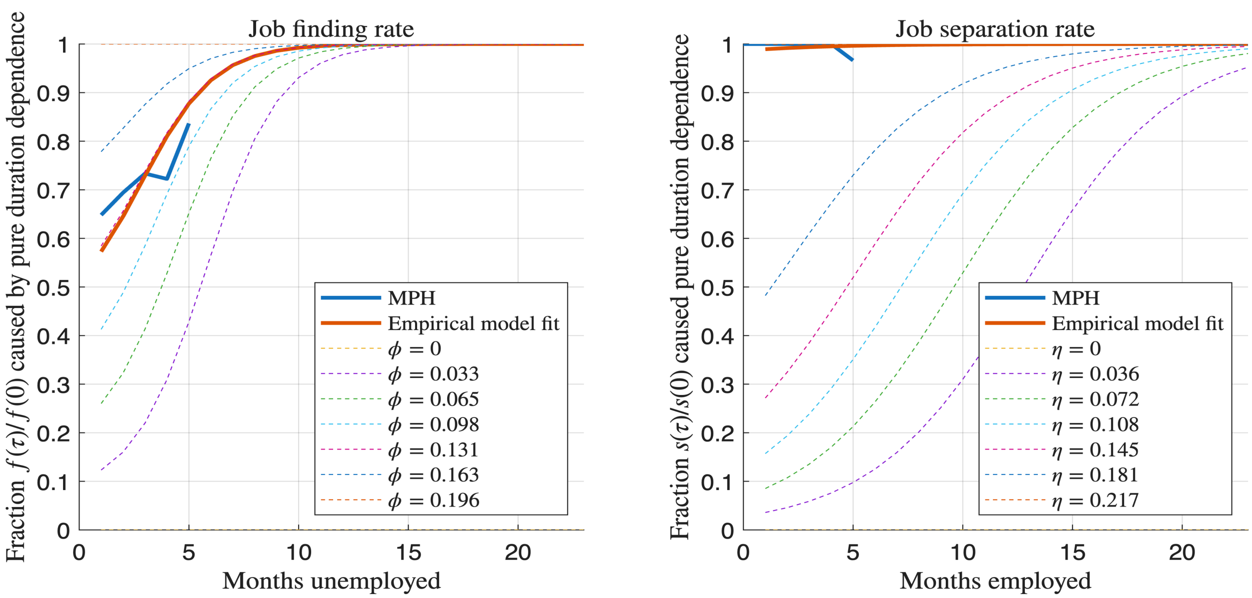

Figure 8: Fraction of decrease in transition rates caused by pure duration dependence

The mixed proportional hazard (MPH) model is estimated on CPS data. The empirical model fit targets the MPH results. Each dotted line refers to a model calibration from the equal-fit curves in Figure 2.

Table 6: Complete calibration results

		DMP	Empirical			Extremes			
f duration dependence		None	Emp.	Emp.	None	Pure DD	Pure DD	Perm. het.	Perm. het.
s duration dependence		None	Emp.	None	Emp.	Pure DD	Perm. het.	Pure DD	Perm. het.
μ	Match efficiency	0.321	0.596	0.585	0.313	0.510	0.510	0.739	0.739
γ	Finding rate penalty	1.000	0.347	0.350	1.000	0.382	0.382	0.303	0.303
ϕ	Finding transition rate	0.000	0.128	0.120	0.000	0.196	0.196	0.000	0.000
s^h	High separation rate	0.017	0.061	0.017	0.061	0.060	0.264	0.060	0.264
δ	Separation rate penalty	1.000	0.221	1.000	0.220	0.223	0.051	0.223	0.051
η	Separation transition rate	0.000	0.216	0.000	0.223	0.217	0.000	0.217	0.000
π^{hh}	hh share of labor force	1.000	0.838	0.862	0.986	1.000	0.020	0.689	0.010
$\pi^{h\ell}$	$h\ell$ share of labor force	0.000	0.013	0.000	0.014	0.000	0.980	0.000	0.694
$\pi^{\ell h}$	ℓh share of labor force	0.000	0.149	0.138	0.000	0.000	0.000	0.311	0.010
κ	Vacancy posting cost	0.181	0.198	0.167	0.214	0.214	0.181	0.165	0.138

The complete set of parameters behind Table 3. The f and s duration dependence rows refer to the duration dependence assumption invoked for finding and separation rates. These assumptions can be "None," referring to no duration dependence or heterogeneity in transition rates at all, "Emp.," referring to the empirical calibration, or "Pure DD" or "Perm het.," which assume that observed duration dependence is entirely caused by pure duration dependence or permanent heterogeneity.

Table 7: Calibration fits

	Data	DMP	Empirical			Extremes			
f duration dependence		None	Emp.	Emp.	None	Pure DD	Pure DD	Perm. het.	Perm. het.
s duration dependence		None	Emp.	None	Emp.	Pure DD	Perm. het.	Pure DD	Perm het.
u	0.050	0.050	0.048	0.050	0.049	0.048	0.048	0.048	0.048
f	0.321	0.321	0.321	0.328	0.313	0.321	0.321	0.321	0.321
λ_1	0.166		0.164	0.165		0.164	0.164	0.164	0.164
λ_2	0.267		0.265	0.266		0.265	0.265	0.265	0.265
λ_3	0.475		0.459	0.465		0.459	0.459	0.459	0.459
ξ_1	0.013		0.013		0.013	0.013	0.013	0.013	0.013
ξ_2	0.047		0.047		0.047	0.047	0.047	0.047	0.047
ξ_3	0.721		0.736		0.730	0.736	0.736	0.736	0.736

All target values in the data and model for each calibration in Table 6.

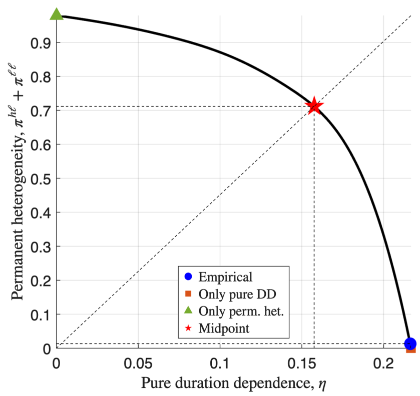

Figure 9: Locus of equal fits for separation duration dependence with midpoint calibration
Equivalent to the right panel of Figure 2 with the addition of the separation midpoint calibration, which bisects the equal-fit curve.

C.3 Complete Calibration Results

Table 6 lists every parameter value for every calibration, and Table 7 displays the fit of each calibration to its targeted moments.

D Additional Results

D.1 Volatility Results

Table 8 reports the standard deviation for model variables in simulations.

D.2 Separation Midpoint Calibration

The calibration results in Section 3 suggest that the empirical calibration for the separation rate is virtually indistinguishable from the pure duration dependence calibration. In this section, I examine an alternative separation-rate calibration that lies approximately at the midpoint between the extreme calibrations of pure duration dependence and permanent heterogeneity. Its simulation results closely match those of the empirical calibration, suggesting that the effect of pure duration dependence in separation rates is highly concave: once there is a sufficient level of pure duration dependence, adding more has little impact.

Table 8: Standard deviations of model variables in simulations

	DMP	Empirical			Extremes			
f duration dependence	None	Emp.	Emp.	None	Pure DD	Pure DD	Perm. het.	Perm. het.
s duration dependence	None	Emp.	None	Emp.	Pure DD	Perm. het.	Pure DD	Perm het.
$SD(u_t)$	0.140	0.147	0.140	0.149	0.158	0.140	0.134	0.114
$SD(\theta_t)$	0.108	0.093	0.103	0.099	0.096	0.105	0.094	0.102
$SD(f_t)$	0.043	0.057	0.061	0.040	0.070	0.075	0.042	0.042
$SD(x_t)$	0.000	0.036	0.035	0.000	0.047	0.048	0.029	0.029
$SD(s_t)$	0.131	0.141	0.131	0.140	0.141	0.121	0.141	0.123
$SD(y_t)$	0.000	0.095	0.000	0.097	0.095	0.067	0.096	0.057

SD refers to standard deviation. This table corresponds to Table 4.

Table 9: Decomposition of volatility in the model

	Standard parameters				Hagedorn-Manovski parameters			
Calibration Shock	DMP Simul.	Emp. Prod.	Emp. Sep.	Emp. Simul.	DMP Simul.	Emp. Prod.	Emp. Sep.	Emp. Simul.
$SD(u_t)$	0.140	0.049	0.082	0.147	0.310	0.357	0.080	0.422
$SD(\theta_t)$	0.108	0.095	0.031	0.093	0.614	0.691	0.039	0.659
$SD(f_t)$	0.043	0.052	0.039	0.057	0.246	0.379	0.043	0.360
$SD(s_t)$	0.131	0.001	0.134	0.141	0.123	0.008	0.134	0.129
$SD(A_t)$	0.031	0.030	0.000	0.031	0.030	0.030	0.000	0.030
$SD(s_t^h)$	0.131	0.000	0.130	0.131	0.123	0.000	0.130	0.123

SD refers to standard deviation. The model simulations use either the DMP or empirical model, and shocks come from productivity, separations, or both simultaneously. The right-hand side repeats the same exercise using HM calibrations.

The "midpoint" calibration is depicted in Figure 9. I bisect the equal-fit curve for the separation side of the model and use the parameters at the red star. While this calibration should not be interpreted as a 50-50 split between pure duration dependence and permanent heterogeneity, it at least resembles the mix in the empirical finding-rate calibration.

Figure 10 adds IRFs from the midpoint calibration to Figure 4, illustrating the effects of a separation shock under different separation-rate calibrations. Note that there is little difference in the response of the unemployment rate to a separation rate shock between the empirical and midpoint calibrations. [28]

D.3 Finding-rate Volatility and the Hagedorn-Manovski Calibration

The main results suggest that the aggregate separation rate is significantly more volatile than the aggregate finding rate over the business cycle. In Figure 6, the separation rate increases twice as much as the finding rate decreases.

The higher volatility of separation rates implies that separation shocks generate most of the unemployment volatility in my model. Table 9 decomposes the volatility of the simulated model under the empirical calibration. To do so, I estimate AR(1) processes parameters for A_t and s_t^h that replicate their properties in the VAR process, then feed each shock into the

[28]Behind the scenes, there is some difference; the separation shock no longer increases the aggregate finding rate, and the path of y_t is slightly different.

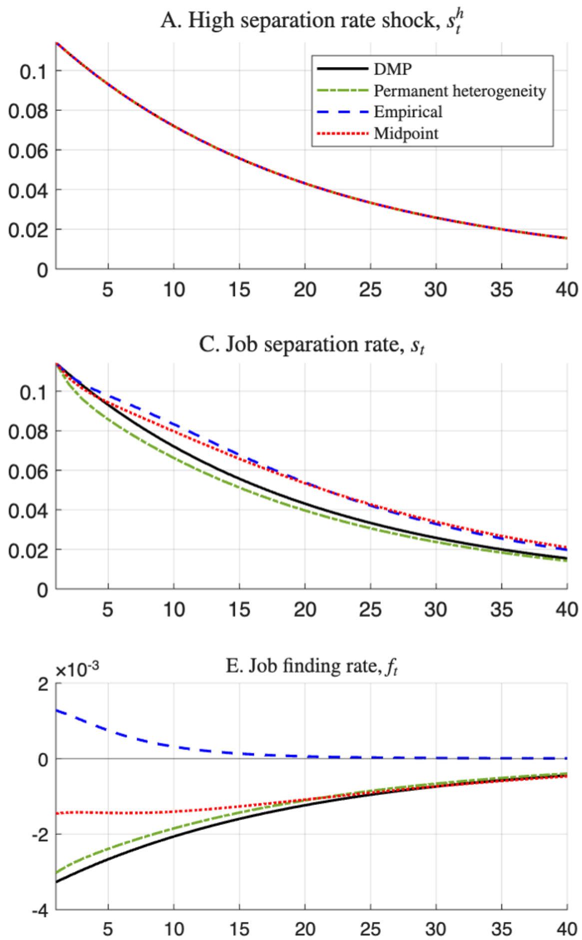

Figure 10: Impulse response functions of separation rate shock with separation duration dependence including midpoint calibration

Adds the IRFs that use the separation midpoint calibration to Figure 4.

model separately. Under the full VAR, the standard deviation of the log unemployment rate is 0.15. With only productivity shocks, it is 0.05, and with only separation shocks, it is 0.08. Thus, roughly 2/3 of the volatility of unemployment comes from separation shocks. This is counterfactual; fluctuations in the unemployment rate are arguably driven more by fluctuations in the aggregate job finding rate than the separation rate.[29]

This result reflects the well-established puzzle in Shimer (2005): when DMP models are calibrated to US data, productivity shocks cannot generate the observed volatility of the finding rate.[30] The problem lies with the free entry condition: since θ_t is a jump variable, its path mirrors the path of A_t, and thus so does f_t. Because productivity fluctuates relatively little over the business cycle, f_t does not fluctuate much in the model. The mechanism is closely related to the persistence problem I address in this paper; since f_t does not persist beyond the shock, unemployment is counterfactually nonpersistent as well.

One way to address the puzzle is through calibration. Hagedorn and Manovskii (2008) (henceforth HM) show that increasing b and decreasing ψ amplifies productivity shocks by increasing the opportunity cost of employment. Because match surplus becomes more sensitive to productivity, θ_t—and thus the finding rate—is more responsive to productivity shocks as well. Thus, in this section, I recalibrate all models with HM parameters $b = 0.955$ and $\psi = 0.052$. This makes no difference in my calibrated parameters except that the cost of posting a job, κ, increases.[31] I then replicate my main results using the HM calibration. The right-hand side of Table 9 confirms that HM parameters increase the volatility of the finding rate; under the HM calibration, 86% of unemployment volatility is driven by productivity shocks.

Figure 11 displays the updated impulse response functions under the HM calibration. Compared to Figure 6, the finding rate is three times more volatile. As a result, finding-rate duration dependence dominates separation-rate duration dependence: the initial increase

[29] See Shimer (2012), Hall (2005), and Elsby et al. (2009). For the view that separations are important for fluctuations in unemployment but that recovery is still mostly driven by outflows, see Elsby et al. (2013), Barnichon (2012), Fujita (2011), Elsby et al. (2010), and Fujita and Ramey (2009).

[30] For overviews, see Mortensen and Nagypal (2007) and Barnichon (2009).

[31] If the model is to match $\theta = 1$ in the steady state but the value of a filled job is greater for firms, then it must be the case that the cost of posting a job is higher.

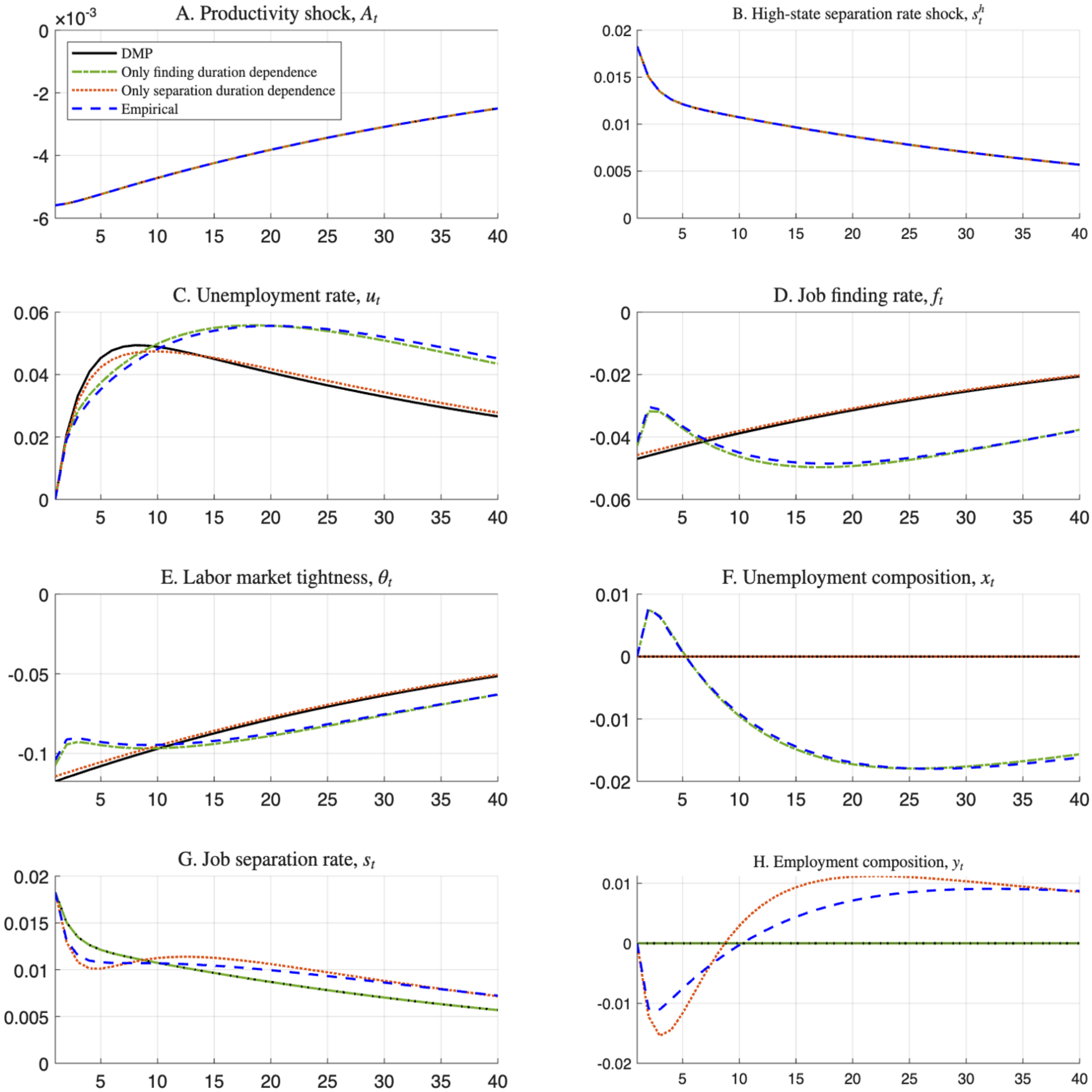

Figure 11: Impulse response functions after a simultaneous shock with Hagedorn-Manovski parameters

A replication of Figure 6 under HM calibrations.

Table 10: Autocorrelations in simulation with Hagedorn-Manovski calibration

	DMP	Empirical			Extremes			
f duration dependence	None	Emp.	Emp.	None	Pure DD	Pure DD	Perm. het.	Perm. het.
s duration dependence	None	Emp.	None	Emp.	Pure DD	Perm. het.	Pure DD	Perm het.
$AC(u_t)$	0.950	0.984	0.982	0.956	0.989	0.987	0.969	0.961
$HL(u_t)$	13.6	42.1	37.2	15.5	64.5	54.5	22.0	17.5
$\%\Delta HL(u_t)$	0.0	209.2	173.8	14.0	373.9	301.0	61.6	28.5
$AC(\theta_t)$	0.955	0.976	0.975	0.956	0.982	0.981	0.965	0.963
$AC(f_t)$	0.955	0.985	0.984	0.956	0.990	0.989	0.967	0.963
$AC(x_t)$		0.953	0.952		0.984	0.982	0.566	0.567
$AC(s_t)$	0.500	0.572	0.500	0.570	0.568	0.329	0.578	0.394
$AC(y_t)$		0.903		0.900	0.901	0.979	0.903	0.927

A replication of Table 4 under HM calibrations.

in x_t is quickly reversed, and the subsequent decrease of x_t is much larger, generating more persistence in the finding rate. Conversely, the response of y_t is slower and relatively smaller. Duration dependence in finding rates also makes θ_t more persistent, further increasing the persistence of f_t. Finally, the HM calibration implies that duration dependence in finding rates makes the unemployment rate more volatile, suggesting that the HM solution to unemployment rate volatility is reinforced by duration dependence.

I replicate my autocorrelation results using the HM calibration in Table 10. The autocorrelation of the unemployment rate is higher in all cases; productivity shocks are more persistent than separation shocks to begin with, so the model will be more persistent when there is a greater emphasis on productivity shocks. With duration dependence in both finding and separation rates, the half-life of unemployment rises by 210%, rather than 90%. The reason is that f_t is more persistent under HM parameters, and when it interacts with the additional persistence generated by duration dependence, the effect multiplies.

D.4 Impulse Response Functions for Analysis of Free Entry Condition

Figure 12 plots the impulse response functions from a productivity shock with and without free entry interactions, as referenced in Section 4.4.

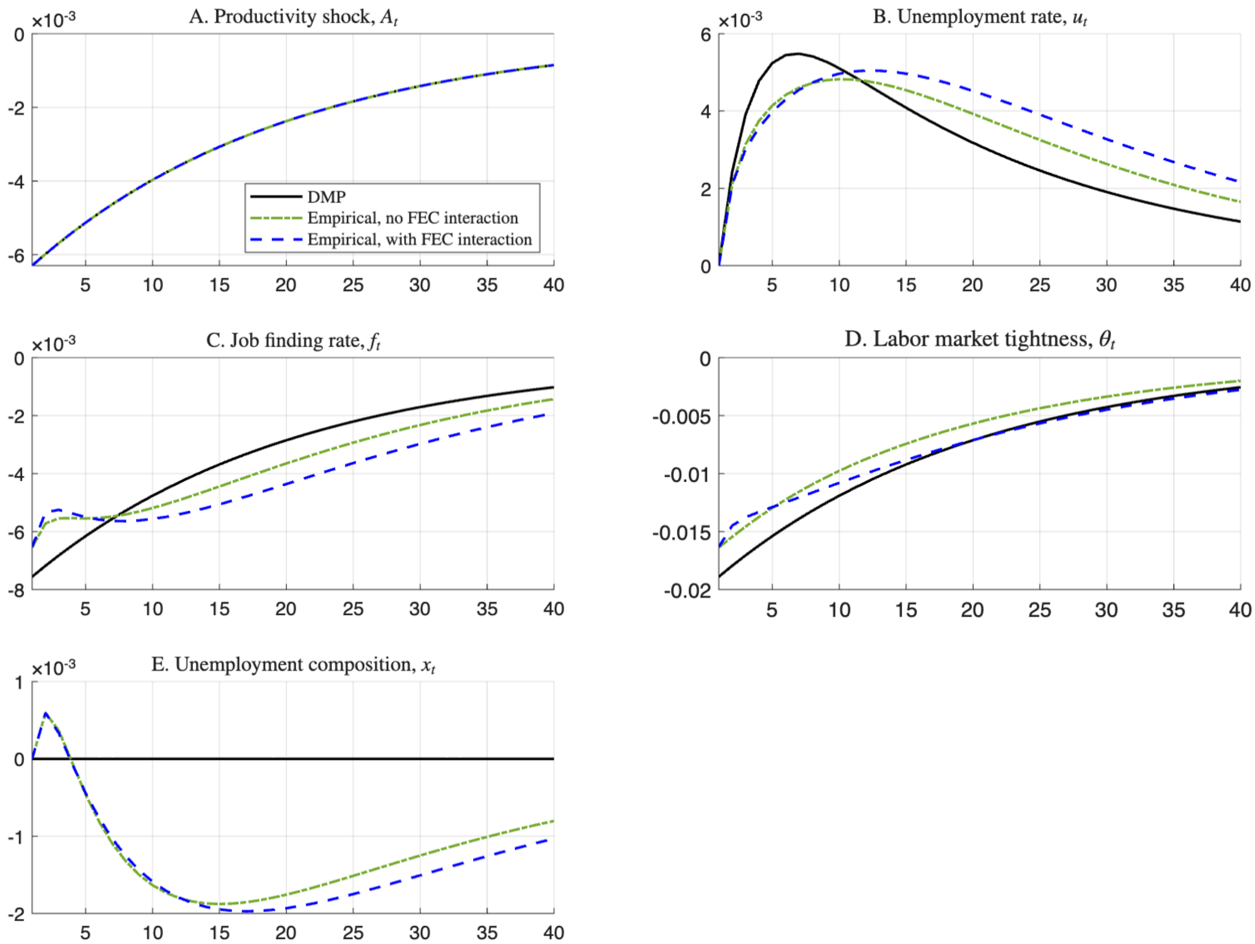

Figure 12: Impulse response functions to productivity shock with and without free entry interactions

Variables are in logs, and the vertical axes show deviations from the steady state. Includes both types of duration dependence using the empirical calibration. Panel A shows the exogenous shock; other panels show endogenous responses.

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