Endogenous Disasters[†]

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Market economies are intrinsically unstable. The standard search model of equilibrium unemployment, once solved accurately with a globally nonlinear algorithm, gives rise endogenously to rare disasters. Intuitively, in the presence of cumulatively large negative shocks, inertial wages remain relatively high, and reduce profits. The marginal costs of hiring run into downward rigidity, which stems from the trading externality of the matching process, and fail to decline relative to profits. Inertial wages and rigid hiring costs combine to stifle job creation flows, depressing the economy into disasters. The disaster dynamics are robust to extensions to home production, capital accumulation, and recursive utility. (JEL E22, E23, E24, E32, J41, J63, N12)

The 2007–2009 Great Recession has raised new challenges for modern macroeconomics. In particular, the current generation of dynamic stochastic general equilibrium models fails to explain the depth and slow recovery of the recent recession (Lindé, Smets, and Wouters 2016). This paper demonstrates that the standard Diamond-Mortensen-Pissarides search model of equilibrium unemployment, once solved accurately with a globally nonlinear algorithm, gives rise endogenously to rare disasters per Rietz (1988) and Barro (2006).

We calibrate a baseline model to the Barro and Ursúa (2008) historical cross-country panel of output and consumption, extended through 2013, as well as the 1929–2013 monthly US unemployment rate series. Applying the Barro-Ursúa peak-to-trough measurement on simulated data, we find that the output disasters in the baseline model have the same average size, about 22 percent, as in the data. The output disaster probability is 5 percent in the model, which is somewhat lower than 7.8 percent

in the data (adjusted for trend growth). For consumption disasters, the probability of 2.9 percent in the model is lower than 8.6 percent in the data, but the average size of 25.6 percent in the model is comparable with 23.2 percent in the data.

We show via comparative statics that two key ingredients, wage inertia and trading externality, combine to endogenize disasters. First, we use a relatively high flow value of unemployment activities, implying (realistically) small profits. More important, a high flow value of unemployment also makes wages inertial. In bad times, output falls, but inertial wages do not fall as much, causing profits to drop disproportionately.

Second, trading externality in the labor market induces downward rigidity in the marginal costs of hiring. If one side of the labor market becomes more abundant than the other side, it will be increasingly difficult for the abundant side to meet and trade with the other side that becomes increasingly scarce. Expansions are periods in which many vacancies compete for a small pool of unemployed workers. The entry of an additional vacancy can cause a pronounced drop in the probability of a given vacancy being filled. This externality raises the marginal costs of hiring, slowing down job creation flows, and making expansions more gradual.

Conversely, recessions are periods in which many unemployed workers compete for a small pool of vacancies. Filling a vacancy occurs quickly, and the marginal costs of hiring are lower. However, in recessions, the congestion in the labor market affects unemployed workers, rather than vacancies. The entry of a new vacancy has little impact on the probability of a given vacancy being filled. Consequently, although the marginal costs of hiring rise rapidly in expansions, the marginal costs decline only slowly in recessions. This downward rigidity is further reinforced by fixed matching costs per Pissarides (2009). By putting a constant component into the marginal costs of hiring, the fixed costs restrict the marginal costs from declining in recessions, further hampering job creation flows. We emphasize that the trading externality and its resulting rigid marginal costs of hiring arise endogenously from the search model of unemployment, but are absent from the neoclassical growth model.

To see how the key ingredients combine to endogenize disasters, consider cumulatively large negative shocks. The small profits become even smaller as productivity falls. Inertial wages remain relatively high, and reduce the small profits still further. To make a bad situation worse, the marginal costs of hiring run into downward rigidity, an inherent attribute of the matching process, which is further buttressed by fixed matching costs. As the marginal costs of hiring fail to decline to counteract shrinking profits, the incentives of hiring are suppressed, and job creation flows stifled. In the mean time, jobs are destroyed at a steady rate. Consequently, aggregate employment falls off a cliff, giving rise to disasters.

The disaster dynamics are robust to several extensions. We first microfound the high flow value of unemployment via home production. The extended model implies an output disaster probability of 10 percent, which is higher than 7.8 percent in the data, and consumption disaster probability of 7.5 percent, which is lower than 8.6 percent in the data. However, the average size is slightly smaller, 18.6 and 18.1 percent for output and consumption, respectively. Also, the disaster dynamics are stronger when market and home goods are less substitutable, and market goods are weighted less in the household's utility.

In the second extension, we incorporate capital into the baseline model. The disaster dynamics are similar to those in the home production model. The disaster probabilities are largely aligned with those in the data, but the average size is slightly smaller. Capital adjustment costs dampen investment dynamics, amplify consumption dynamics, but leave employment and output dynamics largely unaffected. Finally, we incorporate recursive utility into the baseline model. The disaster dynamics are quantitatively close to those in the baseline model. A high risk aversion allows this extended model to match the equity premium in the data. However, the high risk aversion has a small impact on the disaster moments and unemployment dynamics, a finding that echoes Tallarini (2000).

Our work makes four contributions. First, the macro labor literature has traditionally focused on the unemployment volatility (Shimer 2005). We develop a globally nonlinear algorithm for solving the search model, and quantify its overlooked disaster dynamics.[1] Second, we contribute to the disasters literature in finance (Rietz 1988; Barro 2006; and Gourio 2012). The existing studies specify exogenous disasters via large negative productivity shocks. Instead, our log productivity follows an autoregressive process with homoscedastic shocks. As such, our disasters are entirely endogenous. Third, we contribute to the Great Depression literature. Building on a diverse set of studies emphasizing wage inertia in the Great Depression (Eichengreen and Sachs 1985; Bernanke and Carey 1996; Bordo, Erceg, and Evans 2000; Cole and Ohanian 2004; and Ohanian 2009), we show how wage inertia and trading externality combine to endogenize disasters in equilibrium. Finally, building on the seminal work of Christiano, Eichenbaum, and Evans (2005) and Smets and Wouters (2007), a recent literature has embedded the search model into the New Keynesian business cycle framework (Gertler, Sala, and Trigari 2008; and Christiano, Eichenbaum, and Trabandt 2015, 2016). Our work shows the importance of nonlinear dynamics in this class of models.

Section I demonstrates disasters in the baseline model. Section II shows that disasters are robust to extensions to home production, capital accumulation, and recursive utility. Section III concludes. The online Appendix details data, proofs, computation, and supplementary results.

I. The Baseline Model

We present a textbook search and matching model (Diamond 1982; Mortensen 1982; and Pissarides 1985) in Section IA, calibrate it in Section IB, and quantify its disaster dynamics in Section IC.

A. *Environment*

The model is populated by a representative household and a representative firm that uses labor as the single productive input. The household has log utility,

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[1] In subsequent work, Petrosky-Nadeau and Zhang (2017) show that relative to the globally nonlinear algorithm, the commonly adopted loglinearization understates the mean and volatility of unemployment, but overstates the volatility of the labor market tightness and the unemployment-vacancy correlation. In addition, the second-order perturbation in logs can induce approximation errors that are often even larger than those from loglinearization.

$\log(C_t)$, meaning that its stochastic discount factor is given by $M_{t+1} = \beta(C_t/C_{t+1})$, in which C_t is consumption, and β is the time discount factor. Following Merz (1995), we assume that the household has perfect consumption insurance. There exists a continuum of mass 1 of members who are, at any point in time, either employed or unemployed. The fractions of employed and unemployed workers are representative of the population at large. The household pools the income of all the members together before choosing per capita consumption.[2]

Search and Matching.—The representative firm posts a number of job vacancies, V_t, to attract unemployed workers, U_t. Vacancies are filled via a constant returns to scale matching function,

$$(1) \qquad G(U_t, V_t) = \frac{U_t V_t}{\left(U_t^\iota + V_t^\iota\right)^{1/\iota}},$$

in which $\iota > 0$. This matching function, from Den Haan, Ramey, and Watson (2000), has the desirable property that matching probabilities fall between 0 and 1.

In particular, define $\theta_t \equiv V_t/U_t$ as the vacancy-unemployment (V/U) ratio. The probability for an unemployed worker to find a job per unit of time (the job finding rate) is $f(\theta_t) \equiv G(U_t, V_t)/U_t = \left(1 + \theta_t^{-\iota}\right)^{-1/\iota}$. The probability for a vacancy to be filled per unit of time (the vacancy filling rate) is $q(\theta_t) \equiv G(U_t, V_t)/V_t = \left(1 + \theta_t^\iota\right)^{-1/\iota}$. It follows that $f(\theta_t) = \theta_t q(\theta_t)$ and $q'(\theta_t) < 0$, meaning that an increase in the scarcity of unemployed workers relative to vacancies makes it harder to fill a vacancy. As such, θ_t is labor market tightness from the firm's perspective, and $1/q(\theta_t)$ is the average duration of vacancies.

The representative firm incurs costs in posting vacancies. The unit costs per vacancy, κ_t, contain both the proportional costs, κ_0, and the fixed costs, κ_1:

$$(2) \qquad \kappa_t \equiv \kappa_0 + \kappa_1 q(\theta_t),$$

in which $\kappa_0, \kappa_1 > 0$. The fixed costs, paid after a worker is hired, capture training and administrative setup costs of adding the worker to the payroll. The marginal costs of hiring arising from the proportional costs, $\kappa_0/q(\theta_t)$, increase with the mean duration of vacancies, $1/q(\theta_t)$, whereas the marginal "fixed" costs are constant, κ_1. The total marginal costs of hiring equal $\kappa_0/q(\theta_t) + \kappa_1$. In expansions, the labor market is tighter for the firm (θ_t is higher), and the vacancy filling rate, $q(\theta_t)$, is lower. As such, the marginal costs of hiring are procyclical.

Jobs are destroyed at a constant rate of s per period. Employment, N_t, evolves as

$$(3) \qquad N_{t+1} = (1 - s) N_t + q(\theta_t) V_t,$$

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[2] It should be noted that relaxing the perfect consumption insurance might weaken disaster dynamics. With imperfect insurance, unemployed workers would accept jobs at lower wages, reducing unemployment, and dampening disaster dynamics. However, Krusell, Mukoyama, and Sahin (2010) show that the search model with imperfect consumption insurance behaves almost as the representative agent model. Intuitively, individual self-insurance via asset accumulation is effective. Also, wage inertia required for the model to match labor market volatilities counteracts the dampening effect of imperfect insurance.

in which $q(\theta_t) V_t$ is the number of new hires. Population is normalized to be 1, $U_t + N_t = 1$, meaning that N_t and U_t are also the rates of employment and unemployment, respectively.

The Representative Firm.—The firm takes the aggregate productivity, X_t, as given. We specify $x_t \equiv \log(X_t)$ as

$$(4) \qquad x_{t+1} = \rho x_t + \sigma \epsilon_{t+1},$$

in which $\rho \in (0, 1)$ is the persistence, $\sigma > 0$ the conditional volatility, and ϵ_{t+1} an independently and identically distributed standard normal shock. The firm uses labor to produce output, Y_t, with a constant returns to scale production technology,

$$(5) \qquad Y_t = X_t N_t.$$

We abstract from capital, but include it later in a model extension (Section IIB). While Cole and Ohanian (1999) emphasize productivity shocks in the Great Depression, monetary shocks are also likely important (Friedman and Schwartz 1963). We remain agnostic about the origins of disasters, but shed light on the endogenous propagation mechanism from the labor market.

The dividends to the firm's shareholders are given by

$$(6) \qquad D_t = X_t N_t - W_t N_t - \kappa_t V_t,$$

in which W_t is the wage rate. Taking W_t, the household's stochastic discount factor, M_{t+1}, and the vacancy filling rate, $q(\theta_t)$, as given, the firm posts the optimal number of vacancies to maximize the cum-dividend market value of equity, S_t:

$$(7) \qquad S_t \equiv \max_{\{V_{t+\tau}, N_{t+\tau+1}\}_{\tau=0}^{\infty}} E_t\left[\sum_{\tau=0}^{\infty} M_{t+\tau} D_{t+\tau}\right],$$

subject to equation (3) and a nonnegativity constraint on vacancies, $V_t \geq 0$.[3]

Because $q(\theta_t) > 0$, $V_t \geq 0$ is equivalent to $q(\theta_t) V_t \geq 0$. As such, the only source of job destruction is the exogenous separation of workers from the firm. In particular, we abstract from endogenous job destruction to keep the model parsimonious. However, incorporating this ingredient is likely to strengthen, rather than weaken, our quantitative results. Intuitively, job destruction should rise during recessions, reinforcing disaster dynamics. In particular, Den Haan, Ramey, and Watson (2000) show that endogenous job destruction amplifies the impact of aggregate shocks in an equilibrium search model.

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[3] The $V_t \geq 0$ constraint has been ignored so far in the existing literature. Using a globally nonlinear algorithm, we find that the constraint is occasionally binding in the model's simulations. Because a negative vacancy does not make economic sense, we opt to impose the constraint to solve the model accurately. However, this constraint does not form a key ingredient of the model, and matters little for the quantitative results. In our benchmark calibration, for instance, the constraint only binds 0.2 percent of the time, which is very rare.

Let λ_t be the multiplier on $q(\theta_t) V_t \geq 0$. From the first-order conditions with respect to V_t and N_{t+1}, we obtain the intertemporal job creation condition:

$$(8) \quad \frac{\kappa_0}{q(\theta_t)} + \kappa_1 - \lambda_t = E_t\left[M_{t+1}\left(X_{t+1} - W_{t+1} + (1 - s)\left(\frac{\kappa_0}{q(\theta_{t+1})} + \kappa_1 - \lambda_{t+1} \right) \right) \right].$$

Intuitively, the marginal costs of hiring at time t (with $V_t \geq 0$ accounted for) equal the marginal value of hiring to the firm, which in turn equals the marginal benefits of hiring at period $t + 1$, discounted to t with the stochastic discount factor, M_{t+1}. The marginal benefits at $t + 1$ include the marginal product of labor, X_{t+1}, net of the wage rate, W_{t+1}, plus the marginal value of hiring, which equals the marginal costs of hiring at $t + 1$, net of separation. Finally, the optimal vacancy policy also satisfies the Kuhn-Tucker conditions:

$$(9) \quad q(\theta_t) V_t \geq 0, \quad \lambda_t \geq 0, \quad \text{and} \quad \lambda_t q(\theta_t) V_t = 0.$$

The Equilibrium Wage.—The equilibrium wage is determined endogenously by applying the sharing rule per the outcome of a generalized Nash bargaining process between employed workers and the firm. Let $\eta \in (0, 1)$ be the workers' relative bargaining weight, and b the workers' flow value of unemployment activities. The equilibrium wage rate is given by (see the online Appendix)

$$(10) \quad W_t = \eta(X_t + \kappa_t \theta_t) + (1 - \eta) b.$$

The wage rate is increasing in labor productivity, X_t, and the total vacancy costs per unemployed worker, $\kappa_t \theta_t$. Intuitively, the more productive the workers are, and the more costly for the firm to fill a vacancy, the higher the wage rate will be for the employed workers. In addition, the flow value of unemployment, b, and the workers' bargaining weight, η, affect the wage elasticity to labor productivity. The lower η is, and the higher b is, the more the equilibrium wage will be tied with the constant b, inducing a lower wage elasticity to productivity.

Competitive Equilibrium.—The competitive equilibrium consists of vacancy posting, $V_t \geq 0$, multiplier, $\lambda_t \geq 0$, and consumption, C_t, such that V_t and λ_t satisfy the intertemporal job creation condition (8) and the Kuhn-Tucker conditions (9), while taking the stochastic discount factor M_{t+1} and the wage rate in equation (10) as given; and the goods market clears:

$$(11) \quad C_t + \kappa_t V_t = X_t N_t.$$

The Projection Algorithm.—We develop a global projection algorithm to solve for the competitive equilibrium. The state space, (N_t, x_t), consists of employment and productivity. The goal is to solve for the optimal vacancy, $V(N_t, x_t)$, and the multiplier, $\lambda(N_t, x_t)$, from the functional equation (8), while also satisfying the Kuhn-Tucker conditions (9). The standard projection method calls for approximating the V_t and λ_t functions directly. With the $V_t \geq 0$ constraint, the functions are not

smooth, making the approximation tricky and cumbersome. As such, we adapt the Christiano and Fisher (2000) parameterized expectations method by approximating the conditional expectation (the right-hand side) of equation (8), denoted $\mathcal{E}_t \equiv \mathcal{E}(N_t, x_t)$. We then exploit a convenient mapping from $\mathcal{E}_t$ to V_t and λ_t to eliminate the need to parameterize λ_t separately. In particular, after obtaining the parameterized $\mathcal{E}_t$, we first calculate $\tilde{q}(\theta_t) = \kappa_0 / (\mathcal{E}_t - \kappa_1)$. If $\tilde{q}(\theta_t) < 1$, $V_t \geq 0$ is not binding, we set $\lambda_t = 0$ and $q(\theta_t) = \tilde{q}(\theta_t)$. We then solve $\theta_t = q^{-1}(\tilde{q}(\theta_t))$, in which $q^{-1}(\cdot)$ is the inverse function of $q(\theta_t)$, and $V_t = \theta_t(1 - N_t)$. If $\tilde{q}(\theta_t) \geq 1$, $V_t \geq 0$ is binding, we set $V_t = 0$, $\theta_t = 0$, $q(\theta_t) = 1$, and $\lambda_t = \kappa_0 + \kappa_1 - \mathcal{E}_t$. The online Appendix describes our global algorithm in detail.

B. *Data, Calibration, and Basic Moments*

Because we focus on rare disasters, we calibrate the model to a historical cross-country panel of output and consumption compiled by Barro and Ursúa (2008). For unemployment moments, because historical cross-country data for unemployment and vacancies are not available, we calibrate the model to a long US sample constructed by Petrosky-Nadeau and Zhang (2013). For variables such as wages and net payouts, we calibrate the model to the only available postwar US data. Our calibration does not use steady-state relations, which hold very poorly in simulations due to the model's nonlinearity. We take care in reporting a wide range of model moments to compare with data moments. For parameters that are important for our quantitative results, we perform extensive comparative statics to show their impact.

Data.—We obtain the historical cross-country panel from Robert Barro's website. The Barro-Ursúa dataset ends in 2009, and we extend it through 2013. The dataset contains annual real consumption and output series for multiple countries. The starting points of the output series range from 1790 for United States to 1911 for Korea and South Africa, and the starting points of the consumption series range from 1800 for Sweden to 1938 for Greece. We discard countries with missing data (often in the Great Depression) and countries with only postwar data. We impose this restriction to ensure that estimates of disaster moments are relatively unbiased.

Tables 1 and 2 report descriptive statistics for output and consumption growth rates, respectively. From Table 1, the output growth has a volatility of 5.6 percent per annum, a skewness of -1, and a kurtosis of 11.9, all averaged across countries. The first-order autocorrelation is 0.16, but high-order autocorrelations are largely zero. From Table 2, the consumption growth has a volatility of 6.4 percent, a skewness of -0.6, and a kurtosis of 9.2, on average. The first-order autocorrelation is 0.07, but high-order autocorrelations are again close to 0.[4]

Calibration.—We calibrate the model in monthly frequency. The time discount factor, β, is set to 0.9954 to match the average discount rate around 5.7 percent per

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[4]Consistent with Barro and Ursúa (2008), the output growth volatility is lower than the consumption growth volatility in the cross-country panel. As pointed out by Barro and Ursúa, government purchases tend to increase sharply during wartime. This expansion in government spending decreases consumption for a given level of output, and raises the consumption volatility relative to the output volatility.

TABLE 1—PROPERTIES OF THE LOG REAL PER CAPITA ANNUAL OUTPUT GROWTH

	σ_Y	S_Y	K_Y	ρ_1^Y	ρ_2^Y	ρ_3^Y	ρ_4^Y
Argentina	6.62	−0.57	4.48	0.02	−0.11	0.04	−0.07
Australia	6.33	0.4	5.99	−0.05	−0.14	0.13	0.09
Austria	8.33	−6.17	61.39	0.18	0.05	−0.06	−0.15
Belgium	6.97	1.31	21.44	0.32	0.05	0	0.03
Brazil	4.84	−0.44	4.17	0.14	−0.05	−0.03	0.03
Canada	5	−0.78	5.06	0.26	0.11	−0.07	−0.15
Chile	5.77	−1.04	5.47	0.07	−0.15	−0.07	−0.07
China	7.04	−0.78	3.53	0.48	0.19	0.16	0.19
Colombia	2.22	−0.63	4.16	0.34	0.14	−0.05	−0.16
Denmark	3.51	−0.82	7.5	0	−0.12	0.05	0.08
Egypt	4.67	0.92	7.2	−0.08	−0.06	0.29	−0.01
Finland	4.63	−0.70	6.36	0.21	−0.13	0.06	−0.11
France	6.16	−0.81	9.89	0.07	−0.09	0.09	0.08
Germany	10.13	−7.91	86.02	0.3	−0.04	−0.11	−0.16
Iceland	4.93	−0.44	4.5	0.15	0.08	0.04	−0.1
India	4.79	−0.12	4.67	−0.2	0.02	0.3	−0.1
Indonesia	5.69	−2.3	12.74	0.45	0.22	0.11	−0.09
Italy	4.64	−1.33	13.49	0.26	−0.07	−0.03	0.14
Japan	6.22	−2.24	15.35	0.27	0.03	0.16	0.09
Korea	6.93	−1.64	9.59	0.14	−0.1	−0.03	−0.03
Mexico	4.19	−1.33	6.61	0	0.21	0.04	−0.07
Netherlands	6.47	1.1	29.05	0.17	−0.17	−0.07	−0.04
New Zealand	4.56	0.43	5.04	0.15	−0.17	0	0.19
Norway	3.65	−0.58	5.92	0.09	−0.13	0.01	0.07
Peru	4.81	−1.33	5.88	0.44	0.02	−0.16	−0.14
Portugal	4.12	0	4.32	0.01	0.18	0.02	0.18
Russia	8.3	−0.72	6.27	0.34	0.23	0.16	0.04
South Africa	4.8	−1.66	14.61	0.02	0.15	0.04	−0.11
Spain	4.48	−1.70	12.24	0.24	0.04	0.04	0.01
Sri Lanka	4.48	−0.18	3.79	0.08	−0.01	0.19	−0.07
Sweden	4.12	−0.74	5.5	0	−0.16	−0.15	0.11
Switzerland	4.58	−0.24	4.32	−0.01	−0.23	0.09	0
Taiwan	8.77	−4.06	31.39	0.35	0	−0.04	0.03
Turkey	8.11	−0.6	5.3	0.13	0.13	−0.05	−0.09
United Kingdom	2.86	−0.77	5.03	0.3	−0.02	−0.15	−0.2
United States	4.28	0	5.15	0.25	0.06	−0.11	−0.16
Uruguay	7.76	−0.54	3.43	−0.01	−0.05	−0.14	−0.14
Venezuela	8.34	0.44	4.05	0.09	0.15	0.09	−0.08
Average	5.63	−1.02	11.87	0.16	0	0.02	−0.02

Note: σ_Y denotes volatility (in percent), S_Y skewness, K_Y kurtosis, and ρ_i^Y the ith-order autocorrelation.
Source: Barro-Ursúa (2008) historical cross-country panel, extended through 2013

annum in a historical cross-country panel of asset prices (Section IIC). Following Gertler and Trigari (2009), we set the persistence of the log productivity, ρ, to be $0.95^{1/3}$, and choose its conditional volatility, σ, to match the output growth volatility in the data. This procedure yields a value of 0.01 for σ, which implies an output growth volatility of 5.3 percent per annum in the model, which is close to 5.6 percent in the data.

We calibrate the labor market parameters in the spirit of Hagedorn and Manovskii (2008). The workers' bargaining weight, η, is 0.04, which implies a wage elasticity to labor productivity of 0.51, close to 0.47 in the postwar US data. The flow value of unemployment, b, merits more discussion. Shimer (2005) pins down $b = 0.4$ by assuming that the only flow value is unemployment insurance benefits. However, Hagedorn and Manovskii argue that in a perfectly competitive market, b should equal the flow value of employment.

Table 2—Properties of the log Real per Capita Annual Consumption Growth

	σ_C	S_C	K_C	ρ_1^C	ρ_2^C	ρ_3^C	ρ_4^C
Argentina	7.84	0.14	4.21	−0.14	0.04	−0.27	0.08
Australia	4.95	−1.02	8.25	0.15	0.06	0.08	−0.06
Belgium	8.81	−1.14	12.97	0.26	0.19	0	−0.4
Brazil	7.25	0.34	4.14	−0.26	−0.03	0.1	−0.06
Canada	4.65	−1.03	6.19	0	0.16	−0.16	−0.04
Chile	9.1	−1.2	5.26	0.08	−0.13	−0.11	−0.12
Colombia	6.18	0.54	7.18	−0.22	0.04	0.05	−0.3
Denmark	5.25	−0.68	10.34	−0.10	−0.31	0.01	0.21
Egypt	6.09	0.3	6.3	−0.2	−0.15	0.19	−0.01
Finland	5.73	−1.02	7.94	0.14	−0.1	−0.01	−0.04
France	6.27	−0.99	12.94	0.32	0.15	−0.02	−0.27
Germany	5.27	−0.57	7.55	0.24	0.21	0.27	−0.06
Greece	9.83	0.11	12.04	0.24	0.39	0.16	0.11
India	4.31	0.47	5.97	−0.06	0.18	−0.07	0.34
Italy	3.59	0.16	7.76	0.38	0.31	0.1	0.09
Japan	6.78	−1.54	20.71	0.21	0.11	0.18	0.2
Korea	6.6	−1.09	6.26	0.18	0.03	−0.29	−0.07
Mexico	6.03	1.20	11.66	−0.09	−0.04	0.04	−0.02
Netherlands	7.3	−0.79	22.68	0.12	0.14	−0.2	−0.18
New Zealand	5.89	−0.74	7.98	−0.13	−0.14	0.08	0.07
Norway	3.73	−0.27	9.81	0	−0.31	0.14	−0.01
Peru	4.62	−1.15	6.32	0.39	0	−0.12	−0.01
Portugal	4.41	−0.48	3.21	0.22	0.23	−0.01	0.1
Russia	10.4	−1.35	12.27	0.37	0.08	0.2	−0.03
Spain	7.27	−2.81	25.14	−0.02	−0.02	−0.1	−0.06
Sweden	4.85	0.04	4.94	−0.09	−0.12	−0.17	0.13
Switzerland	7.86	0.43	5.39	−0.34	−0.11	0.04	−0.12
Taiwan	8.9	−2.33	16.2	0.28	−0.02	0.05	−0.03
Turkey	7.78	−1.02	6.69	0.15	0.07	0.01	−0.11
United Kingdom	2.65	−0.35	8.48	0.29	0.01	−0.04	−0.04
United States	3.79	−0.06	3.49	0.04	0.07	−0.07	−0.03
Venezuela	9.8	0.18	3.93	−0.03	0.11	−0.11	0.06
Average	6.37	−0.55	9.19	0.07	0.03	0	−0.02

Note: σ_C denotes volatility (in percent), S_C skewness, K_C kurtosis, and ρ_i^C the ith-order autocorrelation.
Source: Barro-Ursúa (2008) historical cross-country panel, extended through 2013

Specifically, b measures not only unemployment insurance, but also home production, self-employment, disutility of work, and leisure. In the model, the mean marginal product of labor is 1, to which b should be close. We set $b = 0.85$, which equals that in Rudanko (2011), close to 0.88 estimated by Christiano, Eichenbaum, and Trabandt (2016), but far less extreme than 0.955 in Hagedorn and Manovskii.

The value of $b = 0.85$ implies a realistic magnitude of profits in our model. The profits-to-output ratio in the model's simulations is on average 8.6 percent (with a cross-simulation standard deviation of 0.8 percent), which is close to 9.1 percent in the US data from 1929 to 2013. In contrast, $b = 0.955$ per Hagedorn and Manovskii (2008) would imply unrealistically tiny profits, and $b = 0.4$ per Shimer (2005) unrealistically huge profits (31 percent of output, Section IC).

We make two more remarks on b based on the outside option of workers and real wage inertia in the Great Depression. First, unemployment insurance played a role in the Great Depression. Benjamin and Kochin (1979) argue that the persistently high unemployment rate in Britain from 1921 to 1938 (on average 14 percent) was

due to high unemployment benefits. Weekly benefits exceeded 50 percent of average weekly wages by 1931, and increased to nearly 60 percent by 1938. The generous benefits were subject to few restrictions, independent of a worker's past wages, payable for spells of unemployment as short as one day, and were collectible indefinitely. Cole and Ohanian (2002) argue that these benefits might be comparable with the market wages of displaced workers, because workers tend to experience large declines in their wages after a layoff. Jacobson, LaLonde, and Sullivan (1993) show that high-tenure workers who separate from distressed firms suffer initial earnings losses of 45 percent and long-term losses of 25 percent per year. However, unemployment insurance was limited outside Britain.

Ramey and Francis (2009) develop comprehensive measures of time use in market work, home production, schooling, and leisure in the United States from 1900 to 2005. Hours of work for prime age individuals are virtually unchanged, as the rise in women's hours compensate the decline in men's hours. Per capita leisure has increased by only 10 percent since 1900, and this increase is tiny relative to that in the real wage (and productivity) of 820 percent. Ramey (2009) also documents that averaged across the entire population, per capita time use in home production is essentially unchanged during the twentieth century.

Second, more important, our b calibration is only a parsimonious metaphor for real wage inertia, which seemed important in the Great Depression. Eichengreen and Sachs (1985), Temin (1989), and Eichengreen (1992) argue that contractionary monetary shocks in the US during the Great Depression were transmitted globally by the gold standard. Eichengreen and Sachs show that real wages were higher, and industrial production lower across countries that remained on (than countries that left) the gold standard. Bernanke and Carey (1996) show that nominal wages adjusted slowly despite deflation, and the resulting increases in real wages depressed employment and output. Using simulations from a monetary model, Bordo, Erceg, and Evans (2000) show that real wage inertia was quantitatively important in the Great Depression.

Cole and Ohanian (2004) argue that New Deal cartelization policies caused wage inertia and the weak recovery in the US after 1933. These policies were designed to limit competition in product markets and to increase labor bargaining power. From 1933 to 1935, the National Industrial Recovery Act suspended antitrust laws, and allowed collusion in some industries in exchange for higher wages and collective bargaining with labor unions. After 1935, the National Labor Relations Act gave even more bargaining power to workers. Cole and Ohanian show that real wages increased significantly across industries covered by the New Deal policies, but decreased in the agriculture industry not covered by these policies.

Ohanian (2009) shows further that President Hoover's industrial labor program prior to New Deal had a large impact in the early stages of the Great Depression. Under this program, starting in late 1929, large manufacturing firms either raised nominal wages or at least kept them fixed at their 1929 levels, and shared work among employees. In return, labor unions agreed to withdraw demands for higher wages and not to strike. By late 1931, real wages in manufacturing had increased by more than 10 percent as a result of Hoover's program and deflation.

Outside the United States, Beaudry and Portier (2002) document that because of deflation, real wages in France increased continuously from 1929 to 1936, and remained roughly constant through 1939. Fisher and Hornstein (2002) show that real wages in Germany were strongly countercyclical, increasing by 11 percent from 1928 to 1931, and returning only slowly to their 1928 levels by 1937. Perri and Quadrini (2002) show that real wages in the tradable sector in Italy increased by more than 20 percent from 1929 to 1933, and declined gradually to their 1929 levels by 1938. Giordano, Piga, and Trovato (2014) show that industrial real wages deflated by the wholesale price index in Italy grew by about 40 percent in the 1929–1934 period.

We set the job separation rate, s, to be 4 percent, which is within the range of estimates from Davis, Faberman, and Haltiwanger (2006). We set the curvature parameter in the matching function, ι, to be 1.25, close to that in Den Haan, Ramey, and Watson (2000). To pin down the proportional and fixed costs of vacancy, κ_0 and κ_1, we first experiment to keep the total unit costs of vacancy, κ_t, around 0.7 on average. This level is necessary for the model to reproduce a realistic unemployment rate of 6.3 percent, which is not far from the average unemployment rate of 7.1 percent in the 1929–2013 US sample. The evidence on the relative weights of the proportional and fixed costs is scarce. To determine κ_0 and κ_1 separately, we target the (quarterly) unemployment volatility of 19.8 percent in the data. This procedure yields $\kappa_0 = \kappa_1 = 0.5$, which implies an unemployment volatility of 23.4 percent.

Is the magnitude of the vacancy (hiring) costs in the model empirically plausible? As noted, the marginal costs of vacancy posting in terms of labor productivity (output per worker) equal 0.7 in the model, which is the average of $\kappa_0 + \kappa_1 q(\theta_t)$ in simulations. The marginal costs of hiring, $\kappa_0 / q(\theta_t) + \kappa_1$, are on average 1.9. Merz and Yashiv (2007) estimate the marginal costs of hiring to be 1.5 times the average output per worker with a standard error of 0.6. As such, 1.9 is at least plausible. For the total costs of vacancy, $\kappa_t V_t$, the average in the model is about 0.7 percent of annual wages (2.6 percent of quarterly wages). This magnitude is also plausible. The estimated labor adjustment costs in Bloom (2009) imply hiring and firing costs of about 1.8 percent of annual wages and high fixed costs of around 2.1 percent of annual revenue. Silva and Toledo (2009) estimate total turnover costs to be about 3.6 percent of quarterly wages for a fully productive worker and 4.3 percent of those for a newly hired worker.

Implicitly in our calibration, we assume the same matching technology within and outside disasters. Figure 1 plots the long-term US Beveridge curve from April 1929 to December 2013. Most important, the 1929–1939 observations, as well as the 1940–1950 observations, form a natural extension of the postwar Beveridge curve into the high-unemployment-low-vacancy and low-unemployment-high-vacancy regions, respectively. We interpret the evidence as indicating the stability of the underlying matching technology over the past eight-and-a-half decades. In particular, the Great Depression was not associated with any visible shift in the Beveridge curve. Finally, the vacancy rate experienced large declines during the Great Depression, consistent with our model. The vacancy rate dropped from 2 percent in September 1929 to 0.44 percent in March 1933, representing a steep decline of 78 percent (the online Appendix).
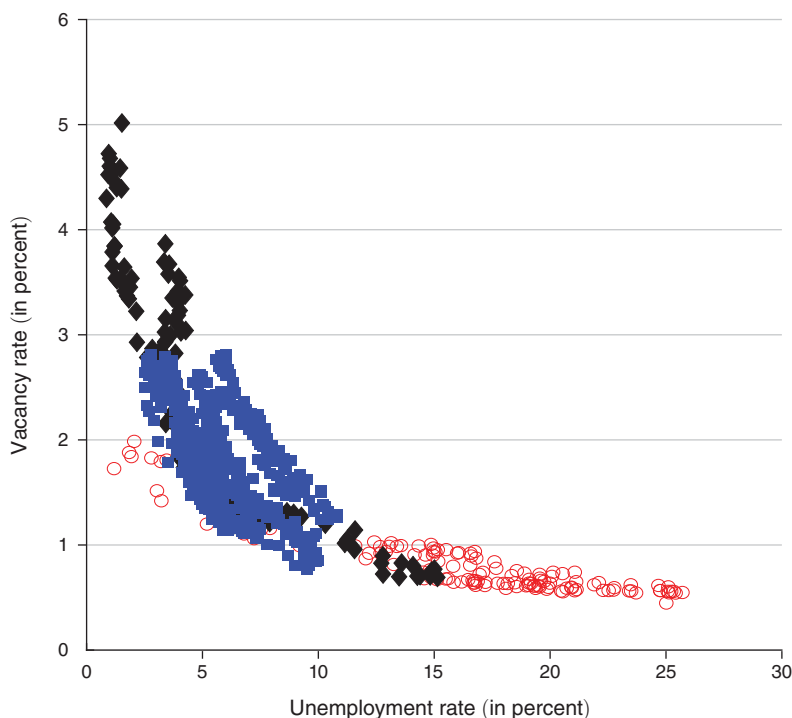
FIGURE 1. THE US BEVERIDGE CURVE, APRIL 1929–DECEMBER 2013

Notes: The April 1929–December 1939 observations are in red circles, the January 1940–December 1950 observations are in black diamonds, and the remaining observations are in blue squares.
Source: The unemployment and vacancy rate series from Petrosky-Nadeau and Zhang (2013)

Basic Moments.—From the baseline model's stationary distribution (after 6,000 burn-in months), we repeatedly simulate 10,000 samples, each with 1,836 months. On each sample, we time-aggregate the monthly output into 153 annual observations and the first 1,656 monthly consumption observations into 138 annual observations. Time-aggregation means that we add up 12 monthly observations within a given year, and treat the sum as the year's annual observation. The sample lengths match the cross-country average sample lengths in Tables 1 and 2. We then calculate the annual volatilities, skewness, kurtosis, and autocorrelations of log consumption and output growth. For each moment, we report the mean as well as the 5th and 95th percentiles across the 10,000 simulations. We also report *p*-values that are the frequencies with which a given model moment is larger than its data counterpart.

Table 3 shows that the output volatility is 5.3 percent per annum in the model, which is close to the data moment, 5.6 percent. The consumption volatility of 4.7 percent in the model is smaller than 6.4 percent in the data. Both output and consumption growth rates are somewhat negatively skewed in the data, with coefficients of -1 and -0.6, respectively. However, the output and consumption growth rates in the model are slightly positively skewed with a coefficient about 0.9. The model

Table 3—Basic Moments in the Baseline Model

	Data	Mean	5 percentile	95 percentile	*p*-value
Panel A. Output growth					
σ_Y	5.63	5.31	2.90	11.56	0.31
S_Y	−1.02	0.85	−0.39	3.35	0.99
K_Y	11.87	12.8	3.08	34.99	0.41
ρ_1^Y	0.16	0.24	0.01	0.63	0.58
ρ_2^Y	0	−0.11	−0.31	0.23	0.16
ρ_3^Y	0.02	−0.12	−0.32	0.08	0.1
ρ_4^Y	−0.02	−0.11	−0.31	0.08	0.23
Panel B. Consumption growth					
σ_C	6.37	4.65	2.12	11.26	0.21
S_C	−0.55	0.91	−0.50	3.57	0.96
K_C	9.19	14.4	3.16	38.59	0.54
ρ_1^C	0.07	0.23	−0.02	0.65	0.79
ρ_2^C	0.03	−0.12	−0.33	0.24	0.14
ρ_3^C	0	−0.12	−0.34	0.09	0.15
ρ_4^C	−0.02	−0.11	−0.32	0.09	0.23
Panel C. Unemployment rate					
$E[U]$	7.12	6.28	4.83	10.54	0.18
σ_U	19.83	23.41	5.45	53.49	0.48
S_U	1.99	3.52	1.49	5.82	0.86
K_U	6.82	19.18	5.24	41.78	0.89

Notes: For each moment, this table reports the mean as well as the 5 and 95 percentiles across the simulations. The *p*-values are the percentages with which a given model moment is larger than its data counterpart. σ_Y and σ_C denote volatilities, S_Y and S_C skewness, K_Y and K_C kurtosis, and ρ_i^Y and ρ_i^C the *i*th-order autocorrelations of log output and consumption growth rates, respectively. $E[U]$, S_U, and K_U are the mean, skewness, and kurtosis of the monthly unemployment rate, respectively, and σ_U is its quarterly volatility. We take quarterly averages of monthly unemployment rates, and detrend the quarterly series as HP-filtered proportional deviations from the mean with a smoothing parameter of 1,600. $\sigma_Y, \sigma_C, E[U]$, and σ_U are in percent.
Sources: The output and consumption data moments are based on the Barro-Ursúa (2008) historical cross-country panel, extended through 2013, and the unemployment data moments are based on the Petrosky-Nadeau-Zhang (2013) US series from April 1929 to December 2013. The model moments are based on authors' calculations from 10,000 simulated samples.

matches the leptokurtic distributions of output and consumption growth in the data. The kurtosis of the output growth is 11.9, and that of the consumption growth 9.2 in the data. The corresponding model moments are 12.8 and 14.4, respectively. Finally, consistent with the data, both output and consumption growth rates are positively autocorrelated at the first lag, but not autocorrelated at longer lags.

From panel C, the mean unemployment rate is 6.3 percent in the model, which is not far from 7.1 percent in the data. The model also reproduces positively skewed and leptokurtic unemployment rates, with skewness and kurtosis 3.5 and 19.2, and the data moments of 2 and 6.8, respectively, are within the model's 90 percent confidence interval. To compute the unemployment volatility, we take quarterly averages of monthly unemployment rates, and detrend with Hodrick-Prescott (1997, HP) filtered proportional deviations from the mean. The unemployment volatility is 23.4 percent in the model, which is not far from 19.8 percent in the data. The model also implies an unemployment-vacancy correlation of −0.5 (−0.7 in the data).
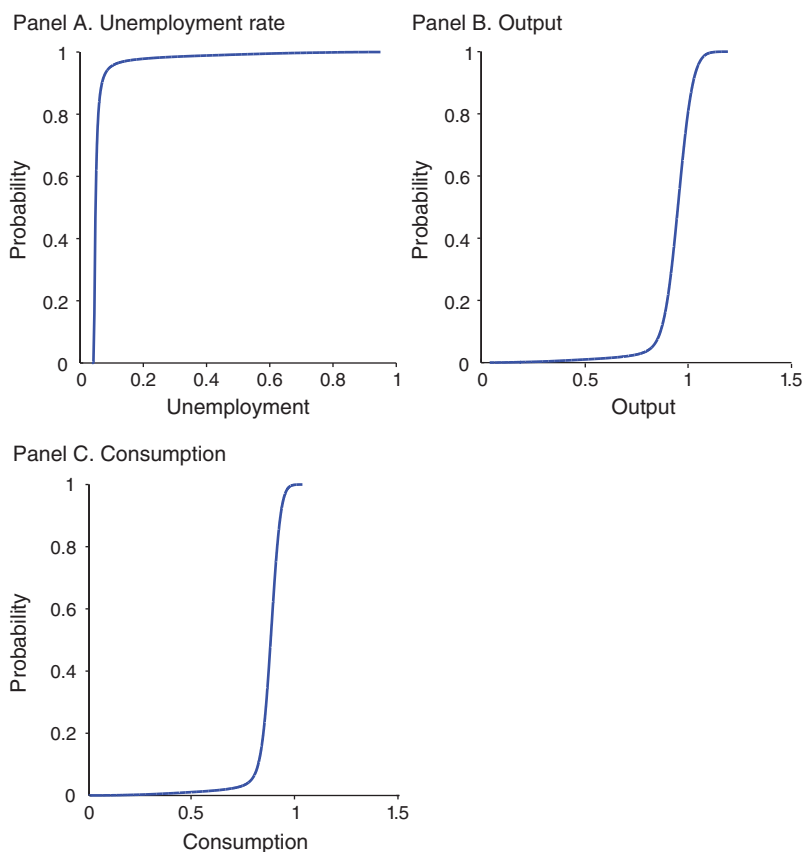
FIGURE 2. EMPIRICAL CUMULATIVE DISTRIBUTION FUNCTIONS: THE BASELINE MODEL

Note: Results are based on one million months simulated from the baseline model.
Source: Authors' calculations

C. *Endogenous Disasters*

Most important, the baseline economy gives rise to endogenous disasters.

Quantitative Results.—We simulate one million months from the model, and report the empirical cumulative distribution functions for unemployment, output, and consumption. Figure 2 shows that unemployment is positively skewed with a long right tail. The mean unemployment rate is 6.2 percent, and the median 4.9 percent. The 2.5th percentile of the unemployment rate, 4.3 percent, is close to the median, whereas the 97.5th percentile is far away, 17 percent. As a mirror image, employment is negatively skewed with a long left tail. Consequently, output and consumption both exhibit rare but deep disasters. With small probabilities, the economy falls off a cliff.[5]

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[5] The sharp drops in output and consumption levels in Figure 2 are consistent with the slightly positive skewness of output and consumption growth rates in Tables 1 and 2. The extreme left tails in the levels give rise to large subsequent growth rates, as their denominators become small. In the extended model with capital (Section IIB), the left

Do the rare disasters arising endogenously from the model resemble those in the data? Barro and Ursúa (2008) apply a peak-to-trough method on their cross-country panel to identify rare disasters, which are defined as cumulative fractional declines in per capita consumption or output of at least 10 percent. Suppose there are two states, normalcy and disaster. The disaster probability measures the likelihood with which the economy shifts from normalcy to disaster in a given year. The number of disaster years is the number of years in the interval between peak and trough for each disaster event. The number of normalcy years is the total number of years in the sample minus the number of disaster years. The disaster probability is calculated as the ratio of the number of disasters divided by the number of normalcy years. For each disaster event, the disaster size is the cumulative fractional decline in per capita output or consumption from peak to trough, and the disaster duration is the number of years from peak to trough.[6]

We apply the peak-to-trough method on the extended cross-country panel. Table 4 shows the estimates. For output, the disaster probability is 7.8 percent, the average size of disasters 22 percent, and the average duration 3.7 years. For consumption, the disaster probability is 8.6 percent, the average size 23.2 percent, and the duration 3.8 years. Our disaster probability estimates, 7.8 percent and 8.6 percent for output and consumption, are higher than those in Barro and Ursúa, 3.7 percent and 3.6 percent, respectively. The crux is that we adjust for trend growth in the data to be consistent with our model with no growth. In particular, we subtract each observation of log annual output growth with its mean of 1.8 percent per annum, and subtract each observation of log annual consumption growth with its mean of 1.7 percent in the historical cross-country panel. Ignoring trend growth in our extended sample yields the disaster probabilities of 3.5 percent for output and 4.2 percent for consumption, which are close to Barro and Ursúa's estimates. The average size and duration estimates are relatively unaffected. Clearly, adjusting for trend growth in the data raises the hurdle for the model.

We simulate 10,000 artificial samples from the model's stationary distribution, each with 1,836 months. On each sample, we time-aggregate monthly output and consumption into annual observations, and then apply the Barro-Ursúa peak-to-trough measurement. Table 4 shows that the output disaster probability in the model is 5 percent, which is lower than 7.8 percent in the data, but the data moment is within two standard deviations from the model (p-value = 0.09). The average disaster size in the model, 22.2 percent, is close to the data moment, 22 percent. The average duration in the model of 4.4 years is also close to 3.7 years in the data. For consumption disasters, the probability is only 2.9 percent in the model, which is substantially lower than 8.6 percent in the data (p-value = 0). The average disaster size is 25.6 percent in the model, which is close to 23.2 percent in the data. The average duration is 4.9 years, which is not far from 3.8 years in the data. Finally, Figure 3 reports the frequency distributions of output and consumption disasters

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tails are less extreme because of the buffeting effect of capital. As a result, the skewness of output and consumption growth rates is only 0.1, albeit still positive.

[6] In continuous time models, disasters are often modeled as jumps in consumption growth. If reformulated in continuous time, disasters in our model would arise from time-varying drift and diffusion of output and consumption growth. However, jumps are only a convenient modeling device in continuous time. In the data and in discrete time models, disasters arising from these different sources are observationally equivalent.

Table 4—Disaster Moments

	Data	Model			
		Mean	5 percentile	95 percentile	*p*-value
Panel A. Output					
Probability	7.83	5.04	2.24	8.57	0.09
Size	21.99	22.22	12.7	46.24	0.33
Duration	3.72	4.44	3.2	6	0.79
Panel B. Consumption					
Probability	8.57	2.86	0.71	5.83	0.00
Size	23.16	25.64	11.26	62.13	0.36
Duration	3.75	4.91	3	7	0.81

Notes: On each artificial sample, we time-aggregate output and consumption into annual observations, and apply the peak-to-trough method to identify disasters as cumulative fractional declines in output or consumption of at least 10 percent. We report the averages, 5 and 95 percentiles, and *p*-values across the simulations. If no disaster appears in a given sample, we set its disaster probability to be 0, and the probability mean and percentiles are calculated across all 10,000 samples, each with 1,836 months. However, disaster size and duration are calculated across samples with at least one disaster. The disaster probabilities and average size are in percent, and the average duration is in terms of years.

Sources: The data moments are estimated from applying the Barro-Ursúa (2008) peak-to-trough method on their cross-country panel, extended through 2013. We adjust for trend growth in the data. The model moments are obtained from authors' calculations based on 10,000 simulations.

by size and duration simulated from the model. The size and duration distributions display similar patterns as those in the data (Barro and Ursúa 2008, Figures 1 and 2). In particular, the size distributions seem to follow a power-law density.[7]

Comparative Statics.—To shed light on the intuition behind the model's disaster dynamics, we conduct six comparative statics. (i, ii) We reduce the flow value of unemployment, b, from 0.85 in the benchmark calibration to 0.825, and then to 0.4. Because of its importance, we consider two alternative values of b. (iii) We lower the job separation rate, s, from 0.04 to 0.035. (iv) We adjust the unit costs of vacancy from $\kappa_t = 0.5 + 0.5q(\theta_t)$ to $\kappa_t = 0.7$, with $\kappa_0 = 0.7$ and $\kappa_1 = 0$ (the average κ_t is 0.7 under the benchmark calibration). (v) We reduce the curvature of the matching function, ι, from 1.25 to 1.1. Finally, (vi) we raise the workers' bargaining power, η, from 0.04 to 0.05. In each experiment, all the other parameters remain unchanged.

Table 5 reports the results. With $b = 0.825$, the output disaster probability reduces from 5 to 3.6 percent, and the consumption disaster probability from 2.9 to 1.6 percent. The average disaster size is lowered from 22.2 to 16.1 percent for output, and from 25.6 to 16.3 percent for consumption. The average duration of disasters increases slightly. The output and consumption volatilities drop to 3.4 and 2.6 percent, and the mean and volatility of the unemployment rate fall to 5 and 11 percent, respectively. With $b = 0.4$, the disaster probability falls further to 2.5 percent for output and 1.3 percent for consumption. The average size drops to 13.4 and 12.4 percent, respectively. The low value of b implies low wages and an

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[7] In the online Appendix, we have worked out a model with leisure in the utility function, $\log(C_t + hU_t)$, in which $h > 0$ is a constant parameter. With $b = 0.5$ and $h = 0.35$, while keeping all other parameter values unchanged, the results, including the disaster moments, are quantitatively close to those from the baseline model.
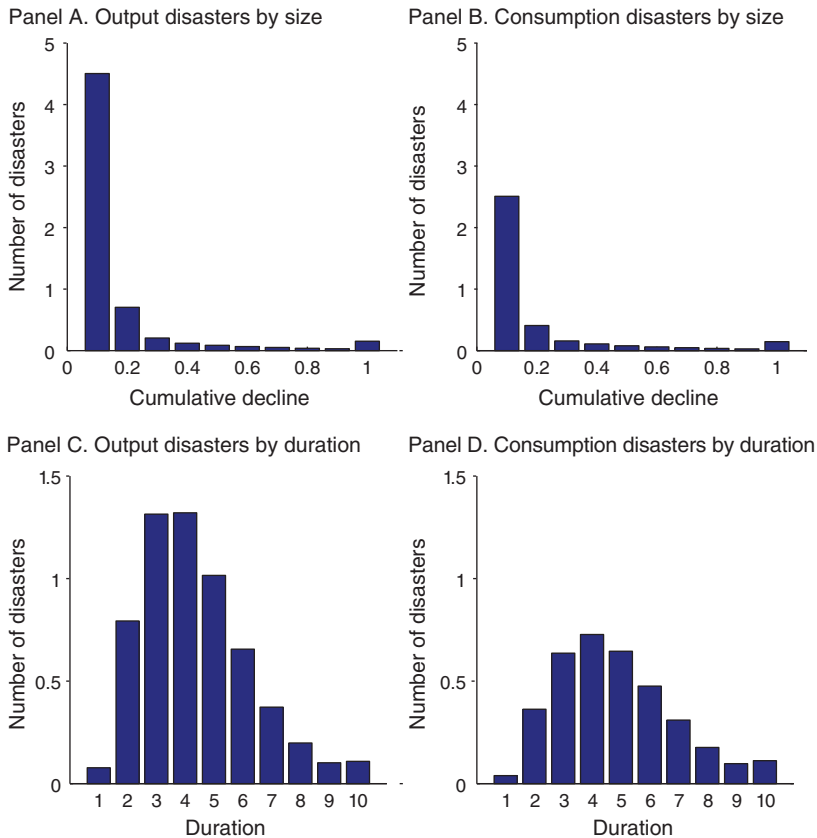
Panel A. Output disasters by size

Panel B. Consumption disasters by size

Panel C. Output disasters by duration

Panel D. Consumption disasters by duration

FIGURE 3. DISTRIBUTIONS OF OUTPUT AND CONSUMPTION DISASTERS BY SIZE AND DURATION
FROM THE BASELINE MODEL

Note: Results are based on 10,000 simulations, each with 1,836 months.
Source: Authors' calculations

exceedingly high profits-to-output ratio of 31 percent. The mean unemployment rate falls to 4 percent, and the unemployment volatility to only 0.14 percent. However, the presence of disaster dynamics with $b = 0.4$ implies that disasters are even more robust to changes in b than the unemployment volatility.

Intuitively, equation (10) shows that with small profits, wages are inertial with respect to productivity shocks. When productivity is low, wages remain high, shrinking the small profits to stifle job creation flows. In contrast, with large profits, wages are sensitive to shocks. With $b = 0.4$, the wage elasticity to productivity increases to 0.66 from 0.51 with $b = 0.85$. As such, when productivity is low, employment falls, but wages drop as well, providing hiring incentives for the firm to counteract job destruction flows. Consequently, disaster dynamics are dampened.

In the third experiment, reducing the separation rate lowers disaster probabilities and size. With $s = 0.035$, the disaster probability is 4.4 percent for output and 2.4 percent for consumption, both of which are still substantial. The disaster size declines somewhat, and the duration rises slightly. Intuitively, because jobs are destroyed at a lower rate, the economy can create enough jobs to shore up employment in time to reduce disaster risk.

TABLE 5—COMPARATIVE STATICS FOR THE DISASTER MOMENTS IN THE BASELINE MODEL

	Benchmark	$b = 0.825$	$b = 0.4$	$s = 0.035$	$\kappa_t = 0.7$	$\iota = 1.1$	$\eta = 0.05$
Panel A. Output							
Probability	5.04	3.61	2.53	4.42	4.05	5.29	5.57
Size	22.22	16.07	13.41	19.87	18.2	21.97	22.69
Duration	4.44	4.57	4.7	4.5	4.51	4.41	4.4
Panel B. Consumption							
Probability	2.86	1.62	1.32	2.43	1.85	3.04	3.59
Size	25.64	16.31	12.35	22.25	20.19	25.05	25.21
Duration	4.91	5.19	5.2	4.97	5.1	4.88	4.78

Notes: The first column reports the disaster moments from the benchmark calibration (Table 4), and the other columns show six comparative statics: (i, ii) $b = 0.825$ and $b = 0.4$ are for the flow value of unemployment set to 0.825 and 0.4, respectively; (iii) $s = 0.035$ is for the job separation rate set to 0.035; (iv) $\kappa_t = 0.7$ is for the proportional unit costs of vacancy $\kappa_0 = 0.7$ and the fixed unit costs $\kappa_1 = 0$; (v) $\iota = 1.1$ is for the curvature of the matching function set to 1.1; and (vi) $\eta = 0.05$ is for the workers' bargaining weight set to 0.05. In each experiment, all the other parameters are identical to those in the benchmark calibration.
Source: Authors' calculations based on 10,000 simulations, each with 1,836 months

Without the fixed costs of vacancy, the disaster probability drops from 5 to 4.1 percent for output, and from 2.9 to 1.9 percent for consumption. The disaster size falls from 22.2 to 18.2 percent for output, and from 25.6 to 20.2 percent for consumption. The output and consumption volatilities decline to 4.1 and 3.3 percent, respectively. The mean unemployment rate falls from 6.3 to 5.5 percent, and its volatility from 23 to 15 percent. While Pissarides (2009) shows the impact of fixed costs on the unemployment volatility, we quantify the important impact on disaster dynamics.

Reducing the curvature of the matching function, ι, from 1.25 to 1.1 raises the disaster probability somewhat to 5.3 percent for output and 3 percent for consumption. The disaster size and duration, as well as output, consumption, and unemployment volatilities all remain relatively unchanged. The mean unemployment rate increases to 6.7 percent. Intuitively, a lower curvature of the matching function means that the labor market is more frictional in matching vacancies with unemployed workers. Because job creation flows are hampered, whereas job destruction flows remain unchanged, the lower curvature raises the unemployment rate, and strengthens somewhat the disaster dynamics.

Finally, increasing the workers' bargaining weight, η, from 0.04 to 0.05 raises the disaster probability to 5.6 percent for output and 3.6 percent for consumption. As workers gain more bargaining power, the mean unemployment rate rises to 6.8 percent, the output volatility to 5.6 percent, and the consumption volatility 5 percent. However, the unemployment volatility is barely changed.

Downward Rigidity in the Marginal Costs of Hiring.—In addition to wage inertia, the other key determinant of the firm's hiring decisions is the marginal costs of hiring, $\kappa_0/q(\theta_t) + \kappa_1$. To illustrate the properties of the marginal costs, Figure 4 plots the vacancy filling rate, $q(\theta_t)$, as well as the marginal costs of hiring in the model with small profits ($b = 0.85$) and with large profits ($b = 0.4$). Each panel has three lines, each corresponding to a different level of productivity.
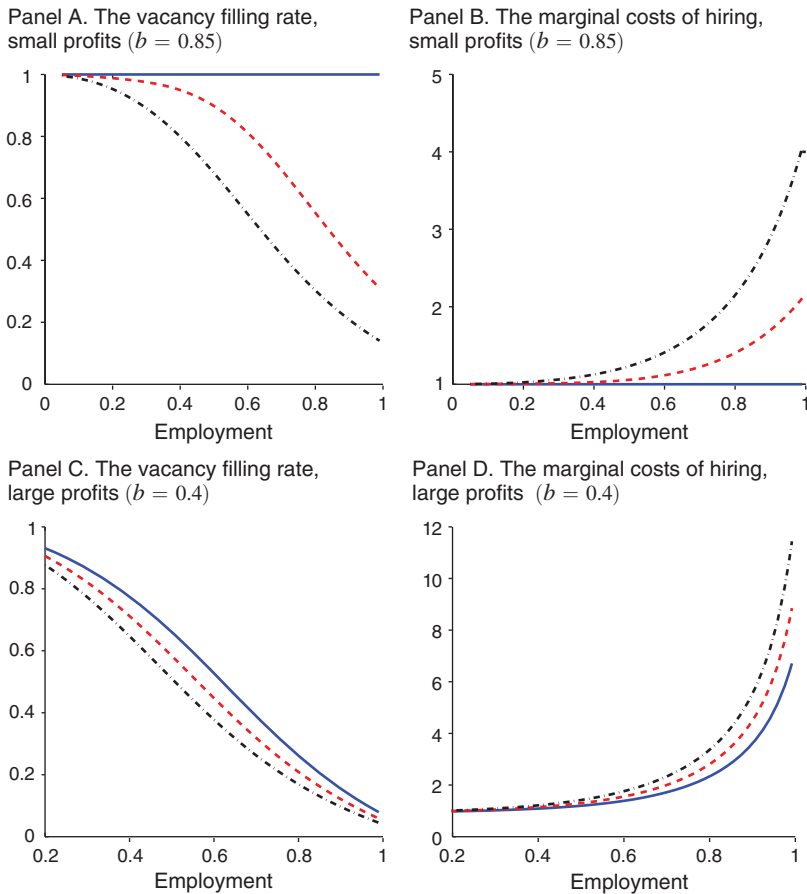
FIGURE 4. THE VACANCY FILLING RATE AND THE MARGINAL COSTS OF HIRING IN THE BASELINE MODEL: SMALL AND LARGE PROFITS

Notes: Let $x_1 < x_2 < \cdots < x_{17}$ denote the x grid. In each panel, the blue solid line is for $x_t = x_3$, the red dashed line for $x_t = x_9$, and the black dashed-dotted line for $x_t = x_{15}$. b is the flow value of unemployment.
Source: Authors' calculations

Panel A shows that when productivity is low, the vacancy filling rate, $q(\theta_t)$, is essentially unity with $b = 0.85$. Intuitively, the labor market is populated by a large number of unemployed workers competing for a few vacancies. Filling a vacancy with an unemployed worker is guaranteed, with no room for the vacancy filling rate to increase further. Accordingly, the marginal costs of hiring equal the constant $\kappa_0 + \kappa_1$, with no room to drop further, giving rise to the downward rigidity in the marginal costs (panel B). The rigid marginal costs suppress the firm's hiring incentives, smothering job creation flows and giving rise to disasters.

Arising from the trading externality of the matching process, this downward rigidity subsists even without the fixed costs of vacancy ($\kappa_1 = 0$). By putting the constant κ_1 into the marginal costs of hiring, the fixed costs further restrict the ability of the marginal costs to decline, fortifying the downward rigidity. This economic

mechanism explains why removing the fixed costs makes disasters less frequent and less severe in the baseline model (Table 5).

Panels C and D show that the downward rigidity in the marginal costs is absent with large profits. The vacancy filling rate, $q(\theta_t)$, is quite sensitive to employment when profits are large (panel C). Intuitively, with $b = 0.4$, vacancies are plentiful even when productivity is low. The labor market is populated by a fair number of both vacancies and unemployed workers. As employment falls, $q(\theta_t)$ keeps climbing, reducing the marginal costs of hiring (panel D). The falling marginal costs stimulate job creation flows, dampening disaster dynamics.

Which Disasters?—The baseline model is a textbook economic model, yet we opt to explain disaster moments from the Barro-Ursúa (2008) dataset. The dataset contains not only economic disasters such as the Great Depression, but also wars and natural disasters such as earthquakes, floods, and epidemics. Our choice merits further discussion.

First, we calibrate the volatility of productivity shocks, σ, to match the output volatility in the data. Because wars and natural disasters are exogenous to the model economy, these impulses can at least in principle be captured by large negative productivity shocks. The model then quantifies the impact of these impulses on endogenous variables such as unemployment and output. As noted, even for the Great Depression, the model does not identify its origins.

Second, disentangling economic disasters empirically from other types of disasters requires judgment calls that are likely arbitrary. Wars could be endogenous responses to harsh economic conditions, which give rise to destructive conflicts among rival nations. Conversely, the Great Depression has been argued to originate from the First World War. Temin (1989, p. 1) writes: "The origins of the Great Depression lie largely in the disruptions of the First World War. Its spread owes much to the hostilities and continuing conflicts that were created by the war and the Treaty of Versailles. And its effects—particularly the victory of National Socialism in Germany—clearly extend to the Second World War." Third, to the extent that wars also propogate shocks, the Barro-Ursúa (2008) disaster moments pose a very high hurdle for any economic model to explain.

We have also experimented with an alternative calibration. Instead of matching the output volatility of 5.6 percent per annum in the cross-country panel, we rescale the volatility of productivity shocks, σ, to match the output volatility of 4.3 percent in the historical 1790–2013 US sample. This target is conservative because it is even lower than 4.9 percent in the 1929–2013 US sample. We target the US data because the damage from world wars on its economy is negligible compared with other nations. Specifically, we set $\sigma = 0.00925$, which implies a volatility of 4.3 percent for output and 3.6 percent for consumption in the baseline model. The unemployment rate is 5.8 percent on average, and its volatility 18.7 percent. More important, disaster dynamics remain substantial. The disaster probability is 4 percent, size 19.6 percent, and duration 4.6 years for output, and 2.1 percent, 22.3 percent, and 5 years, respectively, for consumption. As such, the endogenous disasters in the model are relatively robust to the large σ value required to match the output volatility of 5.6 percent in the Barro-Ursúa (2008) cross-country panel.

II. Extensions

The disaster dynamics are robust to several extensions to the baseline model.

A. *Home Production*

In this subsection, we extend the baseline model to incorporate home production (Benhabib, Rogerson, and Wright 1991). The household derives utility not only from the consumption of market goods, C_{mt}, but also from the consumption of non-market, home-produced goods, C_{ht}. We define the composite consumption bundle as

$$(12) \qquad C_t \equiv \left[a\, C_{mt}^e + (1 - a)\, C_{ht}^e \right]^{1/e},$$

in which $e \in (0, 1]$ and $a \in [0, 1]$. The elasticity of substitution between market and nonmarket goods is $1/(1 - e)$, and a is the relative weight of market goods over nonmarket goods. The household has log utility over the composite consumption, $\log(C_t)$. The marginal utility of the market consumption is $\phi_t \equiv a C_{mt}^{e-1}/C_t^e$, and the stochastic discount factor is

$$(13) \qquad M_{t+1} \equiv \beta \frac{\phi_{t+1}}{\phi_t} = \beta \left(\frac{C_{mt+1}}{C_{mt}} \right)^{e-1} \left(\frac{C_t}{C_{t+1}} \right)^e.$$

The home production technology is given by

$$(14) \qquad C_{ht} = X_h U_t,$$

in which $X_h > 0$ is a constant parameter. This technology is nonstochastic. For instance, Aguiar, Hurst, and Karabarbounis (2013) find no evidence that indicates shocks to home production. Let z_t denote the total flow value of unemployment,

$$(15) \qquad z_t \equiv X_h \left(\frac{1 - a}{a} \right) \left(\frac{C_{mt}}{C_{ht}} \right)^{1-e} + b.$$

As shown in the online Appendix, the equilibrium Nash-wage becomes

$$(16) \qquad W_t = \eta(X_t + \kappa_t \theta_t) + (1 - \eta) z_t.$$

The market-clearing condition becomes $C_{mt} + \kappa_t V_t = X_t N_t$. The rest of the model remains identical to the baseline model.

We set the value of b to 0.5, which is the flow value of unemployment other than home production, such as unemployment insurance, disutility of work, and leisure. In the absence of concrete evidence on home technology, we set its productivity parameter, X_h, to be unity, which is the long-term mean of the market technology. We next calibrate the volatility of market productivity, σ, the relative weight of the

TABLE 6—QUANTITATIVE RESULTS: THE HOME PRODUCTION MODEL

	Data	Model			
σ		0.01	0.014	0.014	0.014
a		0.8	0.8	0.8	0.85
e		0.85	0.85	0.9	0.85
Panel A. Output growth					
σ_Y	5.63	3.41	5.29	4.62	3.9
S_Y	-1.02	0.06	0.15	0.13	0.01
K_Y	11.87	3.83	4.92	4.95	3.42
ρ_1^Y	0.16	0.15	0.16	0.15	0.14
ρ_2^Y	0	-0.13	-0.13	-0.13	-0.12
ρ_3^Y	0.02	-0.1	-0.11	-0.1	-0.1
ρ_4^Y	-0.02	-0.08	-0.08	-0.08	-0.08
Prob$_Y$	7.83	5	9.95	8.2	6.88
Size$_Y$	21.99	15	18.58	17.21	15.43
Dur$_Y$	3.74	4.32	3.74	3.88	3.98
Panel B. Consumption growth					
σ_C	6.37	2.91	4.67	3.74	2.9
S_C	-0.55	0.09	0.2	0.2	0.03
K_C	9.19	4.22	5.73	5.97	3.48
ρ_1^C	0.07	0.15	0.16	0.15	0.14
ρ_2^C	0.03	-0.13	-0.14	-0.14	-0.12
ρ_3^C	0	-0.1	-0.11	-0.11	-0.1
ρ_4^C	-0.02	-0.08	-0.09	-0.08	-0.08
Prob$_C$	8.57	3.35	7.52	4.95	3.43
Size$_C$	23.16	14.42	18.06	16.34	13.81
Dur$_C$	3.75	4.65	3.99	4.31	4.59
Panel C. Unemployment rate					
$E[U]$	7.12	5.97	6.58	5.33	4.5
σ_U	19.83	10.75	19.53	15.3	4.07
S_U	1.99	1.86	2.44	3.06	2.1
K_U	6.82	7.48	10.42	15.73	9.87

Notes: σ is the conditional volatility of the log productivity shocks to the market goods technology, a the relative weight of market goods over nonmarket goods, and $1/(1-e)$ the elasticity of substitution between market and non-market goods. σ_Y and σ_C are the volatilities, S_Y and S_C skewness, K_Y and K_C kurtosis, and ρ_i^Y and ρ_i^C the ith-order autocorrelations of log output and consumption growth rates, respectively. Prob$_Y$, Size$_Y$, and Dur$_Y$, as well as Prob$_C$, Size$_C$, and Dur$_C$ are the probability, size, and duration of output and consumption disasters, respectively. $E[U]$, S_U, and K_U are the mean, skewness, and kurtosis of the monthly unemployment rate, respectively, and σ_U is its quarterly volatility. σ_Y, σ_C, $E[U]$, and σ_U are in percent.
Sources: The output and consumption data moments are based on the Barro-Ursúa (2008) historical cross-country panel, extended through 2013, and the unemployment data moments are based on the Petrosky-Nadeau-Zhang (2013) US series from April 1929 to December 2013. The model moments are based on authors' calculations from 10,000 simulated samples.

market goods, a, and the parameter governing the elasticity between market and home consumption, e, to match three data moments, including the output volatility, as well as the mean and volatility of unemployment. To facilitate comparison, all the other parameter values remain identical to the baseline model.

This procedure yields $\sigma = 0.014$, $a = 0.8$, and $e = 0.85$. Table 6 reports the results. Together, these parameter values imply an output volatility of 5.3 percent. The mean unemployment rate is 6.6 percent, and its volatility 19.5 percent, which is close to 19.8 percent in the data. The market consumption volatility is 4.7 percent,

which is identical to that in the baseline model. The model also reproduces the positively skewed and leptokurtic unemployment rate distribution.

More important, disaster dynamics are robust to home production. The disaster probability is 10 percent for output, which is even higher than 7.8 percent in the data and 5 percent in the baseline model. The probability is 7.5 percent for consumption, which is lower than 8.6 percent in the data, but higher than 2.9 percent in the baseline model. However, the disaster size is smaller, 18.6 percent for output and 18.1 percent for consumption. The disaster duration is close to the data, 3.7 years for output and 4 for consumption.

Table 6 also reports three comparative statics. First, not surprisingly, reducing the volatility of productivity shocks from 0.014 to 0.01, which is the value in the baseline model, lowers the output volatility to 3.4 percent. The mean unemployment rate falls to 6 percent, and its volatility to 10.8 percent. Even with $\sigma = 0.01$, the disaster probability is still 5 percent for output and 3.4 percent for consumption. However, the disaster size is smaller, 15 percent for output, and 14.4 percent for consumption. Finally, the duration rises to 4.3 years for output and 4.7 for consumption.[8]

Increasing the e parameter governing the elasticity of substitution between market and home goods from 0.85 to 0.9 weakens disaster dynamics. Both the disaster probability and size decrease, and duration increases. The mean unemployment rate falls from 6.6 to 5.3 percent, and volatility from 19.5 to 15.3 percent. The market consumption dominates the home consumption in magnitude (C_{mt}/C_{ht} is 15.4 on average). As e increases, equation (15) implies that the flow value of unemployment, z_t, falls. Intuitively, a higher e means that the two types of consumption become more substitutable, and the home consumption loses its relative appeal, despite its small size. As such, z_t falls from 0.87 to 0.83 on average, reducing unemployment and its volatility, and dampening disaster dynamics.

Increasing the relative weight of market goods, a, from 0.8 to 0.85 also dampens the disaster dynamics. The disaster probability falls from 10 to 6.9 percent for output, and the disaster size from 18.6 to 15.4 percent. More drastically, the mean unemployment rate falls from 6.6 to 4.5 percent, and its volatility from 19.5 to only 4.1 percent. As a increases, equation (15) implies that the flow value of unemployment, z_t, falls. Intuitively, as the relative weight of market goods increases in the utility function, home goods become less valuable to the household. As a result, z_t falls from on average 0.87 to 0.77, which greatly reduces unemployment and its volatility, weakening disaster dynamics.

Our calibration is parsimonious in that, to facilitate comparison, all parameters except for the volatility of productivity shocks, σ, are identical to those in the baseline model. In particular, this strategy yields $e = 0.85$, which implies an elasticity of 6.67 between market and home goods. This e value is not far from 0.8 calibrated in Benhabib, Rogerson, and Wright (1991), but is higher than the estimates in Rupert, Rogerson, and Wright (1995, Table 4) based on microdata, ranging from 0.36 to 0.75. However, comparative statics show that, all else equal, increasing e to 0.9

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[8]Rescaling σ to 0.012 matches the output volatility of 4.3 percent in the 1790–2013 US sample. The mean unemployment rate falls to 6.2 percent, and the unemployment volatility 14.8 percent. The disaster dynamics remain substantial. The disaster probability is 7.5 percent, size 16.7 percent, and duration 4 years for output, and the probability 5.4 percent, size 16.1 percent, and duration 4.3 years for consumption.

dampens disaster dynamics. As such, alternative calibrations with a lower value of e are likely to strengthen the disasters in the model.

B. *Capital*

In this subsection, we augment the baseline model in Section I with capital, which is standard in the business cycle literature (Kydland and Prescott 1982). The firm uses labor, N_t, and capital, K_t, to produce with a constant return of scale technology,

$$(17) \qquad Y_t = X_t K_t^\alpha N_t^{1-\alpha},$$

in which Y_t is output, and $\alpha \in (0, 1)$ is the capital's weight. We specify $x_t = \log(X_t)$ as

$$(18) \qquad x_{t+1} = (1 - \rho)\bar{x} + \rho x_t + \sigma \epsilon_{t+1},$$

in which $\bar{x}$ is the unconditional mean of x_t. We rescale $\bar{x}$ to make the average marginal product of labor around unity to ease comparison with the baseline model.

The firm incurs adjustment costs when investing. Capital accumulates as

$$(19) \qquad K_{t+1} = (1 - \delta) K_t + \Phi(I_t, K_t),$$

in which δ is the capital depreciation rate, I_t is investment, and

$$(20) \qquad \Phi(I_t, K_t) \equiv \left[a_1 + \frac{a_2}{1 - 1/\nu} \left(\frac{I_t}{K_t} \right)^{1 - 1/\nu} \right] K_t$$

is the installation function with the supply elasticity of capital $\nu > 0$. We set $a_1 = \delta/(1 - \nu)$ and $a_2 = \delta^{1/\nu}$ to ensure no adjustment costs in the deterministic steady state (Jermann 1998).

The investment Euler equation is given by

$$(21) \qquad \frac{1}{a_2} \left(\frac{I_t}{K_t} \right)^{1/\nu} = E_t \left[M_{t+1} \left(\alpha \frac{Y_{t+1}}{K_{t+1}} + \frac{1}{a_2} \left(\frac{I_{t+1}}{K_{t+1}} \right)^{1/\nu} (1 - \delta + a_1) + \frac{1}{\nu - 1} \frac{I_{t+1}}{K_{t+1}} \right) \right],$$

and the intertemporal job creation condition becomes

$$(22) \qquad \frac{\kappa_0}{q(\theta_t)} + \kappa_1 - \lambda_t = E_t \left[M_{t+1} \left((1 - \alpha) \frac{Y_{t+1}}{N_{t+1}} - W_{t+1} + (1 - s) \left(\frac{\kappa_0}{q(\theta_{t+1})} + \kappa_1 - \lambda_{t+1} \right) \right) \right].$$

The equilibrium wage, W_t, which the firm takes as given, follows

$$(23) \qquad W_t = \eta \left[(1 - \alpha) \frac{Y_t}{N_t} + \kappa_t \theta_t \right] + (1 - \eta) b.$$

The goods market-clearing condition becomes $C_t + I_t + \kappa_t V_t = Y_t$. Finally, the extended model with capital is more challenging to solve than the baseline model.

Capital, K_t, becomes a new state variable in addition to x_t and N_t. Also, the investment Euler equation (21) must be solved together with the intertemporal job creation condition (22).

We set the capital's weight in production, α, to $1/3$, and the depreciation rate, δ, to 0.01. We calibrate the unconditional mean of log productivity, $\bar{x} = -0.771$, to make the long-term average of the marginal product of labor, $(1 - \alpha) Y_t / N_t$, around 1 in simulations. For the capital elasticity, ν, we vary it from 0.5 to 2, covering a wide range of empirically plausible values. To facilitate comparison, all the other parameter values are identical to those in the baseline model.

With capital added to the baseline model, the model column with $\sigma = 0.01$ (and $\nu = 2$) in Table 7 shows the smoothing effect of investment. The output volatility drops to 3.4 percent, and the consumption volatility to 2.4 percent. The mean unemployment rate falls to 6 percent, and volatility to 14 percent. The disaster probabilities and size, as well as the skewness and kurtosis of output and consumption growth all decline. Specifically, the output disaster size falls to 15.8 percent, but its disaster probability drops only slightly to 4.6 percent, which remains substantial.

We rescale the conditional volatility of productivity shocks, σ, to 0.014 to obtain an output volatility of 5.1 percent (with $\nu = 2$), which is close to 5.3 percent in the baseline model. The consumption volatility is 3.7 percent, which is lower than 4.7 percent in the baseline model. The mean unemployment rate is 7.5 percent, and its volatility 22.5 percent. The investment growth volatility is 7 percent, which, although much lower than 23.3 percent in the 1929–2013 US sample, is not far from 8.9 percent from 1951 onward. Because a historical cross-country panel of investment is unavailable, we do not estimate disaster moments for investment. As in the data, investment growth in the model is positively autocorrelated at the first lag, but negatively autocorrelated at longer lags.

Most important, disaster dynamics are robust to the inclusion of capital. The disaster probability is 9.5 percent for output, which is somewhat higher than 7.8 percent in the data. The disaster probability is 5.3 percent for consumption, which is still lower than 8.6 percent in the data. However, the disaster size is smaller, 19 percent for output versus 22 percent in the data, and 17.7 percent for consumption versus 23.2 percent in the data. The disaster duration is somewhat higher than those in the data.[9]

The rest of the model columns in Table 7 examines the impact of the supply elasticity of capital, ν, on the quantitative results. Reducing ν from 2 to 1.5 and further to 0.5 dampens investment dynamics, but amplifies consumption dynamics. The investment volatility drops from 7 to 6.1 and further to 2.9 percent, whereas the consumption volatility rises from 3.7 to 4 and further to 4.8 percent. The consumption disaster probability goes up from 5.3 to 6 and further to 8.2 percent, the disaster size increases slightly, and duration decreases slightly. Intuitively, ν governs the magnitude of capital adjustment costs. A falling ν means rising adjustment costs, which dampen investment dynamics, but amplify consumption dynamics. Finally, varying ν shows only weak impact on output and unemployment dynamics. As ν falls from

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[9] Rescaling the volatility of productivity shocks, σ, to 0.012 implies an output volatility of 4.3 percent, which equals that in the 1790–2013 US sample. The consumption volatility is 3.1 percent, and the investment volatility 5.9 percent. The mean unemployment rate is 6.8 percent, and the unemployment volatility 18.8 percent. The disaster dynamics remain substantial. The disaster probability is 7.2 percent, size 17.5 percent, and duration 4.2 years for output, and the disaster probability is 3.7 percent, size 16.3 percent, and duration 4.8 years for consumption.

TABLE 7—QUANTITATIVE RESULTS: THE CAPITAL MODEL

	Data	Model			
σ		0.01	0.014	0.014	0.014
ν		2	2	1.5	0.5
Panel A. Output growth					
σ_Y	5.63	3.35	5.11	5.1	4.93
S_Y	-1.02	0.1	0.12	0.11	0.1
K_Y	11.87	4.11	4.5	4.49	4.34
ρ_1^Y	0.16	0.18	0.19	0.19	0.17
ρ_2^Y	0	-0.1	-0.09	-0.1	-0.12
ρ_3^Y	0.02	-0.08	-0.07	-0.08	-0.09
ρ_4^Y	-0.02	-0.07	-0.06	-0.07	-0.08
Prob_Y	7.83	4.55	9.45	9.4	9.07
Size_Y	21.99	15.76	18.97	18.81	18.08
Dur_Y	3.72	4.58	3.89	3.87	3.8
Panel B. Consumption growth					
σ_C	6.37	2.38	3.74	4	4.75
S_C	-0.55	0.08	0.12	0.14	0.17
K_C	9.19	4.67	5.18	5.1	4.79
ρ_1^C	0.07	0.21	0.22	0.2	0.17
ρ_2^C	0.03	-0.08	-0.07	-0.09	-0.12
ρ_3^C	0	-0.07	-0.06	-0.08	-0.09
ρ_4^C	-0.02	-0.06	-0.06	-0.06	-0.08
Prob_C	8.57	2.08	5.31	5.95	8.18
Size_C	23.16	14.9	17.69	17.68	17.98
Dur_C	3.75	5.39	4.51	4.33	3.9
Panel C. Investment growth					
σ_I	23.33	4.52	6.98	6.06	2.88
S_I	-0.79	0.2	0.2	0.17	0
K_I	8.72	4.51	4.94	4.92	4.66
ρ_1^I	0.22	0.17	0.17	0.18	0.19
ρ_2^I	-0.04	-0.12	-0.12	-0.11	-0.1
ρ_3^I	-0.54	-0.09	-0.09	-0.09	-0.08
ρ_4^I	-0.2	-0.08	-0.07	-0.07	-0.07
Panel D. Unemployment rate					
$E[U]$	7.12	5.98	7.46	7.45	6.92
σ_U	19.83	14	22.51	22.57	22.27
S_U	1.99	2.51	2.55	2.55	2.64
K_U	6.82	11	11.09	11.12	11.65

Notes: σ is the conditional volatility of the log productivity shocks, and ν the supply elasticity of capital. σ_Y, σ_C, and σ_I are the volatilities, S_Y, S_C, and S_I skewness, K_Y, K_C, and K_I kurtosis, and ρ_i^Y, ρ_i^C, and ρ_i^I the ith-order autocorrelations of log output, consumption, and investment growth rates, respectively. Prob_Y, Size_Y, and Dur_Y, as well as Prob_C, Size_C, and Dur_C are the probability, size, and duration of outputs and consumption disasters, respectively. $E[U]$, S_U, and K_U are the mean, skewness, and kurtosis of the monthly unemployment rate, respectively, and σ_U is its quarterly volatility. σ_Y, σ_C, σ_I, $E[U]$, and σ_U are in percent.

Sources: The output and consumption data moments are based on the Barro-Ursúa (2008) historical cross-country panel, extended through 2013. The investment data moments are based on the real US gross private domestic investment from National Income and Product Accounts Table 1.1.6 from 1929 to 2013. The unemployment data moments are based on the Petrosky-Nadeau-Zhang (2013) US series from April 1929 to December 2013. The model moments are based on authors' calculations.

2 to 0.5, the output volatility falls from 5.1 slightly to 4.9 percent, the disaster probability from 9.5 to 9.1 percent, and the disaster size and duration are unaffected. The mean unemployment rate falls from 7.5 to 6.9 percent, but its volatility, skewness, and kurtosis are unchanged.

C. *Recursive Utility*

In this subsection, we augment the baseline model in Section I with recursive preferences, which are standard in the asset pricing literature. Instead of log utility, the household maximizes recursive utility, denoted J_t, over consumption by trading risky shares issued by the representative firm and a risk-free bond. As in Epstein and Zin (1989), the recursive utility function is given by

$$
(24) \qquad J_t = \left[(1 - \beta) C_t^{1 - \frac{1}{\psi}} + \beta \left(E_t [J_{t+1}^{1-\gamma}] \right)^{\frac{1 - 1/\psi}{1 - \gamma}} \right]^{\frac{1}{1 - 1/\psi}},
$$

in which ψ is the elasticity of intertemporal substitution, and γ is the relative risk aversion. The stochastic discount factor, M_{t+1}, becomes

$$
(25) \qquad M_{t+1} \equiv \beta \left(\frac{C_{t+1}}{C_t} \right)^{-\frac{1}{\psi}} \left(\frac{J_{t+1}}{E_t[J_{t+1}^{1-\gamma}]^{\frac{1}{1-\gamma}}} \right)^{\frac{1}{\psi} - \gamma},
$$

and the risk-free rate is given by $R_{t+1}^f = 1/E_t[M_{t+1}]$.

The consumption Euler equation implies $1 = E_t[M_{t+1}R_{t+1}]$, in which $R_{t+1} \equiv S_{t+1}/(S_t - D_t)$ is the stock return (S_t is the cum-dividend equity value). Under constant returns to scale,

$$
(26) \qquad R_{t+1} = \frac{X_{t+1} - W_{t+1} + (1 - s)[\kappa_0/q(\theta_{t+1}) + \kappa_1 - \lambda_{t+1}]}{\kappa_0/q(\theta_t) + \kappa_1 - \lambda_t}.
$$

Intuitively, the stock return is the trade-off between the marginal benefits of hiring over period $t + 1$ and the marginal costs of hiring in period t. The rest of the model remains identical to the baseline model.

We set the risk aversion $\gamma = 10$, and the elasticity of intertemporal substitution $\psi = 1.5$. We set the time discount factor $\beta = 0.9976$ to help match the mean interest rate. With the volatility of productivity shocks, $\sigma = 0.01$, the recursive utility model implies an output volatility of 7.3 percent, higher than 5.6 percent in the data. We rescale σ to 0.0093 for an output volatility of 5.7 percent. We also report three comparative statics: $\gamma = 7.5$; $\psi = 1$; and $\gamma = \psi = 1$ (log utility), all with $\sigma = 0.0093$.

Table 8 shows that disaster dynamics are robust to recursive utility. With $\gamma = 10$ and $\psi = 1.5$, the disaster probability is 4.6 percent, the disaster size 23.4 percent, and duration 4.5 years for output, and the disaster probability is 2.5 percent, size 28.8 percent, and 4.8 years for consumption. Although the disaster probabilities are smaller than those in the data, the disaster size is comparable.[10]

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[10] Rescaling σ to 0.00875 yields an output volatility of 4.3 percent, which equals that in the 1790–2013 US sample. The consumption volatility in the model falls to 3.7 percent. The mean unemployment rate falls to 5.7 percent,

TABLE 8—QUANTITATIVE RESULTS: THE RECURSIVE UTILITY MODEL

	Data	Model			
γ		10	7.5	10	1
ψ		1.5	1.5	1	1
Panel A. Output growth					
σ_Y	5.63	5.67	4.97	5	4.1
S_Y	-1.02	0.87	0.81	0.76	0.59
K_Y	11.87	15.47	14.21	12.4	10.25
ρ_1^Y	0.16	0.21	0.19	0.23	0.19
ρ_2^Y	0	-0.14	-0.14	-0.12	-0.13
ρ_3^Y	0.02	-0.13	-0.12	-0.12	-0.12
ρ_4^Y	-0.02	-0.1	-0.1	-0.11	-0.1
Prob_Y	7.83	4.58	4.15	4.62	4
Size_Y	21.99	23.4	21.57	21.6	18.66
Dur_Y	3.72	4.45	4.52	4.48	4.56
Panel B. Consumption growth					
σ_C	6.37	5.06	4.34	4.35	3.43
S_C	-0.55	0.88	0.81	0.82	0.65
K_C	9.19	17.11	15.7	14.25	11.83
ρ_1^C	0.07	0.19	0.17	0.22	0.19
ρ_2^C	0.03	-0.15	-0.15	-0.13	-0.14
ρ_3^C	0	-0.13	-0.12	-0.13	-0.12
ρ_4^C	-0.02	-0.1	-0.09	-0.11	-0.1
Prob_C	8.57	2.51	2.13	2.51	1.97
Size_C	23.16	28.76	26.58	25.63	21.7
Dur_C	3.75	4.83	4.98	4.89	5.06
Panel C. Unemployment rate					
$E[U]$	7.12	6.25	5.88	6.23	5.68
σ_U	19.83	25.63	22.01	22.96	17.78
S_U	1.99	3.67	3.58	3.46	3.46
K_U	6.82	20.77	20.79	18.48	18.5
Panel D. Asset prices					
$E[R - R^f]$	4.69	4.45	1.1	4.97	0.22
$E[R^f]$	1.04	2.58	2.87	2.6	2.93
σ_R	20	15.79	15.14	15.73	14.5
σ_{R^f}	12.32	1.64	1.39	1.98	1.53

Notes: γ is the relative risk aversion, and ψ the elasticity of intertemporal substitution. σ_Y and σ_C are the volatilities, S_Y and S_C skewness, K_Y and K_C kurtosis, and ρ_i^Y and ρ_i^C the ith-order autocorrelations of log output and consumption growth rates, respectively. Prob_Y, Size_Y, and Dur_Y, as well as Prob_C, Size_C, and Dur_C are the probability, size, and duration of outputs and consumption disasters, respectively. $E[U]$, S_U, and K_U are the mean, skewness, and kurtosis of the monthly unemployment rate, respectively, and σ_U is its quarterly volatility. $\sigma_Y, \sigma_C, \sigma_I, E[U]$, and σ_U are in percent. $E[R - R^f]$ is the equity premium, $E[R^f]$ the risk-free rate, σ_R the stock market volatility, and σ_{R^f} the interest rate volatility, all in percent per annum. *Sources:* The output and consumption data moments are based on the Barro-Ursúa (2008) historical cross-country panel, extended through 2013. The unemployment data moments are based on the Petrosky-Nadeau-Zhang (2013) US series from April 1929 to December 2013. The asset pricing data moments are based on a historical cross-country panel of real stock market returns and real interest rates compiled from Global Financial Data and the Dimson-Marsh-Staunton (2002) dataset updated through 2013. The model moments are based on authors' calculations from 10,000 simulated samples.

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and its volatility 19.4 percent. The disaster dynamics remain substantial. The disaster probability is 3.6 percent, size 19.9 percent, and duration 4.6 years for output, and the disaster probability is 1.8 percent, size 24.5 percent, and duration 5.1 years for consumption.

The disaster moments are robust to utility parameters. Reducing γ to 7.5 lowers the disaster probability to 4.2 percent for output and 2.1 percent for consumption, but the disaster size and duration are only slightly lower. Reducing ψ to 1 lowers the disaster size to 21.6 percent for output and 25.6 percent for consumption, but disaster probabilities are barely changed. Even with log utility ($\gamma = \psi = 1$), the disaster dynamics remain substantial. The disaster probability is 4 percent for output and 2 percent for consumption, and the average size 18.7 percent for output and 21.7 percent for consumption. The durations are largely unaffected.

The utility parameters do affect output and consumption volatilities. Moving from recursive utility with $\gamma = 10$ and $\psi = 1.5$ to log utility, the output volatility falls from 5.7 to 4.1 percent, and the consumption volatility from 5.1 to 3.4 percent. For labor market moments, the mean unemployment rate drops from 6.3 to 5.7 percent, and its volatility from 25.6 to 17.8 percent. However, the unemployment skewness and kurtosis are relatively unaffected.

For asset pricing moments, we compile a historical cross-country panel of real stock market returns and real interest rates, by drawing from Global Financial Data and the Dimson, Marsh, and Staunton (2002) dataset updated through 2013. The panel contains 20 countries. The starting points range from 1801 for the United Kingdom to 1901 for Canada and Switzerland. Table 8 reports that the equity premium in the cross-country panel is 4.7 percent per annum, and the stock market volatility 20 percent. Both are adjusted for financial leverage. The interest rate is on average 1 percent, and its volatility 12.3 percent. The high interest rate volatility likely reflects sovereign default risk during disasters. The United States is relatively immune to sovereign default. In its historical 1836–2013 sample, the interest rate volatility is only 5.5 percent, and the mean interest rate 1.8 percent (the equity premium is 4.5 percent, and the stock market volatility 14.1 percent).[11]

The recursive utility model does a good job in matching asset prices. With $\gamma = 10$ and $\psi = 1.5$, the model implies an equity premium of 4.5 percent and a stock market volatility of 15.8 percent. However, the mean interest rate is 2.6 percent, which is higher than 1 percent in the cross-country panel and 1.8 percent in the historical US sample. The model also implies a low interest rate volatility of 1.6 percent because we do not model sovereign default. This interest rate volatility is much lower than those in Jermann (1998) and Boldrin, Christiano, and Fisher (2001). Both models feature internal habit, which implies that the elasticity of intertemporal substitution, ψ, is close to 0. Intuitively, with a lower ψ, the household cares more about consumption smoothing, and is less willing to substitute consumption over time to interest rate changes. As such, it takes a larger interest rate change to induce the household to accept a given change in consumption, raising the interest rate volatility. In contrast, recursive utility allows a high intertemporal elasticity, which is separate from the high risk aversion, giving rise to a stable interest rate.

Table 8 shows that the equity premium is tightly linked to the relative risk aversion, γ. Lowering γ to 7.5 is sufficient to shrink the equity premium to only 1.1 percent, although the stock market volatility falls only slightly. In contrast, quantity

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[11] The asset pricing literature has overwhelmingly focused on the postwar US data. In the 1951–2013 US sample, the equity premium is 5.5 percent per annum, the stock market volatility 12.8 percent, both of which are adjusted for financial leverage. The real interest rate is 1 percent on average, and its volatility 2.2 percent.

dynamics are more robust to the change in γ. The output volatility falls from 5.7 only to 5 percent, and the output disaster probability from 4.6 to 4.2 percent (the disaster size from 23.4 to 21.6 percent). For unemployment, the mean drops from 6.3 slightly to 5.9 percent, and the volatility from 25.6 to 22 percent. Unlike the risk aversion, the equity premium is robust to changes in the intertemporal elasticity of substitution, ψ. Lowering ψ from 1.5 to 1 even raises the equity premium somewhat to 5 percent. Finally, with log utility, the equity premium vanishes at 0.2 percent. Overall, echoing Tallarini (2000), although critical for asset prices, the risk aversion seems unimportant for quantities.

It is well known that explaining the equity premium in general equilibrium production economies is challenging (Rouwenhorst 1995). Dividends are often counterfactually countercyclical in these models. Intuitively, dividends equal profits minus investment, and profits equal output minus wages. When the labor market is frictionless, wages equal the marginal product of labor. Profits are proportional to, and as procyclical as output. Because investment is more procyclical than output and profits due to consumption smoothing, dividends (profits minus investment) must be countercyclical (Kaltenbrunner and Lochstoer 2010).

The search model avoids the pitfall of countercyclical dividends. The crux is that wages are delinked from the marginal product of labor. The wage elasticity to labor productivity is 0.54 in the model, which is not far from 0.47 in the postwar US data. Because of wage inertia, profits are more procyclical than output. Working as operating leverage, wage inertia magnifies the procyclical dynamics of profits. This amplified procyclicality of profits is sufficient to overcome the procyclicality of vacancy costs to turn dividends procyclical.[12]

The dividend and profit dynamics in the model are largely consistent with those in the data. Dividends in production economies correspond to net payout (dividends plus stock repurchases minus new equity issues) in the data. In the postwar US data, the cyclical component of real net payout has a correlation of 0.54 with the cyclical components of both real output and consumption. The relative volatility of net payout (the volatility of its leverage-adjusted cyclical component divided by that of real output) is 20.2. In the model, the correlation between dividends and output is 0.59, and that between dividends and consumption is 0.65. The relative volatility of dividends is 12.8 in the model (with a standard deviation of 3), which is low relative to that in the data. Finally, the relative volatility of profits to output is 5.2 in the data. The model counterpart is 4.1, with a standard deviation of 1.14.

III. Conclusion

In the spirit of Lucas and Rapping (1972), we ask whether disasters such as the Great Depression can be explained in an equilibrium framework with rational, optimizing agents. Our key insight is that the standard search model of equilibrium unemployment, once solved accurately with a globally nonlinear algorithm, gives

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[12] Danthine and Donaldson (2002) show that the priority status of wages magnifies dividend risk. However, with this mechanism alone, their model only produces an equity premium of about 1 percent per annum. Favilukis and Lin (2016) quantify the role of infrequent wage renegotiations in a general equilibrium production economy with long-run risk and labor adjustment costs. In contrast, wage inertia arises endogenously in our search model, and the equity premium stems from endogenous disaster risk.

rise endogenously to disasters. Intuitively, in bad times, inertial wages remain relatively high, reducing profits. The marginal costs of hiring run into downward rigidity, which stems from the trading externality of the matching process, and fail to decline relative to profits. Inertial wages and rigid hiring costs combine to stifle job creation flows, depressing the economy into disasters. In all, market economies are intrinsically unstable.

Productivity shocks are only a modeling device in our setup. We shed light on endogenous disasters from the labor market, but not the origins of disasters. Contractionary monetary shocks were the likely impulse in the Great Depression. Friedman and Schwartz (1963) show that the money supply in the United States fell by more than one-third from August 1929 to March 1933. In the concurrent banking crises, the number of commercial banks dropped by over one-third due to the suspension of operations, liquidations, and mergers. As a result, commercial bank deposits plummeted by more than 40 percent. The deflationary shocks were in turn transmitted globally via the gold standard (Temin 1989; Eichengreen 1992). As other countries lost gold to the United States because of its stringent monetary policy, their central banks were forced to deflate to defend their gold parities, leading to worldwide deflation. Future work can embed our structure into a monetary business cycle framework as in, for example, Christiano, Motto, and Rostagno (2003), to quantify the role of different shocks in the Great Depression.

We keep our setup simple to highlight endogenous disasters from the labor market. A large literature has shown the importance of financial frictions in understanding business cycles. Bernanke (1983) suggests that the 1930–1933 banking crises deepened the Great Depression by disrupting the credit intermediation process, as fear of bank runs led to substantial drops in deposits and increases in reserves. Bernanke, Gertler, and Gilchrist (1999) embed this mechanism into a monetary business cycle model. Christiano, Eichenbaum, and Evans (2005) show that working capital constraints, which require firms to borrow to pay wages up front, reduce marginal costs after an expansionary monetary shock to help explain the inflation inertia and output persistence in a New Keynesian model. Bigio (2015) shows how asymmetric information on the quality of capital endogenously determines working capital constraints, which are in turn key to explaining sizable recessions. Finally, Christiano, Eichenbaum, and Trabandt (2015) show that the working capital channel plays a critical role in explaining the small drop in inflation in the Great Recession. Future work can study the interaction between financial frictions and labor market frictions in endogenizing disasters.

The competitive equilibrium in the search economy is not socially optimal. The equilibrium violates the Hosios (1990) condition, which requires the workers' share of the matching surplus to equal the elasticity of the matching function with respect to unemployment. With the Den Haan, Ramey, and Watson (2000) matching technology, this elasticity is time-varying, depending on the labor market tightness, whereas the workers' share is constant. As such, government policies can be used to combat disasters. Our comparative statics show that disaster risk rises with the flow value of unemployment, meaning that making unemployment benefits procyclical likely reduces disaster risk. In related studies, Mitman and Rabinovich (2015) show that optimal unemployment benefits should be procyclical in a search model. However, Jung and Kuester (2015) show that optimal hiring subsides and layoff

taxes should rise in recessions, but the effect of optimal unemployment insurance is small. Christiano, Eichenbaum, and Trabandt (2016) show that the effect of raising unemployment benefits is greater if the central bank is more aggressive in fighting inflation. It seems important to study optimal policies aimed to mitigate disaster risk in the search economy.

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