Endogenous Disasters

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Abstract

Market economies are intrinsically unstable. The standard search model of equilibrium unemployment, once solved accurately with a global algorithm, gives rise endogenously to rare disasters. Intuitively, in the presence of cumulatively large negative shocks, 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. 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.

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Keywords: Search and matching frictions, the Great Depression, general equilibrium, unemployment, home production, capital accumulation, the equity premium

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1 Introduction

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 (Linde, Smets, and Wouters 2016). This paper demonstrates that the standard Diamond-Mortensen-Pissarides search model of equilibrium unemployment, once solved accurately with a global nonlinear algorithm, gives rise endogenously to rare disasters per Rietz (1988) and Barro (2006).

We calibrate the baseline model to the Barro-Ursúa (2008) historical cross-country panel of output and consumption, extended through 2013, as well as the 1929–2013 monthly U.S. 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%, as in the data. The output disaster probability is 5% in the model, which is somewhat lower than 7.8% in the data (adjusted for trend growth). For consumption disasters, the probability of 2.9% in the model is lower than 8.6% in the data, but the average size of 25.6% in the model is comparable with 23.2% in the data.

Comparative statics show that two key ingredients, including wage inertia and trading externality, combine to give rise to endogenous 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 sticky wages do not fall as much, causing profits to drop disproportionately.

Second, trading externality 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. The trading externality and its resulting rigid marginal costs of hiring are absent in 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. All the while, jobs are destroyed at a steady rate. Consequently, aggregate employment falls off a cliff, giving rise to endogenous disasters.

The disaster dynamics are robust to several model extensions. We first microfound the high flow value of unemployment via home production. The extended model implies an output disaster probability of 10%, which is even higher than 7.8% in the data, as well as a consumption disaster probability of 7.5%, which is still lower than 8.6% in the data. However, the average size is slightly smaller, 18.6% and 18.1% for output and consumption, respectively. We also find that the disaster dynamics are stronger when market and home goods are less substitutable, and when 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. We also show that 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 global nonlinear algorithm for solving the search model, and quantify its largely overlooked disaster dynamics.[1] Second, we contribute to the disasters literature in finance (Rietz 1988; Barro 2006; 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; 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; Christiano, Eichenbaum, and Trabandt 2015, 2016). Our work shows the potential importance of nonlinear dynamics in this class of models.

Section 2 shows disasters in the baseline model. Section 3 shows that disasters are robust to extensions to home production, capital accumulation, and recursive utility. Section 4 concludes. A separate online appendix details data, proofs, computation, and additional results.

2 The Baseline Model

We present a textbook search and matching model (Diamond 1982; Mortensen 1982; Pissarides 1985) in Section 2.1, and quantify its disaster dynamics in Sections 2.2 and 2.3.

[1] In subsequent work, Petrosky-Nadeau and Zhang (2016) show that relative to the global algorithm, 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 larger than loglinearization.

2.1 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, $\log(C_t)$, 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 one 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:

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

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

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 $q(\theta_t) \equiv G(U_t, V_t)/V_t = (1 + \theta_t^\iota)^{-1/\iota}$. 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,

[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 in 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.

contain two components, the proportional costs, κ_0, and the fixed costs, κ_1:

$$\kappa_t \equiv \kappa_0 + \kappa_1 q(\theta_t), \tag{2}$$

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:

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

in which $q(\theta_t)V_t$ is the number of new hires. Population is normalized to be one, $U_t + N_t = 1$, 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:

$$x_{t+1} = \rho x_t + \sigma \epsilon_{t+1}, \tag{4}$$

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,

$$Y_t = X_t N_t. \tag{5}$$

We abstract from capital, but include it later in a model extension (Section 3.2). While Cole and Ohanian (1999) emphasize productivity shocks in the Great Depression, monetary shocks play an important role (Friedman and Schwartz 1963). We remain agnostic about the origins of disasters, but shed light on the endogenous mechanism from the labor market.

The dividends to the firm's shareholders are given by:

$$D_t = X_t N_t - W_t N_t - \kappa_t V_t, \tag{6}$$

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:

$$S_t \quad \equiv \quad \max_{\{V_{t+\tau}, N_{t+\tau+1}\}_{\tau=0}^{\infty}} E_t \left[\sum_{\tau=0}^{\infty} M_{t+\tau} \left(X_{t+\tau} N_{t+\tau} - W_{t+\tau} N_{t+\tau} - \kappa_{t+\tau} V_{t+\tau} \right) \right], \tag{7}$$

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 $q(\theta_t) V_t \geq 0$, 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.

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

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

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.

[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 is not a key ingredient of the model. It matters little for the quantitative results. In our benchmark calibration, for instance, the constraint only binds for 0.2% of the time, which is rare.

Finally, the optimal vacancy policy also satisfies the Kuhn-Tucker conditions:

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

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 (the online appendix):

$$W_t = \eta\left(X_t + \kappa_t \theta_t\right) + (1-\eta)b. \tag{10}$$

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 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 wage rate 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 wages in equation (10) as given; and the goods market clears:

$$C_t + \kappa_t V_t = X_t N_t. \tag{11}$$

The Projection Algorithm

We use 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.

2.2 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 Ursua (2008). For unemployment moments, because historical cross-country data for unemployment and vacancies are not available, we calibrate the model to a long U.S. 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 U.S. 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 Web site. The Barro-Ursua 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 and countries with only postwar data. We impose this restriction to ensure that estimates of disaster moments are relatively unbiased.

Table 1 reports descriptive statistics for output and consumption growth rates. From Panel A, the output growth has a volatility of 5.6% 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 Panel B, the consumption growth has a volatility of 6.4%, 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 zero.[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% per annum in a historical cross-country panel of asset prices (Section 3.3). 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% per annum in the model, which is close to 5.6% 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 in the model, close to 0.47 in the postwar U.S. data. The flow value of unemployment activities, b, merits more discussion. Shimer (2005) pins down $b = 0.4$ by assuming that the only flow value of unemployment is unemployment insurance benefits. However, Hagedorn and Manovskii argue that in a perfectly competitive market, b should equal the flow value of employment. Specifically, b measures not only unemployment insurance, but also the total value of home production, self-employment, disutility of work, and leisure. In the model, the mean marginal product of labor is one, to which b should be close. We set $b = 0.85$, which is equal to that calibrated 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% (with a cross-simulation standard

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

Table 1 : Properties of Real Per Capita Output and Consumption Growth

Results are based on the Barro-Ursua (2008) historical cross-country panel extended through 2013. σ_Y and σ_C denote volatilities (in percent), 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 annual output and consumption growth, respectively.

Panel A: 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
U.K.	2.86	−0.77	5.03	0.3	−0.02	−0.15	−0.2
U.S.	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

Panel B: 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
U.K.	2.65	−0.35	8.48	0.29	0.01	−0.04	−0.04
U.S.	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

deviation of 0.8%), which is close to 9.1% in the U.S. 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% of output, Section 2.3).

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%) was due to high unemployment benefits. Weekly benefits exceeded 50% of average weekly wages by 1931, and increased to nearly 60% 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, as workers tend to experience large declines in their market 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% and long-term losses of 25% per year. However, unemployment insurance was limited outside Britain in the Great Depression.

Ramey and Francis (2009) develop comprehensive measures of time use in market work, home production, schooling, and leisure in the U.S. 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 capital leisure has increased by only 10% since 1900, and this increase is tiny relative to that in the real wage (and productivity) of 820%. 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, perhaps more important, we view our b calibration only as a parsimonious metaphor for real wage inertia, which seemed important in the Great Depression. Choudhri and Kochin (1980), Eichengreen and Sachs (1985), Temin (1989), and Eichengreen (1992) argue that contractionary monetary shocks in the U.S. 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 business cycle 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 U.S. 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% as a result of Hoover's program and deflation.

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

For the remaining parameters, we set the job separation rate, s, to be 4%, 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, which is close to that in Den

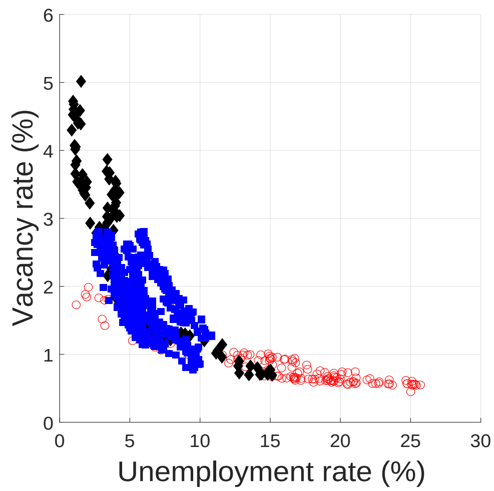
Haan, Ramey, and Watson (2000). To pin down the proportional and fixed costs of vacancy, κ_0 and κ_1, we first experiment to keep the total unit costs of vacancy, κ_t, around 0.7 on average in simulations. This level is necessary for the model to reproduce a realistic unemployment rate of 6.3%, which is not far from the average unemployment rate of 7.1% in the 1929–2013 U.S. sample. The evidence on the relative weights of the proportional and fixed costs of vacancy seems scarce. To determine κ_0 and κ_1 separately, we target the (quarterly) unemployment volatility of 19.8% in the data. This procedure yields $\kappa_0 = \kappa_1 = 0.5$, which implies an unemployment volatility of 23.4% in the model.

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% of annual wages (2.6% 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% of annual wages and high fixed costs of around 2.1% of annual revenue. Silva and Toledo (2009) estimate total turnover costs to be about 3.6% of quarterly wages for a fully productive worker and 4.3% 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 U.S. Beverage 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 Beverage 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 Beverage curve. Finally, the vacancy rate experienced large declines during the Great Depression, consistent with our model. The vacancy rate dropped from 2% in September 1929 to 0.44% in March 1933, representing a steep decline of 78% (the online appendix).

Figure 1 : The U.S. Beveridge Curve, April 1929–December 2013

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.



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 Table 1. 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 5 and 95 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 in Table 1.

Table 2 shows that the output volatility is 5.3% per annum in the model, which is close to the data moment, 5.6%. The consumption volatility of 4.7% in the model is smaller than 6.4% in the data. Also, 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

Table 2 : Basic Moments in the Baseline Model

The output and consumption moments are based on the Barro-Ursua (2008) historical cross-country panel extended through 2013, and the unemployment moments on the U.S. sample from April 1929 to December 2013 from Petrosky-Nadeau and Zhang (2013). The model moments are from 10,000 simulated samples. For each moment, we report 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 ith-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. σ_Y, σ_C, $E[U]$, and σ_U are in percent.

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

consumption growth rates in the model are slightly positively skewed with a coefficient about 0.9. The model 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 is 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, and weakly negatively autocorrelated at longer lags in the model.

From Panel C, the mean unemployment rate is 6.3% in the model, which is not far from 7.1% 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% 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% in the model, which is not far from 19.8% in the data. The model also implies an unemployment-vacancy correlation of -0.5 (-0.7 in the data).

2.3 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%, and the median 4.9%. The 2.5 percentile of the unemployment rate, 4.3%, is close to the median, whereas the 97.5 percentile is far away, 17%. 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]

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, defined as cumulative fractional declines in per capita consumption or output of at least 10%.[6] We apply the peak-to-trough method on the extended cross-country panel. Table 3 shows the estimates. For output, the disaster probability is 7.8%, the average size of disasters 22%, and the average duration 3.7 years. For consumption, the disaster probability is 8.6%, the average size 23.2%, and the duration 3.8 years.[7]

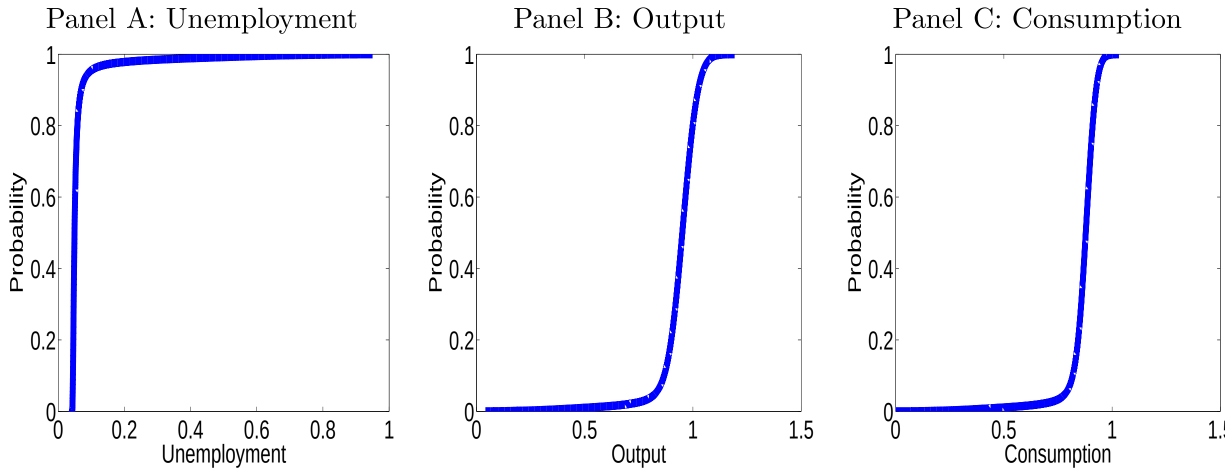
[5]The sharp drops in output and consumption levels in Figure 2 are consistent with the slightly positive skewness of output and consumption growth rates in Table 2. The extreme left tails in the levels give rise to large subsequent growth rates, as their denominators become small. In the extended model with capital (Section 3.2), the left 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]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. Finally, the disaster probability is the ratio of the number of disasters over the number of normalcy years.

[7]In continuous time models, disasters are often modeled as jumps in consumption growth. If reformulated

Figure 2 : Empirical Cumulative Distribution Functions, the Baseline Model

Results are based on one million months simulated from the baseline model's stationary distribution.



Our disaster probability estimates, 7.8% and 8.6% for output and consumption, are higher than those in Barro and Ursúa, 3.7% and 3.6%, respectively. The crux is that we adjust for trend growth in the data, 1.8% per annum for output and 1.7% for consumption, to be consistent with our model with no growth. Ignoring trend growth in our extended sample yields the disaster probabilities of 3.5% for output and 4.2% for consumption, which are close to Barro and Ursúa's. 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-Ursua peak-to-trough measurement. Table 3 shows that the output disaster probability in the model is 5%, which is lower than 7.8% 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%, is close to the data moment, 22%. The average duration in the model of 4.4 years is also close to 3.7 years in the data. For

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 as well as in discrete time, disasters arising from these different sources are observationally equivalent.

Table 3 : Disaster Moments

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 from 10,000 simulations, each with 1,836 months. 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%. 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 zero, and the probability mean and percentiles are calculated across all 10,000 samples. 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.

	Data	Model			
		Mean	5%	95%	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

consumption disasters, the probability is only 2.9% in the model, which is substantially lower than 8.6% in the data (p-value = 0). The average disaster size is 25.6% in the model, which is close to 23.2% in the data. The average duration is 4.9 years, which is not far from 3.75 years in the data. Finally, Figure 3 reports the frequency distributions of output and consumption disasters by size and duration simulated from the model. The size and duration distributions display similar patterns as those in the data (Barro and Ursua 2008, Figures 1 and 2). In particular, the size distributions seem to follow a power-law density.[8]

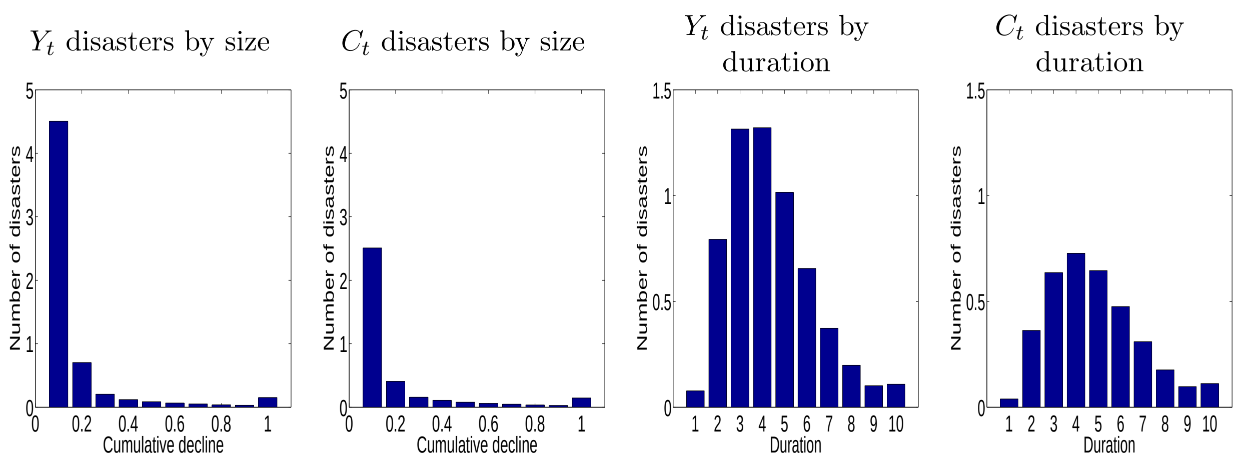
Comparative Statics

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

[8] 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, the quantitative results including the disaster moments are largely aligned with those from the baseline model.

Figure 3 : Distributions of Output and Consumption Disasters by Size and Duration from the Baseline Model's Stationary Distribution

Results are based on 10,000 simulations. Y_t is output, and C_t consumption.



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 4 reports the results. With $b = 0.825$, the output disaster probability reduces from 5% to 3.6%, and the consumption disaster probability from 2.9% to 1.6%. The average disaster size is lowered from 22.2% to 16.1% for output, and from 25.6% to 16.3% for consumption. The average duration of disasters increases slightly. The output and consumption volatilities drop to 3.4% and 2.6%, and the mean and volatility of the unemployment rate fall to 5% and 11%, respectively. With $b = 0.4$, the disaster probability falls further to 2.5% for output and 1.3% for consumption. The average size drops to 13.4% and 12.4%, respectively. The low value of b implies low wages and an exceedingly high profits-to-output ratio of 31%. The mean unemployment rate falls to 4%, and the unemployment volatility to only 0.14%. However, the presence of disaster dynamics with $b = 0.4$ implies that disasters are even more

Table 4 : Comparative Statics for the Disaster Moments in the Baseline Model

The first column reports the disaster moments from the benchmark calibration (Table 3), as well as 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. All the model moments are based on 10,000 simulations.

	Baseline	$b = 0.825$	$b = 0.4$	$s = 0.035$	$\kappa_t = 0.7$	$\iota = 1.1$	$\eta = 0.05$
	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

robust to changes in b than the unemployment volatility.

Intuitively, with small profits, wages are sticky 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% for output and 2.4% 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.

Without the fixed costs of vacancy, the disaster probability drops from 5% to 4.1% for output, and from 2.9% to 1.9% for consumption. The disaster size falls from 22.2% to 18.2% for output, and from 25.6% to 20.2% for consumption. The output and consumption volatilities decline to 4.1% and 3.3%, respectively. The mean unemployment rate falls from 6.3% to 5.5%, and its volatility from 23% to 15%, consistent with Pissarides (2009).

Reducing the curvature of the matching function, ι, from 1.25 to 1.1 raises the disaster probability somewhat to 5.3% for output and 3% 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%. Intuitively, a lower matching curvature 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 unemployment rate rises, and disaster dynamics strengthen.

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

Downward Rigidity in the Marginal Costs of Hiring

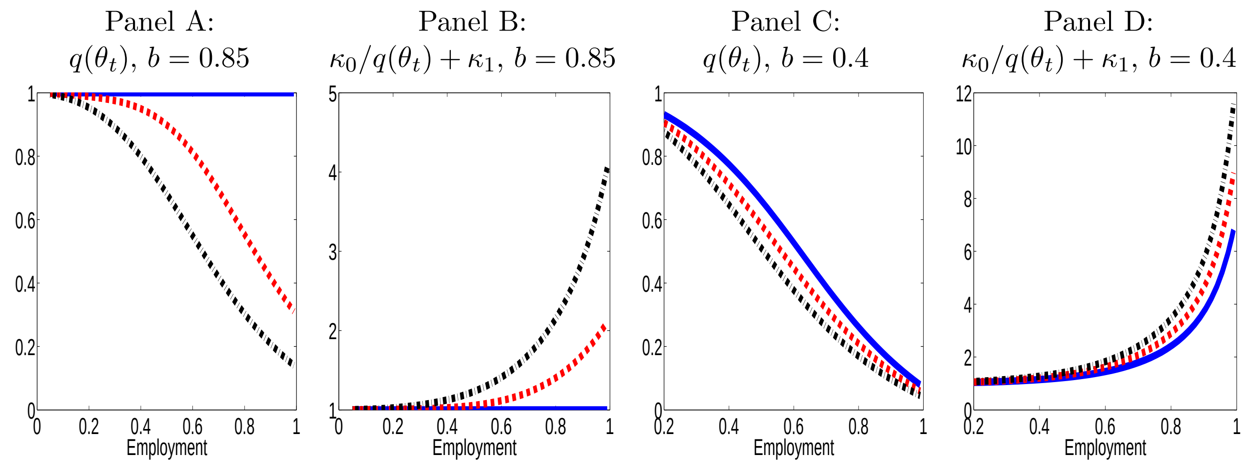
In addition to wage inertia, the other key determinant of the firm's hiring decisions is the marginal costs of hiring, $\kappa_0/q(\theta_t) + \kappa_1$. To illustrate the properties of the marginal costs, Figure 4 plots the vacancy filling rate, $q(\theta_t)$, as well as the marginal costs of hiring 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.

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

Figure 4 : The Vacancy Filling Rate and the Marginal Costs of Hiring in the Baseline Model, Small and Large Profits

Let $x_1 < x_2 < \ldots < x_{17}$ 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 dashdot line for $x_t = x_{15}$.



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 4).

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-Ursua (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. Since 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 judgement 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 provide an independent propagation mechanism, beyond the original impulses, the Barro-Ursua (2008) disaster moments pose a very high hurdle for any economic model to match.

We have also experimented with an alternative calibration. Instead of matching the output volatility of 5.6% per annum in the cross-country panel, we rescale the volatility of productivity shocks, σ, to match the output volatility of 4.3% in the historical 1790–2013 U.S. sample. This target is conservative because it is even lower than 4.9% in the 1929–2013 U.S. sample. We target the U.S. 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% for output and 3.6% for consumption in the baseline model. The unemployment rate is 5.8% on average, and its volatility 18.7%. More important, disaster dynamics remain substantial. The disaster probability is 4%, size 19.6%, and duration 4.6 years for output, and 2.1%, 22.3%, 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% in the Barro-Ursua (2008) cross-country panel.

3 Extensions

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

3.1 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 nonmarket, home produced goods, C_{ht}. We define the composite consumption bundle as:

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

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 $\phi_t \equiv aC_{mt}^{e-1}/C_t^e$, and the stochastic discount factor is:

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

The home production technology is given by:

$$C_{ht} = X_h U_t, \tag{14}$$

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

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

As shown in the Online Appendix, the equilibrium Nash-wage becomes:

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

The market clearing condition becomes $C_{mt} + \kappa_t V_t = X_t N_t$. The rest of the model, including the intertemporal job creation condition, 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

Table 5 : Quantitative Results, The Home Production Model

The model results are based on 10,000 simulations. 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 ith-order autocorrelations of log output and consumption growth, 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 monthly unemployment rates, respectively, and σ_U is the quarterly volatility. σ_Y, σ_C, $E[U]$, and σ_U are in percent.

	Data	Model					Data	Model			
σ		0.01	0.014	0.014	0.014	σ		0.01	0.014	0.014	0.014
a		0.8	0.8	0.8	0.85	a		0.8	0.8	0.8	0.85
e		0.85	0.85	0.9	0.85	e		0.85	0.85	0.9	0.85
σ_Y	5.63	3.41	5.29	4.62	3.9	σ_C	6.37	2.91	4.67	3.74	2.9
S_Y	−1.02	0.06	0.15	0.13	0.01	S_C	−0.55	0.09	0.2	0.2	0.03
K_Y	11.87	3.83	4.92	4.95	3.42	K_C	9.19	4.22	5.73	5.97	3.48
ρ_1^Y	0.16	0.15	0.16	0.15	0.14	ρ_1^C	0.07	0.15	0.16	0.15	0.14
ρ_2^Y	0	−0.13	−0.13	−0.13	−0.12	ρ_2^C	0.03	−0.13	−0.14	−0.14	−0.12
ρ_3^Y	0.02	−0.1	−0.11	−0.1	−0.1	ρ_3^C	0	−0.1	−0.11	−0.11	−0.1
ρ_4^Y	−0.02	−0.08	−0.08	−0.08	−0.08	ρ_4^C	−0.02	−0.08	−0.09	−0.08	−0.08
Prob_Y	7.83	5	9.95	8.2	6.88	Prob_C	8.57	3.35	7.52	4.95	3.43
Size_Y	21.99	15	18.58	17.21	15.43	Size_C	23.16	14.42	18.06	16.34	13.81
Dur_Y	3.74	4.32	3.74	3.88	3.98	Dur_C	3.75	4.65	3.99	4.31	4.59
$E[U]$	6.98	5.97	6.58	5.33	4.5	S_U	2.02	1.86	2.44	3.06	2.1
σ_U	21.76	10.75	19.53	15.3	4.07	K_U	7.26	7.48	10.42	15.73	9.87

of concrete evidence on home technology, we set its productivity parameter, X_h, to be one, which is the long-term mean of the market technology. We next calibrate the volatility of market productivity, σ, the relative weight of the 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 5 reports the results. Together, these parameter values imply an output volatility of 5.3%. The mean unemployment rate is 6.6%, and its volatility is 19.5%, which is close to 19.8% in the data. The market consumption volatility is 4.7%, which is identical to that in the baseline model. The model also reproduces the positively skewed and leptokurtic unemployment rate distribution.

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

Table 5 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%. The mean unemployment rate falls to 6%, and its volatility to 10.8%. Even with $\sigma = 0.01$, the disaster probability is still 5% for output and 3.4% for consumption. However, the disaster size is smaller, 15% for output, and 14.4% for consumption. Finally, the duration rises to 4.3 years for output and 4.7 for consumption.[9]

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%, and volatility from 19.5% to 15.3%. Intuitively, the magnitude of market consumption dominates that of home consumption (C_{mt}/C_{ht} is 15.4 on average). As e increases, the two types of consumption become more substitutable. Home consumption loses its relative appeal, despite its small size. As such, the flow value of unemployment, z_t, falls from on average 0.87 to 0.83, which reduces unemployment and its volatility, 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% for output, and the disaster size from 18.6% to 15.4%. More drastically, the mean unemployment rate falls from 6.6% to 4.5%, and its volatility from 19.5% to only 4.1%. Intuitively, as the relative weight of market goods increases in the utility function, home production becomes less valuable to the household. As a result, the flow value of unemployment, 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

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

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 micro data, ranging from 0.36 to 0.75. However, comparative statics show that, all else equal, increasing e to 0.9 dampens disaster dynamics. As such, alternative calibrations with a lower value of e are likely to strengthen the endogenous disasters in the model.

3.2 Capital

In this subsection, we augment the baseline model in Section 2 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 returns of scale technology:

$$Y_t = X_t K_t^{\alpha} N_t^{1-\alpha}, \tag{17}$$

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

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

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

The firm incurs adjustment costs when investing. Capital accumulates as:

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

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

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

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:

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

and the intertemporal job creation condition becomes:

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

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

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

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 be 1/3. 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 one 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 two model columns with $\sigma = 0.01$ (and $\nu = 2$) in Table 6 show the smoothing effect of investment. The output volatility drops to 3.4%, and the consumption volatility to 2.4%. The mean unemployment rate falls to 6%, and volatility to 14%. 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%, but its disaster probability drops only slightly to 4.6%, which remains substantial.

We rescale the conditional volatility of productivity shocks, σ, to 0.014 to obtain an output volatility of 5.1% (with $\nu = 2$), which is close to 5.3% in the baseline model. The consumption volatility is 3.7%, which is lower than 4.7% in the baseline model. The mean unemployment rate is 7.5%, and its volatility 22.5%. The investment growth volatility is

Table 6 : Quantitative Results, The Capital Model

The model results are based on 10,000 simulations. 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 ith-order autocorrelations of log output, consumption, and investment growth, 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 monthly unemployment rates, respectively, and σ_U is the quarterly volatility. $\sigma_Y, \sigma_C, \sigma_I$, $E[U]$, and σ_U are in percent.

	Data	Model					Data	Model			
σ		0.01	0.014	0.014	0.014	σ		0.01	0.014	0.014	0.014
ν		2	2	1.5	0.5	ν		2	2	1.5	0.5
σ_Y	5.63	3.35	5.11	5.1	4.93	σ_C	6.37	2.38	3.74	4	4.75
S_Y	−1.02	0.1	0.12	0.11	0.1	S_C	−0.55	0.08	0.12	0.14	0.17
K_Y	11.87	4.11	4.5	4.49	4.34	K_C	9.19	4.67	5.18	5.1	4.79
ρ_1^Y	0.16	0.18	0.19	0.19	0.17	ρ_1^C	0.07	0.21	0.22	0.2	0.17
ρ_2^Y	0	−0.1	−0.09	−0.1	−0.12	ρ_2^C	0.03	−0.08	−0.07	−0.09	−0.12
ρ_3^Y	0.02	−0.08	−0.07	−0.08	−0.09	ρ_3^C	0	−0.07	−0.06	−0.08	−0.09
ρ_4^Y	−0.02	−0.07	−0.06	−0.07	−0.08	ρ_4^C	−0.02	−0.06	−0.06	−0.06	−0.08
Prob_Y	7.83	4.55	9.45	9.4	9.07	Prob_C	8.57	2.08	5.31	5.95	8.18
Size_Y	21.99	15.76	18.97	18.81	18.08	Size_C	23.16	14.9	17.69	17.68	17.98
Dur_Y	3.72	4.58	3.89	3.87	3.8	Dur_C	3.75	5.39	4.51	4.33	3.9
σ_I	23.33	4.52	6.98	6.06	2.88	$E[U]$	6.98	5.98	7.46	7.45	6.92
S_I	−0.79	0.2	0.2	0.17	0	σ_U	21.76	14	22.51	22.57	22.27
K_I	8.72	4.51	4.94	4.92	4.66	S_U	2.02	2.51	2.55	2.55	2.64
ρ_1^I	0.22	0.17	0.17	0.18	0.19	K_U	7.26	11	11.09	11.12	11.65
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						

7%, which, although much lower than 23.3% in the 1929–2013 U.S. sample, is not far from 8.9% from 1951 onward. 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% for output, which is somewhat higher than 7.8% in the data. The disaster probability is 5.3% for consumption, which is still lower than 8.6% in the data. However, the disaster size is smaller, 19% for output versus 22% in the data, and 17.7% for consumption versus 23.2% in the data. The disaster duration is somewhat higher than those in the data.[10]

[10]Rescaling the volatility of productivity shocks, σ, to 0.012 implies an output volatility of 4.3%, which equals that in the 1790–2013 U.S. sample. The consumption volatility is 3.1%, and the investment volatility 5.9%. The mean unemployment rate is 6.8%, and the unemployment volatility 18.8%. The disaster

The rest of the model columns in Table 6 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%, whereas the consumption volatility rises from 3.7% to 4% and further to 4.8%. The consumption disaster probability goes up from 5.3% to 6% and further to 8.2%, 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 2 to 0.5, the output volatility falls from 5.1% slightly to 4.9%, the disaster probability from 9.5% to 9.1%, and the disaster size and duration are unaffected. The mean unemployment rate falls from 7.5% to 6.9%, but its volatility, skewness, and kurtosis are unchanged.

3.3 Recursive Utility

In this subsection, we augment the baseline model in Section 2 with recursive preferences, which are standard in the asset pricing literature (Bansal and Yaron 2004).

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:

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

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

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

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 $R_{t+1} \equiv S_{t+1}/(S_t -$

dynamics remain substantial. The disaster probability is 7.2%, size 17.5%, and duration 4.2 years for output, and 3.7%, 16.3%, and 4.8 years, respectively, for consumption.

D_t) is the stock return (S_t is the cum-dividend equity value). Under constant returns:

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

Intuitively, the stock return is the tradeoff between the marginal benefits of hiring over period $t+1$ and the marginal costs of hiring in period t. The rest of the model, including the job creation condition and wages, remains identical to the baseline model.

We set the risk aversion $\gamma = 10$, and the elasticity of intertemporal substitution $\psi = 1.5$ (Bansal and Yaron 2004). We set the time discount factor $\beta = 0.9976$ to help match the mean interest rate. With the volatility of productivity shocks, $\sigma = 0.01$, as in the baseline model, the recursive utility model implies an output volatility of 7.3%, which is higher than 5.6% in the data. We rescale σ to 0.0093 for an output volatility of 5.7%. We also report three comparative statics: $\gamma = 7.5$; $\psi = 1$; and $\gamma = \psi = 1$ (log utility), all with $\sigma = 0.0093$.

Table 7 shows that disaster dynamics are robust to recursive utility. With $\gamma = 10$ and $\psi = 1.5$, the disaster probability is 4.5%, the disaster size 23.9%, and duration 4.5 years for output, and 2.5%, 28.9%, and 4.8, respectively, for consumption. Although the disaster probabilities are smaller than those in the data, the disaster size is comparable.[11]

The disaster moments are robust to utility parameters. Reducing γ to 7.5 lowers the disaster probability to 4% for output and 2.1% for consumption, but the disaster size and duration are unaffected. Reducing ψ to one lowers the disaster size to 21.9% for output and 25.6% for consumption, but disaster probabilities are barely changed. Even with log utility ($\gamma = \psi = 1$), the disaster moments are close to those with $\gamma = 10$ and $\psi = 1.5$. The disaster probability is 5% for output and 2.8% for consumption, and the average size falls slightly to 22.3% for output and 25.7% 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%, and the consumption volatility from 5.1% to 3.4%. For labor market moments, the

[11] Rescaling σ to 0.00875 yields an output volatility of 4.3%, which equals that in the 1790–2013 U.S. sample. The consumption volatility in the model falls to 3.7%. The mean unemployment rate falls to 5.7%, and its volatility 19.4%. The disaster dynamics remain substantial. The disaster probability is 3.4%, size 20.7%, and duration 4.7 years for output, and 1.8%, 24.5%, and 5.1, respectively, for consumption.

Table 7 : Quantitative Results, Recursive Utility

The model results are based on 10,000 simulated samples. σ_Y and σ_C denote 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, respectively. Prob_Y, Size_Y, and Dur_Y are the probability, size, and duration of output disasters, respectively, and Prob_C, Size_C, and Dur_C are analogously defined for consumption disasters. $E[U]$, S_U, and K_U are the mean, skewness, and kurtosis of monthly unemployment rates, respectively, and σ_U is the quarterly unemployment 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.

	Data	Model					Data	Model			
γ		10	7.5	10	1	γ		10	7.5	10	1
ψ		1.5	1.5	1	1	ψ		1.5	1.5	1	1
σ_Y	5.63	5.67	4.97	4.99	4.11	σ_C	6.37	5.05	4.35	4.35	3.44
S_Y	−1.02	0.87	0.81	0.76	0.61	S_C	−0.55	0.88	0.81	0.81	0.67
K_Y	11.87	15.47	14.18	12.36	10.36	K_C	9.19	17.09	15.69	14.2	11.9
ρ_1^Y	0.16	0.21	0.19	0.23	0.20	ρ_1^C	0.07	0.19	0.18	0.22	0.19
ρ_2^Y	0	−0.14	−0.14	−0.12	−0.12	ρ_2^C	0.03	−0.15	−0.15	−0.13	−0.14
ρ_3^Y	0.02	−0.13	−0.12	−0.12	−0.12	ρ_3^C	0	−0.13	−0.12	−0.13	−0.12
ρ_4^Y	−0.02	−0.1	−0.1	−0.11	−0.1	ρ_4^C	−0.02	−0.1	−0.09	−0.11	−0.1
Prob_Y	7.83	4.49	4.03	4.53	5.03	Prob_C	8.57	2.51	2.12	2.51	2.84
Size_Y	21.99	23.92	22.17	21.92	22.25	Size_C	23.16	28.86	26.51	25.6	25.7
Dur_Y	3.72	4.46	4.56	4.5	4.45	Dur_C	3.75	4.84	5.01	4.9	4.93
$E[U]$	6.98	6.26	5.88	6.23	5.7	$E[R-R^f]$	4.69	4.45	1.1	4.97	0.22
σ_U	21.76	25.67	21.99	22.93	17.88	$E[R^f]$	1.04	2.58	2.87	2.6	2.93
S_U	2.02	3.66	3.57	3.46	3.29	σ_R	20	15.79	15.15	15.73	14.5
K_U	7.26	20.71	20.75	18.48	18	σ_{R^f}	12.32	1.64	1.39	1.98	1.54

mean unemployment rate drops from 6.3% to 5.7%, and its volatility from 25.7% to 17.9%. 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-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 7 reports that the equity premium in the cross-country panel is 4.7% per annum, and the stock market volatility is 20%. Both are adjusted for financial leverage. The interest rate is on average 1%, and its volatility 12.3%. The high interest rate volatility likely reflects sovereign default risk during disasters. The U.S. is relatively immune to sovereign default.

In its historical 1836–2013 sample, the interest rate volatility is only 5.5%, and the mean interest rate is 1.8% (the equity premium is 4.5%, and the stock market volatility 14.1%).[12]

The recursive utility model does a decent job in matching asset prices. With $\gamma = 10$ and $\psi = 1.5$, the model implies an equity premium of 4.5% and a stock market volatility of 15.8%. However, the mean interest rate is 2.6%, which is higher than 1% in the cross-country panel and 1.8% in the historical U.S. sample. The model also implies a low interest rate volatility of 1.6%, since 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 zero. 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 7 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%, although the stock market volatility falls only slightly. In contrast, quantity dynamics are more robust to the change in γ. The output volatility falls from 5.7% only to 5%, and the output disaster probability from 4.5% to 4% (the disaster size from 23.9% to 22.2%). For unemployment, the mean drops from 6.3% slightly to 5.9%, and the volatility from 25.7% to 22%. Unlike the risk aversion, the equity premium is robust to changes in the intertemporal elasticity of substitution, ψ. Lowering ψ from 1.5 to unity even raises the equity premium somewhat to 5%. Finally, with log utility, the equity premium vanishes at 0.2%. Overall, echoing Tallarini (2000), although critical for asset prices, the risk aversion seems unimportant for quantity dynamics.

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 mi-

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

nus 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 procylical 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 U.S. 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.[13]

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 U.S. 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.

4 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 accu-

[13]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% per annum. Favilukis and Lin (2015) 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 framework, and the equity premium stems from endogenous disaster risk.

rately with a global algorithm, gives 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 derives from the trading externality of the matching process, and fail to decline. 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 U.S. fell by more than 1/3 from August 1929 to March 1933. In the concurrent banking crises, the number of commercial banks dropped by over 1/3 due to the suspension of operations, liquidations, and mergers. As a result, commercial bank deposits plummeted by more than 40%. The deflationary shocks were in turn transmitted globally via the gold standard (Temin 1989, Eichengreen 1992). As other countries lost gold to the U.S. 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. Future work can also study the interaction of financial frictions with labor market frictions in propagating disaster dynamics. A long 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 (that 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 generating sizeable 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.

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-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. 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 policy design aimed to curb disaster risk in the search economy.

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