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# Searching for the equity premium[☆]

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ABSTRACT

A dynamic stochastic general equilibrium model with recursive utility, search frictions, and capital accumulation is a good start to forming a unified theory of asset prices and business cycles. The model reproduces an equity premium of 4.27% per annum, a stock market volatility of 12.42%, and an average interest rate of 1.97%, while retaining plausible business cycle dynamics. The equity premium and stock market volatility are strongly countercyclical, whereas the interest rate and consumption growth are largely unpredictable. Because of wage inertia, dividends are procyclical despite consumption smoothing via investment. The welfare cost of business cycles is huge, 33.6%.

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## 1. Introduction

Mehra and Prescott (1985) show that the equity premium (the average difference between the stock market return and the risk-free interest rate) in the Arrow–Debreu economy is negligible relative to its historical average. Subsequent studies have succeeded in specifying preferences and cash flow dynamics to explain the equity premium in endowment economies (Campbell and Cochrane, 1999; Bansal and Yaron, 2004; Barro, 2006). However, explaining the equity premium in general equilibrium production economies, in which cash flows arise endogenously, has proven more challenging.[1] To date, no consensus frame-

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[1] Rouwenhorst (1995) shows that the standard real business cycle model cannot explain the equity premium. Optimal investment of firms provides a powerful mechanism for the representative household to

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work has emerged, and finance and macroeconomics have largely developed dichotomously. Finance specifies "exotic" preferences and exogenous cash flow dynamics to match asset prices but ignores firms, whereas macroeconomics analyzes full-fledged general equilibrium production economies but ignores asset prices with primitive preferences (Christiano et al., 2005; Smets and Wouters, 2007).

This macro-finance dichotomy has left many fundamental questions unanswered. What are the microfoundations underlying the exogenously specified, often complex cash flow dynamics in finance models (Bansal et al., 2012; Nakamura et al., 2013)? What are the essential ingredients in the production side that can endogenize the key elements of cash flow dynamics necessary to explain the equity premium? To what extent do time-varying risk premiums matter quantitatively for macroeconomic dynamics? How large is the welfare cost of business cycles in a general equilibrium production economy that can explain the equity premium?

Our long-term objective is to formulate a unified equilibrium theory of asset prices and business cycles. The main hurdle is to explain the equity premium puzzle in general equilibrium, while simultaneously retaining plausible business cycle dynamics. To this end, we embed the standard Diamond–Mortensen–Pissarides search model of equilibrium unemployment into a dynamic stochastic general equilibrium framework with recursive utility and capital accumulation.

When calibrated to the consumption growth volatility in the Jordà–Schularick–Taylor macrohistory database, our model succeeds in yielding an equity premium (adjusted for financial leverage) of 4.27% per annum, which is close to 4.36% in the historical data. The average interest rate is 1.97%, which is not far from 0.82% in the data. The stock market volatility is 12.42% in the model, which falls somewhat short of 16% in the data. In addition, the model gives rise to strong time series predictability for stock market excess returns and volatilities, some predictability for consumption volatility, and weak to no predictability for consumption growth and the real interest rate. Quantitatively, the model explains stock market predictability but overstates somewhat the predictability of consumption volatility in the macrohistory database.

Wage inertia plays a key role in our model. To keep the model parsimonious, we work with the Nash wage that features a low bargaining weight of workers and a high flow value of unemployment. This calibration implies a wage elasticity to labor productivity of 0.278 in the model. Hagedorn and Manovskii (2008) estimate this elasticity to be 0.449 in a postwar U.S. sample (1951–2004). Drawing from historical sources (Kendrick, 1961; Officer, 2009), we extend their evidence and estimate the wage elasticity to be 0.267 in a historical U.S. sample (1890–2015).

Unlike endowment economies, in which cash flows are exogenously specified to fit the equity premium, the main challenge facing general equilibrium production economies is that cash flows tend to be endogenously countercyclical.[2] With wage inertia, profits are more procyclical than output. The magnified procyclicality of profits is sufficient to overcome the procyclicality of investment (and vacancy costs) to render dividends procyclical. In addition, the impact of wage inertia is stronger in bad times when profits are smaller. This time-varying wage inertia amplifies risks and risk premiums in bad times, giving rise to time series predictability of the equity premium and stock market volatility. Finally, despite adjustment costs, investment still absorbs a large amount of shocks, rendering consumption growth and the interest rate largely unpredictable.

Risk aversion strongly affects quantity dynamics, overturning Tallarini (2000). In comparative statics, reducing risk aversion from ten to five lowers the equity premium to 0.45% per annum. More important, consumption volatility falls from 5.43% to 4.03%, and consumption disaster probability drops from 6.66% to 4.41%. A lower discount rate raises the marginal benefit of hiring and reduces the unemployment rate from 9.4% to 4.3%. Echoing Hall (2017), our general equilibrium results indicate that it is imperative to study quantities and prices jointly.

With constant returns to scale, the stock return equals the value-weighted average of the investment and hiring returns. The investment return is the ratio of the next-period marginal benefit of investment over its current-period marginal cost. The hiring return is defined analogously. Despite a high labor share in output calibrated to 74.6% per Gollin (2002), the value weight of the hiring return (the labor share in the market equity) in the model is on average only 7.4%. Intuitively, the market equity is the present value of dividends, from which high labor costs are expensed as payments to workers. Also, the mean and volatility of the hiring return are an order of magnitude higher than those of the investment return. However, given the low labor share in value, labor market frictions affect the stock return primarily via the investment return.

Despite recursive utility calibrated to feature early resolution of uncertainty, the timing premium (the fraction of the consumption stream that the investor is willing to trade for the early resolution) is only 16.1% in our model. Intuitively, the expected consumption growth and conditional consumption volatility in our economy are much less persistent than those typically calibrated in the long-

smooth consumption so as to eliminate consumption risks. With internal habit preferences, Jermann (1998) and Boldrin et al. (2001) adopt capital adjustment costs and cross-sector immobility, respectively, to restrict consumption smoothing to match the equity premium. However, both models struggle with excessively high interest rate volatilities because of low elasticities of intertemporal substitution. With recursive utility, Tallarini (2000) shows that increasing risk aversion in a real business cycle model improves its fit with the market Sharpe ratio but does not materially affect macroeconomic quantities. However, the model fails to match the equity premium and its volatility. Kaltenbrunner and Lochstoer (2010) show that long-run consumption risks arise endogenously from consumption smoothing in a real business cycle model, but the model falls short in explaining the equity premium and stock market volatility.

[2] With frictionless labor markets, wages equal the marginal product of labor, which is almost as procyclical as output and profits (output minus wages). Alas, investment is more procyclical than output because of consumption smoothing, making dividends (profits minus investment) countercyclical (Kaltenbrunner and Lochstoer, 2010).

run risks literature, thereby avoiding its pitfall of implausibly high timing premiums.

Finally, the average welfare cost of business cycles is huge, 33.6%, which is more than 670 times Lucas (2003)'s estimate of 0.05%. In addition, the welfare cost is countercyclical with a long, right tail. In simulations, its 5th percentile, 21.3%, is not far below its median, 29%, but its 95th percentile is substantially higher, 63.3%. As such, countercyclical policies aimed to dampen disaster risks are even more important than what the average welfare cost of 33.6% would suggest.

We view this work as a solid progress report toward a unified theory of asset prices and business cycles. This holy grail of macro-finance has proven elusive for decades. Petrosky-Nadeau et al. (2018) show that the standard search model exhibits disaster dynamics. However, their asset pricing results are limited because of no capital. Capital is particularly important for asset prices because it represents the core challenge of endogenizing procyclical dividends in production economies (Jermann, 1998). We embed capital accumulation and recursive utility together to study asset prices with production while overcoming the ensuing heavy computational burden. Bai (2021) incorporates defaultable bonds to study the credit spread. We instead focus on the equity premium.

Embedding exogenous disasters per Rietz (1988) and Barro (2006) into a real business cycle model, Gourio (2012) shows that disaster risks significantly affect quantity dynamics. Echoing Gourio, we show that Tallarini (2000)'s separation between prices and quantities breaks down in a more realistic setting. However, we differ from Gourio in that disaster risks arise endogenously from labor market frictions. We also endogenize operating leverage via wage inertia to explain the equity premium and stock market volatility. In contrast, Gourio relies on exogenous leverage to generate volatile cash flows but "does not address the volatility of the unlevered return on capital (p. 2737)." Kilic and Wachter (2018) embed the exogenous Rietz–Barro disasters into the search model of unemployment to yield a high unemployment volatility and examine its relation with a high stock market volatility. While our work differs from Kilic and Wachter's in many details, the most important distinction is, again, the endogenous nature of disasters in our setting.[3]

The rest of the paper is organized as follows. Section 2 constructs the general equilibrium model. Section 3 presents our key quantitative results on the equity premium, stock market volatility, and their predictability. Section 4 examines several additional implications of the model, including the welfare cost of business cycles. Section 5 concludes. The Appendix describes our computational algorithm. A separate Internet Appendix details derivations and supplementary results.

## 2. A general equilibrium production economy

The economy consists of a representative household and a representative firm. Following Merz (1995), we assume that the household has perfect consumption insurance. A continuum of mass one of members is 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.

The household maximizes recursive utility, denoted $J_t$, given by:

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

in which $C_t$ is consumption, $\beta$ is the time preference, $\psi$ is the elasticity of intertemporal substitution, and $\gamma$ is the relative risk aversion (Epstein and Zin, 1989; Weil, 1990). The consumption Euler equation is given by:

$$1 = E_t[M_{t+1} r_{St+1}], \tag{2}$$

in which $r_{St+1}$ is the firm's stock return and $M_{t+1}$ is the household's stochastic discount factor:

$$M_{t+1} \equiv \beta\left(\frac{C_{t+1}}{C_t}\right)^{-\frac{1}{\psi}}\left(\frac{J_{t+1}}{E_t\left[J_{t+1}^{1-\gamma}\right]^{\frac{1}{1-\gamma}}}\right)^{\frac{1}{\psi}-\gamma}. \tag{3}$$

The riskfree rate is $r_{ft+1} = 1/E_t[M_{t+1}]$, which is known at the beginning of period $t$.

The representative firm uses capital, $K_t$, and labor, $N_t$, to produce output, $Y_t$, with a constant elasticity of substitution (CES) production technology (Arrow et al., 1961):

$$Y_t = X_t\left[\alpha\left(\frac{K_t}{K_0}\right)^{\omega} + (1-\alpha)N_t^{\omega}\right]^{\frac{1}{\omega}}, \tag{4}$$

in which $\alpha$ is the distribution parameter and $e \equiv 1/(1-\omega)$ is the elasticity of substitution between capital and labor. When $\omega$ approaches zero in the limit, Eq. (4) reduces to the special case of the Cobb-Douglas production function with a unitary elasticity. To facilitate calibration, we work with the "normalized" CES function in Eq. (4), in which $K_0 > 0$ is a scaler that makes the unit of $K_t/K_0$ comparable to the unit of $N_t$ (Klump and La Grandville, 2000). Specifically, we calibrate $K_0$ to ensure that $1-\alpha$ matches the average labor share in the data (Section 3.2). Doing so eliminates the distribution parameter, $\alpha$, as a free parameter.[4] Finally, the CES production function is of constant returns to scale, i.e., $Y_t = K_t \partial Y_t/\partial K_t + N_t \partial Y_t/\partial N_t$ (the Internet Appendix).

[3] Several recent studies have examined the equity premium in general equilibrium production economies but outside the disasters framework. Croce (2014) embeds exogenous long-run productivity risks into an equilibrium production economy. While long-run risks increase the equity premium, the return volatility is only about one-quarter of that in the data. Kung and Schmid (2015) endogenize long-run productivity risks via firms' research and development in an endogenous growth model. Favilukis and Lin (2016) examine the impact of infrequent wage renegotiations in a stochastic growth model with long-run productivity risks. Finally, Chen (2017) examines a production model with external habit and emphasizes the role of endogenous consumption volatility risks.

[4] In contrast, in prior applications of the CES production function in asset pricing, the distribution parameter, $\alpha$, is largely treated as a free parameter (Bai, 2021; Favilukis and Lin, 2016; Kilic and Wachter, 2018).

The firm takes the aggregate productivity, $X_t$, as given, with $x_t \equiv \log(X_t)$ governed by:

$$x_{t+1} = (1-\rho_x)\bar{x} + \rho_x x_t + \sigma_x \epsilon_{t+1}, \tag{5}$$

in which $\bar{x}$ is the unconditional mean, $\rho_x \in (0,1)$ is the persistence, $\sigma_x > 0$ is the conditional volatility, and $\epsilon_{t+1}$ is an independently and identically distributed (i.i.d.) standard normal shock. We scale $\bar{x}$ to make the average marginal product of labor around one in simulations to ease the economic interpretation of parameters.

The representative firm posts a number of job vacancies, $V_t$, to attract unemployed workers, $U_t$. Vacancies are filled via the Den Haan et al. (2000) matching function:

$$G(U_t, V_t) = \frac{U_t V_t}{\left(U_t^{\iota} + V_t^{\iota}\right)^{1/\iota}}, \tag{6}$$

in which $\iota > 0$ is the curvature parameter. This function is desirable in that matching probabilities fall between zero and one. Let $\theta_t \equiv V_t/U_t$ be 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 job filling rate) is $q(\theta_t) \equiv G(U_t, V_t)/V_t = \left(1+\theta_t^{\iota}\right)^{-1/\iota}$. Also, $f(\theta_t) = \theta_t q(\theta_t)$ and $q'(\theta_t) < 0$. An increase in the scarcity of unemployed workers relative to vacancies makes it harder to fill a vacancy. As such, $\theta_t$ is labor market tightness, and $1/q(\theta_t)$ is the average duration of vacancies.

The representative firm incurs costs in posting vacancies. The unit cost, $\kappa_t$, is specified as:

$$\kappa_t = \kappa_0 + \kappa_1 q(\theta_t), \tag{7}$$

in which $\kappa_0 > 0$ is the proportional cost, and $\kappa_1$ is the fixed cost. The latter is paid after a worker is hired, such as training and administrative setup costs of adding the worker to the payroll (Pissarides, 2009). The marginal cost of hiring is $\kappa_0/q(\theta_t) + \kappa_1$. Its proportional component, $\kappa_0/q(\theta_t)$, increases with the mean duration of vacancies, $1/q(\theta_t)$, whereas the fixed component, $\kappa_1$, is constant.

In booms, the labor market is tighter for the firm ($\theta_t$ higher); the job filling rate, $q(\theta_t)$, is lower; and the marginal cost of hiring is higher. In recessions, $\theta_t$ is lower, $q(\theta_t)$ is higher, and the marginal cost of hiring is lower. In the limit, $q(\theta_t)$ approaches one, and the marginal cost goes to $\kappa_0 + \kappa_1$, which yields the downward rigidity in the marginal cost (Petrosky-Nadeau et al., 2018).

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

$$N_{t+1} = (1-s)N_t + q(\theta_t)V_t, \tag{8}$$

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

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

$$K_{t+1} = (1-\delta)K_t + \Phi(I_t, K_t), \tag{9}$$

in which $\delta$ is the depreciation rate, $I_t$ is investment, and

$$\Phi_t \equiv \Phi(I_t, K_t) = \left[a_1 + \frac{a_2}{1-1/\nu}\left(\frac{I_t}{K_t}\right)^{1-1/\nu}\right]K_t, \tag{10}$$

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). This parsimonious parametrization involves only one free parameter, $\nu$.

The dividends (net payouts) to the firm's shareholders are given by:

$$D_t = Y_t - W_t N_t - \kappa_t V_t - I_t, \tag{11}$$

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

$$S_t \equiv \max_{\{V_{t+\tau}, N_{t+\tau+1}, I_{t+\tau}, K_{t+\tau+1}\}_{\tau=0}^{\infty}} E_t\left[\sum_{\tau=0}^{\infty} M_{t+\tau} D_{t+\tau}\right], \tag{12}$$

subject to Eqs. (8) and (9) as well as a nonnegativity constraint on vacancies, $V_t \geq 0$. Because $q(\theta_t) > 0$, $V_t \geq 0$ is equivalent to $q(\theta_t)V_t \geq 0$. In contrast, Eq. (10) implies that $\partial\Phi_t/\partial I_t = a_2(I_t/K_t)^{-1/\nu}$, which goes to infinity as investment, $I_t$, goes to zero. As such, $I_t$ is always positive.

From the first-order conditions for $I_t$ and $K_{t+1}$, we obtain the investment Euler equation:

$$\frac{1}{a_2}\left(\frac{I_t}{K_t}\right)^{1/\nu} = E_t\left[M_{t+1}\left[\frac{\partial Y_{t+1}}{\partial K_{t+1}} + \frac{1}{a_2}\left(\frac{I_{t+1}}{K_{t+1}}\right)^{1/\nu}(1-\delta+a_1) + \frac{1}{\nu-1}\frac{I_{t+1}}{K_{t+1}}\right]\right]. \tag{13}$$

Equivalently, $E_t[M_{t+1} r_{Kt+1}] = 1$, in which $r_{Kt+1}$ is the investment return:

$$r_{Kt+1} \equiv \frac{\partial Y_{t+1}/\partial K_{t+1} + (1/a_2)(1-\delta+a_1)(I_{t+1}/K_{t+1})^{1/\nu} + (1/(\nu-1))(I_{t+1}/K_{t+1})}{(1/a_2)(I_t/K_t)^{1/\nu}}. \tag{14}$$

Intuitively, the investment return in Eq. (14) quantifies the dynamic tradeoff between the marginal benefit of investment at time $t+1$ and the marginal cost of investment at $t$. The marginal cost is $1/(\partial\Phi_t/\partial I_t)$. The marginal benefit at $t+1$ includes the marginal product of capital, $\partial Y_{t+1}/\partial K_{t+1}$, and the marginal continuation value net of depreciation, $(1-\delta)/(\partial\Phi_{t+1}/\partial I_{t+1})$. The remaining terms in the numerator amount to the marginal impact of the extra unit of capital on the installation technology, $(\partial\Phi_{t+1}/\partial K_{t+1})/(\partial\Phi_{t+1}/\partial I_{t+1})$ (the Internet Appendix).

Let $\lambda_t$ be the Lagrange 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:

$$\frac{\kappa_0}{q(\theta_t)} + \kappa_1 - \lambda_t = E_t\left[M_{t+1}\left[\frac{\partial Y_{t+1}}{\partial N_{t+1}} - W_{t+1} + (1-s)\left(\frac{\kappa_0}{q(\theta_{t+1})} + \kappa_1 - \lambda_{t+1}\right)\right]\right]. \tag{15}$$

Eq. (15) implies that $E_t[M_{t+1} r_{Nt+1}] = 1$, in which $r_{Nt+1}$ is the hiring return:

$$r_{Nt+1} \equiv \frac{\partial Y_{t+1}/\partial N_{t+1} - W_{t+1} + (1-s)(\kappa_0/q(\theta_{t+1}) + \kappa_1 - \lambda_{t+1})}{\kappa_0/q(\theta_t) + \kappa_1 - \lambda_t}. \tag{16}$$

Intuitively, Eq. (16) quantifies the tradeoff between the marginal benefit of hiring at time $t+1$ and the marginal cost of hiring at $t$ (both with $V_t \geq 0$ accounted for). The marginal benefit at $t+1$ includes the marginal product of labor, $\partial Y_{t+1}/\partial N_{t+1}$, net of the wage rate, plus the marginal value of hiring, which equals the marginal cost of hiring at $t+1$, net of separation. Finally, the optimal vacancy policy also satisfies the Kuhn–Tucker conditions:

$$q(\theta_t)V_t \geq 0, \quad \lambda_t \geq 0, \quad \text{and} \quad \lambda_t q(\theta_t) V_t = 0. \tag{17}$$

Under constant returns to scale, the stock return, $r_{St+1}$, is the value-weighted average of the investment return and the hiring return (the Internet Appendix):

$$r_{St+1} = w_{Kt} r_{Kt+1} + (1 - w_{Kt}) r_{Nt+1}, \tag{18}$$

in which $w_{Kt} \equiv \mu_{Kt}K_{t+1}/(\mu_{Kt}K_{t+1} + \mu_{Nt}N_{t+1})$ is the value weight of the investment return in the stock return, the shadow value of capital, $\mu_{Kt}$, equals the marginal cost of investment, $(1/a_2)(I_t/K_t)^{(1/\nu)}$, and the shadow value of labor, $\mu_{Nt}$, equals the marginal cost of hiring, $\kappa_t/q(\theta_t) - \lambda_t$. Finally, let $P_t \equiv S_t - D_t$ be the ex-dividend market equity: $P_t = \mu_{Kt}K_{t+1} + \mu_{Nt}N_{t+1}$. As such, $w_{Kt}$ is the capital share in value, and $1 - w_{Kt}$ is the labor share in value.

The equilibrium wage rate is determined endogenously by applying the sharing rule per the outcome of a generalized Nash bargaining process between employed workers and the firm (Pissarides, 2000). Let $\eta \in (0, 1)$ be the workers' relative bargaining weight and $b$ be the workers' flow value of unemployment. The equilibrium wage rate is given by (the Internet Appendix):

$$W_t = \eta\left(\frac{\partial Y_t}{\partial N_t} + \kappa_t\theta_t\right) + (1-\eta)b. \tag{19}$$

The wage rate increases with the marginal product of labor, $\partial Y_t/\partial N_t$, and the vacancy cost per unemployed worker, $\kappa_t\theta_t$. Intuitively, the more productive the workers are and the more costly it is for the firm to fill a vacancy, the higher the wage rate is for the employed workers. In addition, the workers' bargaining weight, $\eta$, affects the wage elasticity to labor productivity. The lower $\eta$ is, the more the equilibrium wage is tied with the constant $b$, reducing the wage elasticity to productivity.

The competitive equilibrium consists of optimal investment, $I_t$, vacancy posting, $V_t$, multiplier, $\lambda_t$, and consumption, $C_t$, such that (i) $C_t$ satisfies the consumption Euler Eq. (2); (ii) $I_t$ satisfies the investment Euler Eq. (13), and $V_t$ and $\lambda_t$ satisfy the job creation condition (15) and the Kuhn–Tucker conditions (17), while taking the stochastic discount factor in Eq. (3), the equilibrium wage in Eq. (19), and the job filling rate implied by Eq. (6) as given; and (iii) the goods market clears:

$$C_t + \kappa_t V_t + I_t = Y_t. \tag{20}$$

Solving for the competitive equilibrium is computationally challenging. We adapt the Petrosky-Nadeau and Zhang (2017) globally nonlinear projection method with parameterized expectations to our setting (the Appendix). The state space consists of employment, capital, and productivity. We parameterize the conditional expectation in the right-hand side of Eq. (15) and solve for the indirect utility, investment, and conditional expectation functions from Eqs. (1), (13), and (15), respectively. We use the Rouwenhorst (1995) discrete state method to approximate the log productivity with 17 grid points. We use the finite element method with cubic splines on 50 nodes on the employment space and 50 nodes on the capital space and take their tensor product on each grid point of productivity. To solve the resulting system of 127,500 equations, we use the derivative-free fixed point iteration with a small damping parameter (Judd et al., 2014).

## 3. Quantitative results

We describe our data in Section 3.1 and calibration in Section 3.2. We examine the model's unconditional moments in Section 3.3, sources of the equity premium in Section 3.4, time-varying risks and risk premiums in Section 3.5, and comparative statics in Section 3.6.

### 3.1. Data

For business cycle moments, we use the historical cross-country panel of output, consumption, and investment from Jordà et al (2017), who in turn build on Barro and Ursúa (2008). For asset pricing moments, we use the Jordà et al. (2019) cross-country panel. We obtain the data from the Jordà–Schularick–Taylor macrohistory database.[5] The database contains macro and return series for 17 developed countries. The only missing series are returns for Canada, which we supplement from the Dimson et al. (2002) database purchased from Morningstar. Although the Dimson–Marsh–Staunton database contains asset prices and the Barro–Ursúa database provides consumption and output series for more countries, we rely on the Jordà–Schularick–Taylor database because it provides quantities and asset prices for the same set of countries. More important, it also contains investment series. The sample starts in 1871 and ends in 2015.[6]

Table 1 shows the properties of log growth rates of real consumption, output, and investment per capita in the historical panel. From Panel A, the consumption growth is on average 1.62% per annum, with a volatility of 5.45% and a skewness of −0.67, all averaged across 17 countries. The

[5] http://www.macrohistory.net/data.

[6] More precisely, in the Jordà–Schularick–Taylor database, the consumption, output, and investment series start in 1870, meaning that their growth rates start in 1871. The quantities series end in 2016, but asset prices end in 2015.

**Table 1**
Basic properties of the real consumption, output, and investment growth and asset prices in the historical sample.

The historical cross-country panel is from the Jordà–Schularick–Taylor macrohistory database, except for Canada's asset prices, which we obtain from the Dimson et al. (2002) database purchased from Morningstar. All (annual) series end in 2015. In Panels A and B, the column "Sample" indicates the sample's starting year. In Panels C and D, besides the starting year, the "Sample" column also reports the missing years in parentheses. For example, the real investment growth series for Australia starts in 1871 but is missing from 1947 to 1949. Other than Italy, which has missing asset prices from 1872 to 1884, in Panel D, all other missing years are in the 20th century. In Panel A, $\bar{g}_C$, $\sigma_C$, $S_C$, $K_C$, and $\rho_i^C$ denote the mean (in percent), volatility (in percent), skewness, kurtosis, and $i$th-order autocorrelation, for $i = 1, 2, \ldots, 5$, of log real per capita consumption growth, respectively. In Panel B, $\bar{g}_Y$, $\sigma_Y$, $S_Y$, $K_Y$, and $\rho_i^Y$ denote the mean (in percent), volatility (in percent), skewness, kurtosis, and $i$th-order autocorrelation for log real per capita output growth, respectively. In Panel C, $\bar{g}_I$, $\sigma_I$, $S_I$, $K_I$, and $\rho_i^I$ denote the mean (in percent), volatility (in percent), skewness, kurtosis, and $i$th-order autocorrelation for log real per capita investment growth, respectively. Finally, in Panel D, $E[\widetilde{r}_S]$, $\widetilde{\sigma}_S$, and $E[\widetilde{r}_S - r_f]$ are the average stock market return, stock market volatility, and the equity premium, respectively, without adjusting for financial leverage. $E[r_S - r_f]$ and $\sigma_S$ are the equity premium and stock market volatility, respectively, after adjusting for financial leverage. $E[r_f]$ is the mean real interest rate, and $\sigma_f$ is the interest rate volatility. All asset pricing moments are in annual percent. We require nonmissing stocks, bonds, and bills.

Panel A: Real consumption growth

| | Sample | $\bar{g}_C$ | $\sigma_C$ | $S_C$ | $K_C$ | $\rho_1^C$ | $\rho_2^C$ | $\rho_3^C$ | $\rho_4^C$ | $\rho_5^C$ |
|---|---|---|---|---|---|---|---|---|---|---|
| Australia | 1871 | 1.11 | 5.76 | −0.77 | 6.35 | −0.04 | 0.22 | −0.03 | 0.03 | −0.09 |
| Belgium | 1914 | 1.35 | 8.72 | −1.14 | 13.18 | 0.26 | 0.19 | 0.00 | −0.40 | −0.22 |
| Canada | 1872 | 1.77 | 4.62 | −1.04 | 6.27 | 0.00 | 0.16 | −0.16 | −0.04 | −0.14 |
| Denmark | 1871 | 1.38 | 5.27 | −0.83 | 11.44 | −0.01 | −0.41 | 0.06 | 0.18 | −0.23 |
| Finland | 1871 | 2.07 | 5.54 | −1.13 | 9.01 | 0.16 | −0.08 | 0.02 | −0.04 | −0.23 |
| France | 1871 | 1.37 | 6.57 | −1.06 | 13.69 | 0.39 | 0.19 | −0.06 | −0.28 | −0.14 |
| Germany | 1871 | 1.67 | 5.51 | −0.57 | 7.11 | 0.25 | 0.24 | 0.28 | −0.07 | 0.00 |
| Italy | 1871 | 1.47 | 3.63 | 0.14 | 7.62 | 0.38 | 0.32 | 0.10 | 0.08 | 0.11 |
| Japan | 1875 | 2.11 | 6.74 | −1.53 | 20.90 | 0.21 | 0.10 | 0.18 | 0.20 | 0.20 |
| Netherlands | 1871 | 1.41 | 8.18 | −0.83 | 19.86 | 0.17 | 0.13 | −0.21 | −0.21 | −0.19 |
| Norway | 1871 | 1.83 | 3.65 | −0.32 | 12.65 | −0.06 | −0.34 | 0.26 | 0.07 | −0.24 |
| Portugal | 1911 | 2.36 | 4.36 | −0.49 | 3.30 | 0.22 | 0.23 | −0.02 | 0.09 | −0.16 |
| Spain | 1871 | 1.56 | 7.92 | −2.20 | 17.20 | 0.00 | −0.02 | −0.13 | −0.05 | 0.08 |
| Sweden | 1871 | 1.80 | 4.20 | 0.44 | 7.04 | −0.15 | −0.17 | 0.05 | 0.07 | −0.20 |
| Switzerland | 1871 | 1.22 | 5.85 | 0.35 | 7.34 | −0.20 | −0.10 | −0.11 | −0.10 | 0.04 |
| UK | 1871 | 1.33 | 2.76 | −0.34 | 8.90 | 0.33 | 0.02 | −0.06 | −0.01 | −0.11 |
| USA | 1871 | 1.75 | 3.42 | −0.07 | 3.99 | 0.08 | 0.09 | −0.11 | 0.00 | −0.10 |
| Mean | | 1.62 | 5.45 | −0.67 | 10.34 | 0.12 | 0.04 | 0.00 | −0.02 | −0.09 |
| Median | | 1.56 | 5.51 | −0.77 | 8.90 | 0.16 | 0.10 | −0.02 | −0.01 | −0.13 |

Panel B: Real output growth

| | Sample | $\bar{g}_Y$ | $\sigma_Y$ | $S_Y$ | $K_Y$ | $\rho_1^Y$ | $\rho_2^Y$ | $\rho_3^Y$ | $\rho_4^Y$ | $\rho_5^Y$ |
|---|---|---|---|---|---|---|---|---|---|---|
| Australia | 1871 | 1.45 | 4.11 | −0.90 | 5.49 | 0.04 | 0.27 | −0.10 | −0.03 | −0.05 |
| Belgium | 1871 | 1.63 | 7.45 | 1.26 | 19.01 | 0.33 | 0.05 | 0.00 | 0.03 | −0.29 |
| Canada | 1871 | 1.87 | 4.97 | −0.78 | 5.11 | 0.26 | 0.11 | −0.07 | −0.15 | −0.15 |
| Denmark | 1871 | 1.68 | 3.66 | −1.03 | 8.13 | 0.05 | −0.17 | 0.08 | 0.08 | −0.08 |
| Finland | 1871 | 2.06 | 4.47 | −0.78 | 7.15 | 0.25 | −0.11 | 0.10 | −0.12 | −0.17 |
| France | 1871 | 1.64 | 6.20 | −0.60 | 10.30 | 0.09 | −0.09 | 0.10 | 0.19 | −0.09 |
| Germany | 1871 | 1.62 | 10.66 | −7.62 | 78.70 | 0.30 | −0.04 | −0.11 | −0.16 | −0.13 |
| Italy | 1871 | 1.80 | 4.71 | −1.32 | 13.34 | 0.27 | −0.06 | −0.03 | 0.14 | 0.01 |
| Japan | 1871 | 2.40 | 6.18 | −2.23 | 15.50 | 0.27 | 0.03 | 0.16 | 0.09 | 0.01 |
| Netherlands | 1871 | 1.54 | 6.75 | 0.97 | 32.58 | 0.25 | −0.12 | −0.02 | −0.07 | −0.16 |
| Norway | 1871 | 2.10 | 3.53 | −0.72 | 7.21 | 0.11 | −0.08 | 0.12 | 0.06 | −0.15 |
| Portugal | 1871 | 1.84 | 4.16 | −0.01 | 4.23 | 0.01 | 0.18 | 0.02 | 0.18 | 0.04 |
| Spain | 1871 | 1.86 | 4.98 | −1.58 | 10.94 | 0.18 | 0.05 | 0.03 | 0.04 | 0.14 |
| Sweden | 1871 | 2.02 | 3.39 | −1.32 | 7.30 | −0.08 | −0.04 | 0.02 | 0.18 | −0.17 |
| Switzerland | 1871 | 1.41 | 3.84 | −0.41 | 4.02 | 0.13 | −0.14 | −0.05 | 0.09 | 0.05 |
| UK | 1871 | 1.40 | 2.86 | −0.89 | 5.62 | 0.35 | 0.03 | −0.18 | −0.22 | −0.09 |
| USA | 1871 | 1.91 | 4.77 | −0.08 | 4.83 | 0.25 | 0.08 | −0.13 | −0.19 | −0.19 |
| Mean | | 1.78 | 5.10 | −1.06 | 14.09 | 0.18 | 0.00 | 0.00 | 0.01 | −0.09 |
| Median | | 1.80 | 4.71 | −0.78 | 7.30 | 0.25 | −0.04 | 0.00 | 0.04 | −0.09 |

Panel C: Real investment growth

| | Sample | $\bar{g}_I$ | $\sigma_I$ | $S_I$ | $K_I$ | $\rho_1^I$ | $\rho_2^I$ | $\rho_3^I$ | $\rho_4^I$ | $\rho_5^I$ |
|---|---|---|---|---|---|---|---|---|---|---|
| Australia | 1871 (47–49) | 1.60 | 13.56 | −0.72 | 5.06 | 0.15 | 0.09 | −0.07 | −0.16 | −0.07 |
| Belgium | 1901 (14–20, 40–46) | 1.68 | 10.74 | −0.20 | 3.44 | −0.09 | −0.06 | −0.02 | −0.23 | 0.14 |
| Canada | 1872 | 2.17 | 18.12 | −0.18 | 10.68 | 0.27 | 0.02 | −0.18 | −0.19 | −0.16 |
| Denmark | 1871 (15–22) | 1.96 | 10.10 | −0.52 | 6.63 | 0.21 | −0.11 | −0.05 | 0.00 | −0.17 |
| Finland | 1871 | 2.40 | 13.24 | −1.49 | 11.14 | 0.19 | 0.01 | 0.06 | −0.27 | −0.28 |
| France | 1871 (19–20, 45–46) | 1.98 | 19.23 | −1.33 | 16.16 | −0.07 | −0.31 | −0.04 | −0.08 | 0.15 |
| Germany | 1871 (14–20, 40–48) | 2.69 | 14.42 | −0.56 | 5.40 | 0.06 | −0.01 | −0.10 | −0.11 | −0.23 |
| Italy | 1871 | 2.50 | 12.42 | 1.82 | 23.10 | 0.11 | −0.14 | 0.12 | 0.03 | −0.08 |

(continued on next page)

**Table 1**
(*continued*)

| | Panel C: Real investment growth | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Sample | $\bar{g}_I$ | $\sigma_I$ | $S_I$ | $K_I$ | $\rho_1^I$ | $\rho_2^I$ | $\rho_3^I$ | $\rho_4^I$ | $\rho_5^I$ |
| Japan | 1886 (45–46) | 4.21 | 14.36 | −0.77 | 13.61 | 0.14 | −0.04 | −0.07 | 0.00 | 0.08 |
| Netherlands | 1871 (14–21, 40–48) | 1.78 | 8.23 | −0.28 | 3.70 | 0.03 | 0.01 | −0.15 | −0.04 | −0.21 |
| Norway | 1871 (40–46) | 2.69 | 13.33 | 2.08 | 21.86 | −0.13 | −0.16 | 0.02 | −0.04 | −0.05 |
| Portugal | 1954 | 2.64 | 9.58 | −0.22 | 3.08 | 0.22 | 0.21 | 0.06 | −0.13 | 0.08 |
| Spain | 1871 | 2.85 | 13.23 | −0.41 | 4.01 | 0.23 | 0.02 | −0.23 | −0.13 | −0.12 |
| Sweden | 1871 | 2.65 | 12.43 | 0.10 | 4.88 | 0.07 | −0.27 | −0.08 | 0.01 | −0.11 |
| Switzerland | 1871 (14–48) | 2.58 | 11.02 | 0.69 | 5.33 | 0.37 | 0.17 | −0.11 | −0.33 | −0.22 |
| UK | 1871 | 1.98 | 11.68 | 2.82 | 26.62 | 0.35 | −0.14 | −0.12 | −0.03 | −0.08 |
| USA | 1871 | 2.04 | 24.37 | −1.71 | 18.02 | 0.17 | −0.11 | −0.32 | −0.13 | −0.02 |
| Mean | | 2.38 | 13.53 | −0.05 | 10.75 | 0.13 | −0.05 | −0.07 | −0.10 | −0.08 |
| Median | | 2.40 | 13.23 | −0.28 | 6.63 | 0.14 | −0.04 | −0.06 | −0.10 | −0.08 |
| | Panel D: Asset prices | | | | | | | | | |
| | Sample | $E[\widetilde{r}_S]$ | $\widetilde{\sigma}_S$ | $E[r_f]$ | $\sigma_f$ | $E[\widetilde{r}_S - r_f]$ | $E[r_S - r_f]$ | $\sigma_S$ | | |
| Australia | 1900 (45–47) | 7.75 | 17.08 | 1.29 | 4.32 | 6.46 | 4.58 | 12.55 | | |
| Belgium | 1871 (14–19) | 6.31 | 19.88 | 1.21 | 8.43 | 5.10 | 3.62 | 14.62 | | |
| Canada | 1900 | 7.01 | 17.00 | 1.60 | 4.79 | 5.41 | 3.84 | 12.26 | | |
| Denmark | 1875 (15) | 7.47 | 16.43 | 3.08 | 5.68 | 4.39 | 3.12 | 11.91 | | |
| Finland | 1896 | 8.83 | 30.57 | −0.74 | 10.93 | 9.57 | 6.80 | 22.98 | | |
| France | 1871 (15–21) | 3.99 | 22.22 | −0.47 | 7.78 | 4.45 | 3.16 | 16.75 | | |
| Germany | 1871 (23, 44–49) | 8.83 | 27.59 | −0.23 | 13.22 | 9.05 | 6.43 | 20.22 | | |
| Italy | 1871 (1872–84, 15–21) | 6.63 | 27.21 | 0.58 | 10.50 | 6.05 | 4.29 | 20.41 | | |
| Japan | 1886 (46–47) | 8.86 | 27.69 | 0.00 | 11.20 | 8.87 | 6.29 | 21.10 | | |
| Netherlands | 1900 | 6.96 | 21.44 | 0.78 | 4.91 | 6.19 | 4.39 | 15.32 | | |
| Norway | 1881 | 5.67 | 19.82 | 0.90 | 5.98 | 4.77 | 3.39 | 14.53 | | |
| Portugal | 1880 | 3.81 | 25.68 | −0.01 | 9.43 | 3.82 | 2.71 | 19.29 | | |
| Spain | 1900 (36–40) | 6.25 | 21.41 | −0.04 | 6.90 | 6.29 | 4.47 | 15.94 | | |
| Sweden | 1871 | 8.00 | 19.54 | 1.77 | 5.60 | 6.23 | 4.42 | 14.26 | | |
| Switzerland | 1900 (15) | 6.69 | 19.08 | 0.89 | 5.00 | 5.79 | 4.11 | 14.00 | | |
| UK | 1871 | 6.86 | 17.77 | 1.16 | 4.82 | 5.70 | 4.05 | 12.96 | | |
| USA | 1872 | 8.40 | 18.68 | 2.17 | 4.65 | 6.23 | 4.43 | 13.66 | | |
| Mean | | 6.96 | 21.71 | 0.82 | 7.30 | 6.14 | 4.36 | 16.04 | | |
| Median | | 6.96 | 19.88 | 0.89 | 5.98 | 6.05 | 4.29 | 14.62 | | |

first-order autocorrelation is 0.12. The consumption volatility exhibits substantial variation, ranging from 2.76% in the United Kingdom to 8.72% in Belgium. The first-order autocorrelations also vary widely across countries, ranging from −0.2 in Switzerland to 0.39 in France.

From Panel B, averaged across countries, the output growth has a mean of 1.78% per annum, a volatility of 5.1%, a skewness of −1.06, and a first-order autocorrelation of 0.18. The output volatility of 5.1% is lower than the consumption volatility of 5.45%. As explained in Barro and Ursúa (2008), government purchases rise sharply in wartime, decrease consumption relative to output, and raise the consumption volatility relative to the output volatility. Panel C shows that the investment growth volatility is high on average, 13.5% per annum, varying from 8.2% in the Netherlands to 24.4% in the United States. Its first-order autocorrelation is 0.13.

Following Barro (2006), we calculate the leverage-adjusted equity premium as one minus financial leverage times the unadjusted equity premium and calculate the leverage-adjusted stock market volatility as the volatility of the leverage-weighted average of stock market and bill returns. We set leverage to be 0.29, which is the mean market leverage ratio in a cross-country panel estimated in Fan et al. (2012). From Panel D, the leverage-adjusted equity premium is 4.36% per annum on average, varying from 2.71% in Portugal to 6.8% in Finland.[7] The leverage-adjusted stock market volatility is on average 16%, ranging from 11.9% in Denmark to 23% in Finland. For the real interest rate, the mean is only 0.82% across countries. Finland has the lowest mean interest rate, −0.74%, whereas Denmark has the highest, 3.08%. Finally, the real interest rate volatility is on average 7.3%, ranging from 4.32% in Australia to 13.22% in Germany.[8]

The asset pricing literature has traditionally focused on the postwar U.S. data. Table 2 reports basic business cycle and asset pricing moments in the 1950–2015 cross-country sample. The real consumption, output, and in-

[7] The unadjusted equity premium is the adjusted equity premium multiplied by a factor of $1/(1-0.29) = 1.41$. This adjustment is more conservative than Barro (2006)'s. Barro works with a debt-equity ratio of 0.5 based on the postwar U.S. data. This debt-equity ratio implies a leverage ratio (debt/(debt + equity)) of 1/3, which in turn yields an adjustment factor of 1.5. Applying this adjustment factor on the unadjusted equity premium of 6.14% per annum in our dataset implies an adjusted equity premium of 4.09%, which is lower than our estimate of 4.36%.

[8] When calculating the return moments, we require stock, bond, and bill returns to be nonmissing for a given year in a given country. Relaxing this restriction has little impact on the moments. In Table S1 in the Internet Appendix, we recalculate the moments with the longest sample possible for each series. The leverage-adjusted equity premium remains at 4.36% per annum, and the leverage-adjusted stock market volatility rises slightly from 16.04% to 16.08%. The mean real interest rate increases somewhat, from 0.82% to 1.05%, and its volatility rises from 7.3% to 7.53%.

**Table 2**
Basic properties of the real consumption, output, and investment growth and asset prices, 1950–2015.

The historical cross-country panel is from the Jordà–Schularick–Taylor macrohistory database. The only exception is asset prices data for Canada, which we obtain from the Dimson et al. (2002) database purchased from Morningstar. All (annual) series end in 2015. In Panel A, $\bar{g}_C$, $\sigma_C$, $S_C$, $K_C$, and $\rho_i^C$ denote the mean (in percent), volatility (in percent), skewness, kurtosis, and $i$th-order autocorrelation, for $i = 1, 2, \ldots, 5$, of real per capita consumption growth, respectively. In Panel B, $\bar{g}_Y$, $\sigma_Y$, $S_Y$, $K_Y$, and $\rho_i^Y$ denote the mean (in percent), volatility (in percent), skewness, kurtosis, and $i$th-order autocorrelation for real per capita output growth, respectively. In Panel C, $\bar{g}_I$, $\sigma_I$, $S_I$, $K_I$, and $\rho_i^I$ denote the mean (in percent), volatility (in percent), skewness, kurtosis, and $i$th-order autocorrelation for real per capita investment growth, respectively. Finally, in Panel D, $E[\tilde{r}_S]$, $\tilde{\sigma}_S$, and $E[\tilde{r}_S - r_f]$ are the average stock market return, stock market volatility, and the equity premium, respectively, without adjusting for financial leverage. $E[r_S - r_f]$ and $\sigma_S$ are the equity premium and stock market volatility, respectively, after adjusting for financial leverage. $E[r^f]$ is the mean real interest rate, and $\sigma_f$ is the interest rate volatility. All asset pricing moments are in annual percent.

| | Panel A: Real consumption growth | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | $\bar{g}_C$ | $\sigma_C$ | $S_C$ | $K_C$ | $\rho_1^C$ | $\rho_2^C$ | $\rho_3^C$ | $\rho_4^C$ | $\rho_5^C$ |
| Australia | 1.78 | 2.02 | −0.14 | 3.55 | 0.17 | −0.24 | −0.11 | 0.19 | 0.30 |
| Belgium | 1.89 | 1.92 | 0.20 | 3.42 | 0.34 | 0.21 | 0.41 | 0.18 | 0.21 |
| Canada | 2.01 | 1.81 | −0.61 | 4.00 | 0.31 | 0.07 | 0.17 | −0.07 | −0.26 |
| Denmark | 1.24 | 2.43 | −0.03 | 2.95 | 0.22 | 0.01 | 0.03 | −0.17 | −0.30 |
| Finland | 2.62 | 3.17 | −0.40 | 3.04 | 0.40 | −0.08 | −0.05 | −0.05 | −0.03 |
| France | 2.34 | 1.79 | 0.19 | 2.18 | 0.65 | 0.48 | 0.40 | 0.42 | 0.41 |
| Germany | 2.81 | 2.46 | 0.71 | 2.98 | 0.73 | 0.53 | 0.50 | 0.51 | 0.49 |
| Italy | 2.51 | 2.72 | −0.30 | 2.97 | 0.67 | 0.46 | 0.52 | 0.48 | 0.41 |
| Japan | 3.90 | 3.53 | 0.72 | 3.00 | 0.74 | 0.62 | 0.69 | 0.66 | 0.61 |
| Netherlands | 1.92 | 2.47 | −0.16 | 2.45 | 0.67 | 0.32 | 0.15 | 0.08 | 0.13 |
| Norway | 2.39 | 2.19 | 0.21 | 3.76 | 0.23 | −0.02 | −0.18 | −0.14 | −0.13 |
| Portugal | 3.05 | 3.56 | −0.58 | 4.03 | 0.36 | 0.16 | 0.08 | −0.14 | −0.18 |
| Spain | 2.79 | 3.54 | 0.08 | 3.20 | 0.51 | 0.25 | 0.20 | 0.23 | 0.23 |
| Sweden | 1.55 | 1.92 | −0.59 | 3.12 | 0.38 | 0.18 | 0.08 | −0.09 | −0.16 |
| Switzerland | 1.44 | 1.42 | 0.11 | 2.59 | 0.61 | 0.24 | 0.14 | 0.10 | 0.11 |
| UK | 1.97 | 2.09 | −0.13 | 3.11 | 0.45 | 0.05 | −0.11 | −0.11 | 0.00 |
| USA | 2.08 | 1.73 | −0.21 | 2.49 | 0.32 | 0.03 | −0.06 | 0.02 | −0.04 |
| Mean | 2.25 | 2.40 | −0.05 | 3.11 | 0.44 | 0.18 | 0.15 | 0.10 | 0.08 |
| Median | 2.08 | 2.19 | −0.13 | 3.04 | 0.39 | 0.18 | 0.13 | 0.07 | 0.11 |

| | Panel B: Real output growth | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | $\bar{g}_Y$ | $\sigma_Y$ | $S_Y$ | $K_Y$ | $\rho_1^Y$ | $\rho_2^Y$ | $\rho_3^Y$ | $\rho_4^Y$ | $\rho_5^Y$ |
| Australia | 1.95 | 1.86 | −0.56 | 4.19 | 0.19 | −0.03 | −0.07 | 0.09 | 0.24 |
| Belgium | 2.22 | 2.01 | −0.28 | 2.95 | 0.28 | 0.27 | 0.20 | 0.23 | 0.05 |
| Canada | 1.94 | 2.25 | −0.73 | 3.73 | 0.25 | −0.04 | 0.05 | 0.05 | −0.01 |
| Denmark | 1.85 | 2.33 | −0.05 | 3.88 | 0.26 | 0.09 | 0.16 | 0.16 | 0.09 |
| Finland | 2.54 | 3.24 | −0.93 | 5.23 | 0.42 | 0.01 | 0.08 | 0.02 | 0.03 |
| France | 2.37 | 1.87 | −0.27 | 3.35 | 0.56 | 0.41 | 0.47 | 0.44 | 0.40 |
| Germany | 2.80 | 2.69 | 0.18 | 3.93 | 0.48 | 0.17 | 0.31 | 0.48 | 0.36 |
| Italy | 2.69 | 2.71 | −0.79 | 3.56 | 0.51 | 0.35 | 0.42 | 0.39 | 0.39 |
| Japan | 3.80 | 3.69 | 0.26 | 2.72 | 0.69 | 0.59 | 0.61 | 0.53 | 0.48 |
| Netherlands | 2.22 | 2.20 | −0.12 | 3.78 | 0.39 | 0.05 | 0.05 | 0.13 | 0.12 |
| Norway | 2.53 | 1.87 | −0.52 | 2.73 | 0.51 | 0.28 | 0.16 | 0.20 | 0.19 |
| Portugal | 2.93 | 3.48 | −0.34 | 3.87 | 0.51 | 0.23 | 0.26 | −0.01 | 0.02 |
| Spain | 3.15 | 3.21 | 0.07 | 2.62 | 0.50 | 0.32 | 0.23 | 0.22 | 0.14 |
| Sweden | 2.09 | 2.14 | −1.13 | 5.31 | 0.32 | −0.02 | 0.03 | 0.12 | 0.15 |
| Switzerland | 1.62 | 2.29 | −0.65 | 4.06 | 0.30 | −0.04 | −0.03 | 0.08 | 0.02 |
| UK | 1.88 | 1.90 | −0.85 | 4.89 | 0.33 | −0.13 | −0.12 | −0.01 | 0.02 |
| USA | 1.91 | 2.21 | −0.43 | 2.88 | 0.12 | −0.01 | −0.15 | 0.06 | −0.07 |
| Mean | 2.38 | 2.47 | −0.42 | 3.75 | 0.38 | 0.14 | 0.15 | 0.17 | 0.14 |
| Median | 2.22 | 2.25 | −0.43 | 3.78 | 0.39 | 0.09 | 0.15 | 0.11 | 0.10 |

| | Panel C: Real investment growth | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | $\bar{g}_I$ | $\sigma_I$ | $S_I$ | $K_I$ | $\rho_1^I$ | $\rho_2^I$ | $\rho_3^I$ | $\rho_4^I$ | $\rho_5^I$ |
| Australia | 2.33 | 5.70 | −0.45 | 2.82 | 0.09 | −0.29 | −0.08 | 0.16 | 0.07 |
| Belgium | 2.63 | 7.08 | −0.73 | 3.95 | 0.05 | −0.13 | −0.09 | −0.01 | −0.16 |
| Canada | 2.10 | 5.65 | −0.46 | 3.15 | 0.23 | 0.02 | −0.21 | −0.20 | −0.28 |
| Denmark | 1.32 | 9.06 | −1.34 | 6.86 | 0.24 | 0.07 | 0.06 | −0.13 | −0.19 |
| Finland | 2.41 | 9.01 | −0.66 | 4.25 | 0.49 | 0.04 | −0.19 | −0.20 | −0.09 |
| France | 1.86 | 6.18 | −2.56 | 14.73 | 0.14 | −0.03 | −0.18 | −0.13 | −0.19 |
| Germany | 2.60 | 6.41 | 0.28 | 3.78 | 0.39 | −0.06 | −0.08 | −0.02 | 0.03 |
| Italy | 2.37 | 5.53 | −0.63 | 3.12 | 0.41 | 0.11 | 0.18 | 0.22 | 0.10 |
| Japan | 4.11 | 7.86 | 0.56 | 2.84 | 0.52 | 0.19 | 0.30 | 0.30 | 0.28 |
| Netherlands | 2.21 | 6.11 | 0.10 | 3.42 | 0.24 | 0.00 | −0.07 | −0.11 | −0.27 |
| Norway | 2.18 | 8.58 | 0.29 | 4.50 | 0.13 | −0.14 | −0.03 | −0.10 | −0.22 |
| Portugal | 2.64 | 9.58 | −0.22 | 3.08 | 0.22 | 0.21 | 0.06 | −0.13 | 0.08 |
| Spain | 3.60 | 9.32 | −0.20 | 3.40 | 0.45 | 0.30 | −0.07 | −0.12 | −0.27 |
| Sweden | 2.49 | 5.32 | −1.41 | 5.32 | 0.28 | −0.09 | −0.13 | −0.08 | 0.03 |
| Switzerland | 2.25 | 7.93 | 0.46 | 5.96 | 0.35 | 0.03 | −0.04 | −0.21 | −0.24 |
| UK | 2.61 | 5.75 | −0.76 | 4.16 | 0.38 | 0.02 | −0.03 | 0.02 | 0.05 |
| USA | 1.91 | 4.98 | −0.89 | 4.45 | 0.27 | −0.12 | −0.27 | −0.21 | −0.08 |
| Mean | 2.45 | 7.06 | −0.51 | 4.69 | 0.28 | 0.01 | −0.05 | −0.05 | −0.07 |
| Median | 2.37 | 6.41 | −0.46 | 3.95 | 0.27 | 0.02 | −0.07 | −0.10 | −0.09 |

| | Panel D: Asset prices | | | | | | |
|---|---|---|---|---|---|---|---|
| | $E[\tilde{r}_S]$ | $\tilde{\sigma}_S$ | $E[r_f]$ | $\sigma_f$ | $E[\tilde{r}_S - r_f]$ | $E[r_S - r_f]$ | $\sigma_S$ |
| Australia | 7.33 | 20.46 | 1.44 | 3.97 | 5.89 | 4.18 | 14.90 |
| Belgium | 8.07 | 21.05 | 1.60 | 2.91 | 6.47 | 4.59 | 15.02 |
| Canada | 7.47 | 16.33 | 1.80 | 3.12 | 5.66 | 4.02 | 11.51 |
| Denmark | 9.60 | 21.37 | 2.24 | 2.85 | 7.36 | 5.22 | 15.19 |
| Finland | 12.17 | 33.86 | 0.76 | 4.50 | 11.41 | 8.10 | 24.47 |
| France | 6.45 | 26.13 | 1.08 | 3.29 | 5.38 | 3.82 | 18.71 |
| Germany | 12.09 | 27.71 | 1.72 | 1.78 | 10.37 | 7.36 | 19.62 |
| Italy | 6.02 | 25.99 | 1.23 | 3.09 | 4.79 | 3.40 | 18.69 |
| Japan | 9.58 | 22.37 | 1.21 | 3.40 | 8.37 | 5.94 | 16.04 |
| Netherlands | 9.43 | 21.81 | 1.15 | 2.83 | 8.28 | 5.88 | 15.58 |
| Norway | 7.25 | 25.99 | −0.21 | 3.26 | 7.46 | 5.30 | 18.69 |
| Portugal | 4.86 | 33.53 | −0.73 | 4.85 | 5.59 | 3.97 | 24.38 |
| Spain | 7.93 | 24.53 | −0.22 | 4.43 | 8.15 | 5.79 | 17.91 |
| Sweden | 11.14 | 24.01 | 0.82 | 2.58 | 10.32 | 7.33 | 17.23 |
| Switzerland | 8.33 | 21.41 | 0.06 | 2.13 | 8.27 | 5.87 | 15.33 |
| UK | 9.13 | 22.94 | 1.21 | 3.63 | 7.92 | 5.62 | 16.27 |
| USA | 8.56 | 16.83 | 1.41 | 2.25 | 7.15 | 5.08 | 12.03 |
| Mean | 8.55 | 23.90 | 0.97 | 3.23 | 7.58 | 5.38 | 17.15 |
| Median | 8.33 | 22.94 | 1.21 | 3.12 | 7.46 | 5.30 | 16.27 |

vestment growth rates are less volatile, with standard deviations of 2.4%, 2.47%, and 7.06% per annum, respectively, averaged across countries. The U.S. macro volatilities are lower still, at 1.73%, 2.21%, and 4.98%, respectively. Relatedly, the consumption, output, and investment growth rates are more persistent in the postwar sample, with first-order autocorrelations of 0.46, 0.39, and 0.29, respectively. However, the postwar leverage-adjusted equity premium is higher than the historical equity premium, 5.38% versus 4.36%. The leverage-adjusted stock market volatility is also higher in the postwar sample, 17.15% versus 16.04%. The evidence indicates that the postwar U.S. sample might not be representative. As such, we mostly rely on the historical panel to calibrate our model.

For labor markets, to our knowledge, a historical cross-country panel is unavailable. We work with the Petrosky-Nadeau and Zhang (2021) U.S. historical monthly series.[9] Following Weir (1992), in addition to civilian unemployment rates, Petrosky-Nadeau and Zhang construct a separate series of private nonfarm unemployment rates by subtracting farm and government employment from both civilian labor force and civilian employment. Because this unemployment series better depicts the functioning of the private economy (Lebergott, 1964), we focus our calibration on this series. This series dates back to 1890, and the vacancy rate series dates to 1919.

From January 1890 to December 2015, the mean private nonfarm unemployment rate is 8.94%. The skewness and kurtosis of the unemployment rates are 2.13 and 9.5, respectively. In the postwar sample from January 1950 to December 2015, the mean unemployment rate is lower, 7.65%. Skewness is also smaller, 0.55, and kurtosis, 2.92, is close to that of the normal distribution.

Following Shimer (2005), we take quarterly averages of monthly unemployment and vacancy rates to convert to quarterly series, which we then detrend as Hodrick–Prescott (1997, HP) filtered proportional deviations from the mean with a smoothing parameter of 1600. We do not take log deviations, because $V \geq 0$ can be occasionally binding in the model. From 1890 onward, the private nonfarm unemployment volatility is 24.43% per quarter (25.9% with log deviations). From 1919 onward, the vacancy rate volatility is 18.98% (17.36% with log deviations). For labor market tightness (the ratio of the vacancy rate over the private nonfarm unemployment rate), the volatility is 61.62% (but only 38.38% with log deviations). The unemployment-vacancy correlations are −0.57 and −0.79 with the two detrending methods, respectively.[10]

[9] The series are available at https://ars.els-cdn.com/content/image/1-s2.0-S0304393220300064-mmc2.csv.

[10] Labor market volatilities are lower in the postwar sample. The private nonfarm unemployment volatility is 13.81% per quarter, and the vacancy rate volatility is 13.49%. The labor market tightness volatility is 26.17%, and the unemployment-vacancy correlation is −0.9. Detrending with log deviations yields very close estimates.

### 3.2. Calibration

Table 3 lists the parameter values in our benchmark monthly calibration. We set the time discount factor $\beta = 0.9976$ to help match the mean real interest rate. Risk aversion, $\gamma$, is ten per the long-run risks literature (Bansal and Yaron, 2004). The elasticity of intertemporal substitution, $\psi$, is two per Barro (2009), a value in part based on the Gruber (2013) estimate. Following Gertler and Trigari (2009), we set the persistence of the log productivity, $\rho_x$, to be $0.95^{1/3}$, and set its conditional volatility, $\sigma_x$, to match the consumption growth volatility in the data. Instead of the output volatility, we target the consumption volatility, which impacts more directly on asset prices. This procedure yields a value of 0.015 for $\sigma_x$. This value implies a consumption volatility of 5.43% per annum, which is close to 5.45% in the data (Table 1). However, the output volatility is 6.64%, which is higher than 5.1% in the data (although the difference is insignificant).

For the CES production function, we set $\omega = -1.5$. This $\omega$ value implies an elasticity of capital-labor substitution of 0.4, which is the Chirinko and Mallick (2017) estimate. To calibrate the distribution parameter, $\alpha$, we target the average labor share. Gollin (2002) shows that factor shares are roughly constant across time and space. Table S2 in the Internet Appendix reports the labor shares for the 12 countries that are in both the Gollin and the Jordà–Schularick–Taylor databases. The average labor shares across the countries from Gollin's first two adjustment methods are 0.765 and 0.72, respectively, with an average of 0.743. Gollin emphasizes that these two adjustments "give estimated labor shares that are essentially flat across countries and over time" (p. 471). We set $\alpha = 0.25$ to yield an average labor share of 0.746 in simulations.

The distribution parameter, $\alpha$, is close to one minus the average labor share only in the "normalized" CES production function, in which the capital unit is comparable to the labor unit (Klump and La Grandville, 2000). We calibrate the capital scaler, $K_0$, to be 13.98 to set the labor share at the deterministic steady state to 0.75. (Capital at the deterministic steady state is 14.66.) Despite the model's nonlinearity, the labor share is very close across the deterministic and stochastic steady states. We calibrate the long-run mean of the productivity, $\bar{x} = 0.1945$, to target the marginal product of labor, $\partial Y_t/\partial N_t$, around one on average in simulations.[11]

We set the separation rate, $s$, to 3%. The average total nonfarm separation rate in the Job Openings and Labor Turnover Survey (JOLTS) available from December 2000 onward at the Bureau of Labor Statistics (BLS) is about 3.5% per month. However, Bils et al. (2011) estimate the separation rate to be 2% in the Survey of Income and Program Participation (SIPP). In particular, the SIPP data exclude separations that are job-to-job and those that result in recalls to the original employers within four months. Bils et al. argue that job-to-job transitions should be excluded when calibrating search models with only employment-to-

[11] Setting $\partial Y_t/\partial N_t = 1$ at the deterministic steady state yields $\bar{x} = 0.182$. However, $\partial Y_t/\partial N_t$ in the stochastic steady state is somewhat lower than one. With trial and error, we add 0.0125 to $\bar{x}$ to yield the desired outcome.

**Table 3**
Parameter values under the benchmark monthly calibration.
The model parameters include the time discount factor, $\beta$; relative risk aversion, $\gamma$; the elasticity of intertemporal substitution, $\psi$; persistence of the log productivity, $\rho_x$; conditional volatility of the log productivity, $\sigma_x$; elasticity of capital-labor substitution, $e$; the distribution parameter, $\alpha$; the capital scaler, $K_0$; long-run mean of the log productivity, $\bar{x}$; the supply elasticity of capital, $\nu$; capital depreciation rate, $\delta$; the separation rate, $s$; the curvature of the matching function, $\iota$; the bargaining weight of workers, $\eta$; the flow value of unemployment, $b$; the proportional unit vacancy cost, $\kappa_0$; and the fixed unit vacancy cost, $\kappa_1$.

| $\beta$ | $\gamma$ | $\psi$ | $\rho_x$ | $\sigma_x$ | $e$ | $\alpha$ | $K_0$ | $\bar{x}$ | $\nu$ | $\delta$ | $s$ | $\iota$ | $\eta$ | $b$ | $\kappa_0$ | $\kappa_1$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0.9976 | 10 | 2 | $0.95^{1/3}$ | 0.015 | 0.4 | 0.25 | 13.98 | 0.1945 | 1.2 | 0.0125 | 0.03 | 0.9 | 0.015 | 0.91 | 0.05 | 0.025 |

unemployment separations. In addition, short-term “separations” with recalls should be interpreted as a reduction in hours. Our calibrated $s$ value of 3% is within the range of the SIPP and JOLTS estimates.

The matching function curvature, $\iota$, governs the magnitude of matching frictions. A lower $\iota$ implies more severe frictions. Alas, its direct estimates are scarce. We set $\iota$ to be 0.9, which is within the range from 0.407 in Hagedorn and Manovskii (2008) and 1.27 in Den Haan et al. (2000). Both pick the $\iota$ values to match their model moments to data moments. The supply elasticity of capital, $\nu$, governs the magnitude of adjustment costs. A lower $\nu$ implies higher adjustment costs, which reduce the investment volatility but raise the consumption volatility. Alas, direct estimates of $\nu$ are also scarce. We set $\nu$ to 1.2. Finally, the depreciation rate, $\delta$, is 1.25%.

### 3.2.1. Wage inertia

We are left with the bargaining weight of workers, $\eta$, the flow value of unemployment activities, $b$, as well as the proportional and fixed unit costs of vacancy posting, $\kappa_0$ and $\kappa_1$, respectively. To match the equity premium without overshooting the mean unemployment rate, we combine inertial wages and (relatively) low vacancy costs. Specifically, we set $\eta = 0.015$ and $b = 0.91$, which combine to yield a wage elasticity to labor productivity of 0.278 in the model. For the unit vacancy costs, we settle with $\kappa_0 = 0.05$ and $\kappa_1 = 0.025$. As a result, the mean unemployment rate is 9.4%, which is not far from the average private nonfarm unemployment rate of 8.94% in the 1890–2015 sample.

Is the model-implied wage elasticity to labor productivity empirically plausible? Hagedorn and Manovskii (2008) estimate the wage elasticity to labor productivity to be 0.449 in the postwar 1951–2004 quarterly sample from BLS. (Both real wages and labor productivity are in logs and HP-filtered with a smoothing parameter of 1600.) However, a voluminous literature on economic history documents severe wage inertia and quantifies its large impact during the Great Depression.[12] As such, we extend the Hagedorn–Manovskii evidence to a historical U.S. sample.

To construct a historical series of real wages, we draw elements from Gordon (2016). From 1929 to 2015, we obtain compensation of employees from National Income and Product Accounts (NIPA) Tables 6.2A–D (line 3, private industries, minus line 5, farms) at Bureau of Economic Analysis. We obtain the number of full-time equivalent employees from NIPA Tables 6.5A–D (line 3, private industries, minus line 5, farms). Dividing the compensation of employees by the number of employees yields nominal wage rates (compensation per person). We deflate nominal wage rates with the personal consumption deflator from NIPA Table 1.1.4 (line 2) to obtain real wage rates.

From 1890 to 1929, we obtain the average (nominal) hourly compensation of production workers in manufacturing and the consumer price index from measuringworth.com (Officer and Williamson, 2020a; 2020b). The nominal compensation series from their website only has two digits after the decimal. We instead use the average hourly compensation series, with three digits after the decimal, from Officer (2009, Table 7.1). To obtain an index of hours, we divide the index of man-hours by the index of persons engaged in manufacturing from Kendrick (1961, Table D-II). We multiply the average hourly compensation series with the hours index to obtain the nominal compensation per person, which we then deflate with the Officer-Williamson consumer price index to obtain the series of real wages. Finally, we splice this series in 1929 to the NIPA series from 1929 onward to yield an uninterrupted series from 1890 to 2015. Splicing means that we rescale the pre-1929 series so that its value in 1929 is identical to that for the NIPA post-1929 series.[13] Finally, for labor productivity, we use the historical 1890–2015 series from Petrosky-Nadeau and Zhang (2021).[14] We time-aggregate their monthly series into annual by taking the monthly average within a given year.

[12] Prominent examples are Eichengreen and Sachs (1985), Bernanke and Powell (1986), Bernanke and Carey (1996), Hanes (1996); Dighe (1997), Bordo et al. (2000), Cole and Ohanian (2004), and Ohanian (2009).

[13] We differ from Gordon (2016) in two ways. First, Gordon measures real wages as real compensation per man-hour. We instead use real compensation per person, which better fits our model with no hours. This practice seems standard in the macro labor literature (Shimer, 2005). Second, Gordon measures nominal compensation as total compensation of employees from NIPA Table 1.10 (line 2), which includes government and farm employees. We instead use employee compensation for the private nonfarm sector, which matches the measurement of labor productivity.

[14] The monthly series is the ratio of a nonfarm business real output series over a private nonfarm employment series. The real output series draws from Kendrick (1961) and NIPA as well as monthly industrial production series (as monthly indicators) from Miron and Romer (1990) and the Federal Reserve Bank of St. Louis. The private nonfarm employment series draws from Weir (1992) and Current Employment Statistics as well as monthly employment indicators from NBER macrohistory files. From January 1947 onward, the monthly labor productivity series is benchmarked to the BLS quarterly nonfarm business real output per job series.

We detrend the annual real wages and labor productivity series as log deviations from their HP-trends with a smoothing parameter of 6.25, which is equivalent to a quarterly smoothing parameter of 1600.[15] In our postwar 1950–2015 annual sample, regressing the log real wages on the log labor productivity yields a wage elasticity of 0.406, with a standard error of 0.081. The elasticity estimate is not far from the Hagedorn–Manovskii estimate of 0.449 in their 1951–2004 quarterly sample.

More important, in our 1890–2015 historical sample, the wage elasticity to labor productivity is estimated to be 0.267, with a standard error of 0.066. Deflating the pre-1929 nominal compensation series with the Johnston-Williamson (2020) implicit GDP deflator, as opposed to the Officer and Williamson (2020a) consumer price index, yields a similar wage elasticity of 0.263, with a standard error of 0.062. Our evidence that real wages are more inertial in the historical sample accords well with the historical economics literature (footnote [12]). In particular, the relatively low wage elasticity to labor productivity, 0.278, in our model is empirically plausible.

Our value of $b = 0.91$ might seem high, given that the marginal product of labor is around one in the model's simulations. However, the value of $b$ includes unemployment benefits, the value of home production, self-employment, leisure, and disutility of work. Hagedorn and Manovskii (2008) argue that $b$ should equal the marginal product of capital in a perfectly competitive labor market. Ljungqvist and Sargent (2017) show that, to explain the unemployment volatility, a search model must diminish the fundamental surplus, which is the fraction of output allocated to the firm by the labor market. We view our high-$b$ calibration as perhaps the simplest way to achieve this goal. More important, we view our high-$b$-low-$\eta$ calibration as a parsimonious metaphor for real wage inertia. More explicit structures of wage inertia, such as alternating offer bargaining in Hall and Milgrom (2008) or staggered multiperiod Nash bargainng in Gertler and Trigari (2009), are likely to deliver similar quantitative results but would complicate our model structure greatly.[16]

## 3.3. Unconditional moments

### 3.3.1. Business cycle moments

From the model's stationary distribution (after a burn-in period of 1200 months), we repeatedly simulate 10,000 artificial samples, each with 1740 months (145 years). The length of each sample matches the length of the Jordà–Schularick–Taylor database (1871–2015). On each artificial sample, we time-aggregate monthly consumption, output, and investment into annual observations. We add up 12 monthly observations within a given year and treat the sum as the year's annual observation. For each annual series, we compute its volatility, skewness, kurtosis, and autocorrelations of up to five lags of log growth rates. For each moment, we report the mean as well as the 5th, 50th, and 95th percentiles across the 10,000 simulations. We also report the $p$-value that is the fraction with which a given moment in the model is higher than its matching moment in the data. The fraction can be interpreted as the $p$-value for a one-sided test of our model using the moment in question.

Panel A of Table 4 shows that the model does a good job in matching consumption moments. None of the $p$-values are significant at the 5% level. The consumption growth volatility in the model is 5.43% per annum, which is close to 5.45% in the data ($p = 0.49$). Kurtosis is 7.2, which is not far from 10.34 in the data ($p = 0.11$). The first-order autocorrelation is 0.23 in the model, which is higher than 0.12 in the data, but the difference is insignificant ($p = 0.82$). The autocorrelations at higher orders are close to zero in the model as in the data.

From Panel B, the output volatility in the model is 6.64% per annum, which is higher than 5.1% in the data, but the difference is insignificant ($p = 0.88$). The model falls short in explaining the skewness, 0.1 versus −1.06, and kurtosis, 5.2 versus 14.09, of the output growth. Both differences are significant. The model comes close to match the first-order autocorrelation, 0.22 versus 0.18. From Panel C, the investment volatility in the model is only 8.83% per annum, which is lower than 13.53% in the data. The difference is significant, but none of the $p$-values for other investment moments are significant. The kurtosis in the model is 6.57, relative to 10.75 in the data ($p = 0.06$). The first-order autocorrelation is 0.16 in the model, which is close to 0.13 in the data.

### 3.3.2. Labor market moments

Panel D of Table 4 shows that the model does a good job in matching the first four moments of the unemployment rate. The mean unemployment rate is 9.4% in the model, which is close to 8.94% in the data ($p = 0.42$). The skewness is 2.33, relative to 2.13 in the data ($p = 0.46$), and the kurtosis is ten versus 9.5 in the data ($p = 0.3$). The unemployment volatility is 31% per quarter, which is higher than 24% in the data, but the difference is insignificant ($p = 0.71$).

The vacancy rate volatility is 33% per quarter in the model, which is significantly higher than 19% in the data. The volatility of labor market tightness is 35%, which is significantly lower than 62% in the data. However, as noted, this data moment is sensitive to detrending method and is only 38% with log deviations. The unemployment-vacancy correlation is only −0.11 in the model, which is lower in magnitude than −0.57 in the data. However, this moment is also sensitive to detrending method. Using the monthly data simulated from the model with no detrending yields an unemployment-vacancy correlation of −0.51, which is close to the data moment of −0.64, although the difference is still marginally significant ($p = 0.95$). Finally, the wage elasticity to labor productivity is 0.278, and

[15] Ravn and Uhlig (2002) show that the smoothing parameter should be adjusted by the fourth power of the observation frequency ratio (four going from the quarterly to annual frequency). Specifically, $1600/4^4 = 6.25$.

[16] The high-$b$ calibration is also of contemporary interest. Ganong et al. (2020) document that under the 2020 Coronavirus Aid, Relief, and Economic Security Act, the ratio of mean benefits to mean earnings in the data is roughly 100%. The median replacement ratio is even higher at 134%. Finally, 68% of eligible unemployed workers have replacement ratios higher than 100%, and 20% of the workers have replacement ratios higher than 200%.

**Table 4**
Basic moments in the model under the benchmark calibration.
The model moments are based on 10,000 simulated samples, each with 1740 months. On each artificial sample, we calculate the moments and report the mean as well as the 5th, 50th, and 95th percentiles across the 10,000 simulations. $p$-value is the fraction with which a model moment is higher than its data moment. The data moments are from Table 1. In Panel A, $\sigma_C$, $S_C$, $K_C$, and $\rho_i^C$, for $i = 1, 2, \ldots, 5$, denote the volatility (in percent), skewness, kurtosis, and $i$th-order autocorrelation of the log consumption growth, respectively. The symbols in Panels B and C are defined analogously. In Panel D, $E[U]$, $S_U$, and $K_U$ are the mean, skewness, and kurtosis of monthly unemployment rates, and $\sigma_U$, $\sigma_V$, and $\sigma_\theta$ are the volatilities of quarterly unemployment, vacancy, and labor market tightness, respectively. $\rho_{UV}$ is the cross-correlation of quarterly unemployment and vacancy rates, and $e_{w,y/n}$ is the wage elasticity to labor productivity. In Panel E, $E[r_S - r_f]$, $E[r_f]$, $\sigma_S$, and $\sigma_f$ are the average equity premium, average real interest rate, stock market volatility, and interest rate volatility, respectively, all of which are in annual percent.

| | Data | Mean | 5th | 50th | 95th | $p$ | | Data | Mean | 5th | 50th | 95th | $p$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Panel A: Real consumption growth | | | | | | | Panel B: Real output growth | | | | | |
| $\sigma_C$ | 5.45 | 5.43 | 3.13 | 5.42 | 7.77 | 0.49 | $\sigma_Y$ | 5.10 | 6.64 | 4.61 | 6.61 | 8.78 | 0.88 |
| $S_C$ | −0.67 | 0.06 | −0.86 | 0.04 | 1.03 | 0.92 | $S_Y$ | −1.06 | 0.10 | −0.56 | 0.09 | 0.79 | 1.00 |
| $K_C$ | 10.34 | 7.20 | 4.07 | 6.56 | 12.42 | 0.11 | $K_Y$ | 14.09 | 5.20 | 3.41 | 4.86 | 8.09 | 0.00 |
| $\rho_1^C$ | 0.12 | 0.23 | 0.02 | 0.23 | 0.42 | 0.82 | $\rho_1^Y$ | 0.18 | 0.22 | 0.04 | 0.22 | 0.38 | 0.64 |
| $\rho_2^C$ | 0.04 | −0.04 | −0.24 | −0.04 | 0.17 | 0.26 | $\rho_2^Y$ | 0.00 | −0.05 | −0.22 | −0.05 | 0.13 | 0.33 |
| $\rho_3^C$ | 0.00 | −0.04 | −0.23 | −0.04 | 0.16 | 0.36 | $\rho_3^Y$ | 0.00 | −0.05 | −0.21 | −0.05 | 0.12 | 0.33 |
| $\rho_4^C$ | −0.03 | −0.04 | −0.22 | −0.04 | 0.15 | 0.45 | $\rho_4^Y$ | 0.01 | −0.04 | −0.21 | −0.05 | 0.12 | 0.30 |
| $\rho_5^C$ | −0.09 | −0.04 | −0.22 | −0.04 | 0.14 | 0.69 | $\rho_5^Y$ | −0.09 | −0.04 | −0.20 | −0.04 | 0.12 | 0.67 |
| | Panel C: Real investment growth | | | | | | | Panel D: Labor market moments | | | | | |
| $\sigma_I$ | 13.53 | 8.83 | 5.55 | 8.83 | 12.04 | 0.01 | $E[U]$ | 8.94 | 9.40 | 3.67 | 7.94 | 20.20 | 0.42 |
| $S_I$ | −0.05 | 0.29 | −0.51 | 0.26 | 1.19 | 0.76 | $S_U$ | 2.13 | 2.33 | 0.62 | 2.03 | 5.02 | 0.46 |
| $K_I$ | 10.75 | 6.57 | 3.89 | 6.00 | 11.07 | 0.06 | $K_U$ | 9.50 | 10.02 | 1.92 | 5.99 | 30.07 | 0.30 |
| $\rho_1^I$ | 0.13 | 0.16 | −0.02 | 0.17 | 0.33 | 0.62 | $\sigma_U$ | 0.24 | 0.31 | 0.14 | 0.31 | 0.48 | 0.71 |
| $\rho_2^I$ | −0.05 | −0.10 | −0.28 | −0.10 | 0.08 | 0.32 | $\sigma_V$ | 0.19 | 0.33 | 0.23 | 0.32 | 0.49 | 1.00 |
| $\rho_3^I$ | −0.07 | −0.08 | −0.26 | −0.08 | 0.09 | 0.47 | $\sigma_\theta$ | 0.62 | 0.35 | 0.24 | 0.33 | 0.53 | 0.02 |
| $\rho_4^I$ | −0.11 | −0.07 | −0.24 | −0.07 | 0.11 | 0.64 | $\rho_{UV}$ | −0.57 | −0.11 | −0.20 | −0.10 | −0.02 | 0.00 |
| $\rho_5^I$ | −0.08 | −0.06 | −0.23 | −0.06 | 0.11 | 0.58 | $e_{w,y/n}$ | 0.27 | 0.28 | 0.25 | 0.28 | 0.29 | 0.84 |
| | Panel E: Asset pricing moments | | | | | | | | | | | | |
| $E[r_S - r_f]$ | 4.36 | 4.27 | 3.77 | 4.24 | 4.86 | 0.35 | | | | | | | |
| $E[r_f]$ | 0.82 | 1.97 | 1.32 | 2.07 | 2.24 | 0.99 | | | | | | | |
| $\sigma_S$ | 16.04 | 12.42 | 9.82 | 12.41 | 15.13 | 0.02 | | | | | | | |
| $\sigma_f$ | 7.30 | 2.47 | 1.14 | 2.47 | 3.75 | 0.00 | | | | | | | |

the data moment of 0.267 yields an insignificant $p$-value of 0.84.

#### 3.3.3. Asset pricing moments

Most important, Panel E of Table 4 shows that our general equilibrium model succeeds in yielding an equity premium of 4.27% per annum, which is close to 4.36% in the data. The data moment lies within the model's 90% confidence interval ($p = 0.35$). The mean interest rate is 1.97% in the model, which is somewhat higher than 0.82% in the data ($p = 0.99$). The model implies a stock market volatility of 12.42% per annum, which is somewhat lower than the data moment of 16.04% ($p = 0.02$). However, the U.S. volatility of 13.66% (Table 1) falls well within the model's 90% confidence interval. The model's performance in explaining stock market volatility greatly improves over prior attempts in general equilibrium production economies (Gourio, 2012).

The interest rate volatility in the model is 2.47% per annum, which is significantly lower than 7.3% in the data. The most likely reason for this mismatch is that we do not model sovereign default and hyperinflation, which are the driving forces behind the historically high interest rate volatilities in Germany, Italy, and Japan. These destructive forces play only a limited role in the United States, which has an interest rate volatility of only 4.65% (Table 1), although it is still higher than the model moment.

### 3.4. Sources of the equity premium

This subsection examines the driving forces behind the model's equity premium.

#### 3.4.1. Dividend dynamics

Kaltenbrunner and Lochstoer (2010) highlight the difficulty in explaining the equity premium in production economies. Unlike endowment economies, in which dividends are exogenously specified to fit the data, dividends are often endogenously countercyclical in production economies. Dividends equal profits (output minus wages) minus investment. Intuitively, with frictionless labor markets, wages equal the marginal product of labor, which is virtually as procyclical as output. With the Cobb-Douglous production function, the marginal product of labor is exactly proportional to output. As such, profits are no more procyclical than output. However, due to consumption smoothing, investment is more procyclical than output and profits, rendering dividends countercyclical.

In contrast, dividends are endogenously procyclical in our search economy. Under the benchmark calibration, wages are more inertial than the marginal product of labor, making profits more procyclical than output. The magnified procyclical dynamics of profits then overpower the procyclical dynamics of va-

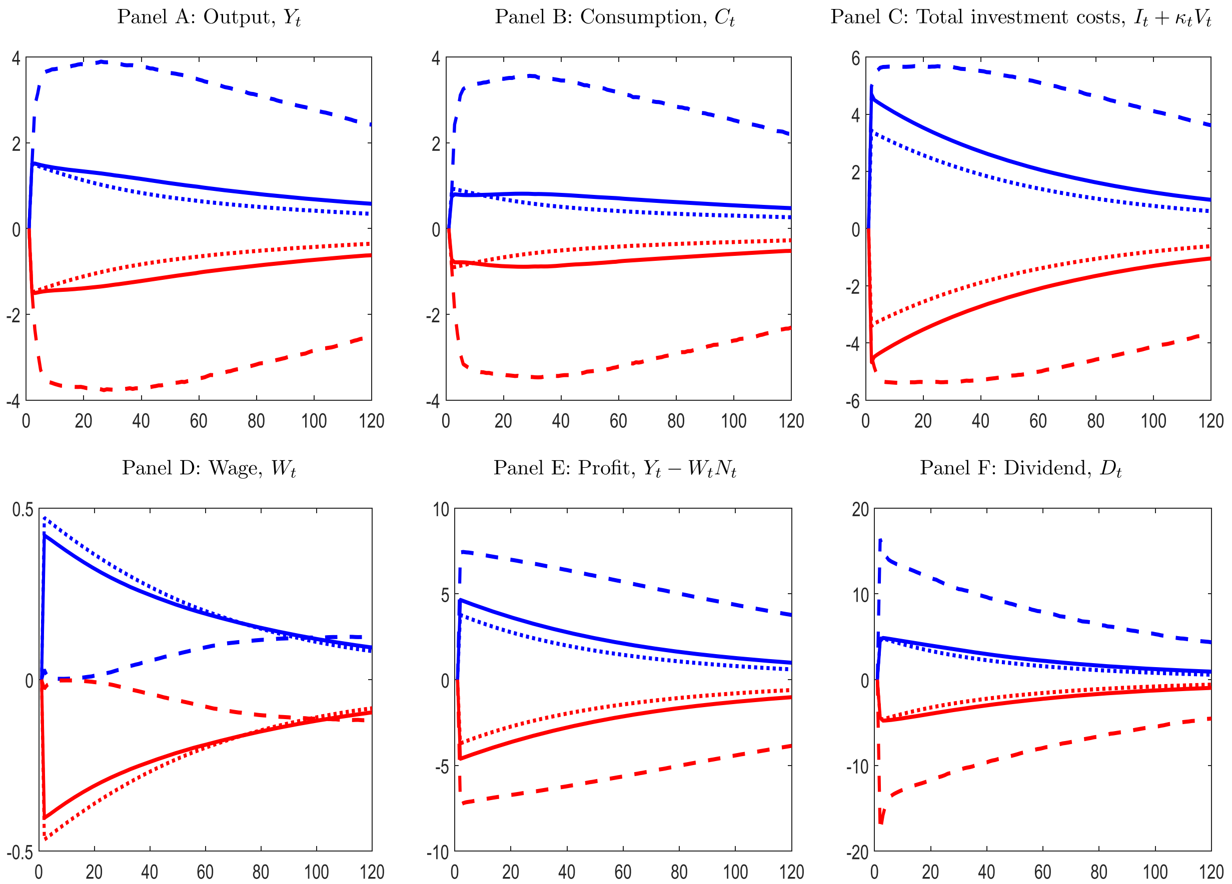


**Fig. 1.** Nonlinear impulse responses. Impulses are a 1-$\sigma_x$ shock to the log productivity, both positive (in blue) and negative (in red), from one of three initial conditions: bad, median, and good economies. The bad economy is the 10th percentile of the model's stationary distribution of employment, capital, and log productivity, the median economy is the 50th percentile, and the good economy is the 90th percentile. Across the three economies, the unemployment rate is 26.45%, 3.12%, and 2.98%, capital is 11.81, 15.44, and 16.48, and log productivity is 0.0917, 0.1945, and 0.3005, respectively. The responses in the bad economy are in broken lines; those in the median economy are in solid lines; and those in the good economy are in dotted lines. Responses are changes in levels (in percent) scaled by the respective pre-impulse level, averaged across 10,000 simulations, each with 120 months. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

cancy costs and capital investment, making dividends procyclical.[17]

Fig. 1 shows the impulse responses to a 1-$\sigma_x$ shock to the log productivity, both positive and negative. The responses are computed as percentage changes in levels scaled by the respective pre-impulse level. Because of the model's nonlinearity, the responses depend on the initial condition (Petrosky-Nadeau and Zhang, 2017). We consider three such conditions, including bad, median, and good economies. The bad economy is the 10th percentile of the model's stationary, trivariate distribution of employment, capital, and log productivity; the median is the 50th percentile, and the good economy is the 90th percentile.[18] Starting from each initial condition, we calculate the impulse responses by averaging across 10,000 simulations, each with 120 months.

Fig. 1 highlights two patterns. First, because of wage inertia, dividends are procyclical. Starting from the median economy, in responding to a negative 1-$\sigma_x$ shock to the log productivity, output falls by 1.5% upon impact, but wages decline by only 0.4%. As a result, profits drop more, by 4.6%. Due to consumption smoothing, total investment costs (investment plus vacancy costs, $I_t + \kappa_t V_t$) decline by 4.67%, and consumption falls by 0.9%. However, because profits are on average larger than total investment costs (0.3 versus 0.23 in the model's simulations), their differences (dividends) fall more, by 4.78%. The responses from the good economy are largely similar.

Second, more important, the responses are substantially larger in magnitude in the bad economy. The impact of wage inertia on procyclical dividends is particularly strong. In responding to a negative 1-$\sigma_x$ shock, output falls by a

[17] Petrosky-Nadeau et al. (2018) examine this mechanism in a baseline search model without capital. However, with capital, consumption smoothing via investment strengthens the countercyclicality of dividends. We overcome this core challenge via wage inertia, for which we also provide new, supportive evidence (Section 3.2.1).

[18] Across the bad, median, and good economies, the unemployment rates are 26.45%, 3.12%, and 2.98%, capital is 11.81, 15.44, and 16.48, and log productivity is 0.0917, 0.1945, and 0.3005 in the model's simulations, respectively.

maximum of 3.77% in about two years. However, wages remain virtually constant for two years and reach the maximum response of 0.12% only toward the end of the ten-year horizon. Intuitively, because the job filling rate, $q(\theta_t)$, is countercyclical (and approaches one in the limit), the unit vacancy cost, $\kappa_t = \kappa_0 + \kappa_1 q(\theta_t)$, is also countercyclical. Because $\kappa_t$ enters the wage rule in Eq. (19), the countercyclical $\kappa_t$ strengthens wage inertia in the bad economy. In contrast, this $\kappa_t$ mechanism is weak in the median and good economies because $q(\theta_t)$ is small. Consequently, profits fall by a maximum of 7.31%. Despite a decline of 5.4% for total investment costs, dividends drop by a whopping 17.77%. Consumption only drops by 3.47%.

To what extent are the model's implied dividend dynamics quantitatively plausible? For each country, the Jordà–Schularick–Taylor macrohistory database provides separate capital gain, $P_t/P_{t-1}$, in which $P_t$ is the nominal price level of a stock market index; dividend-to-price, $D_t/P_t$, in which $D_t$ is nominal dividends delivered by the index; and consumer price index series. To construct the real dividend series, we first back out the $P_t$ series by cumulating the capital gain series, then construct the $D_t$ series by multiplying $P_t$ with the dividend-to-price series. We scale nominal dividends by consumer price index to yield real dividends. The total number of nonmissing dividends between 1870 and 2015 in the Jordà–Schularick–Taylor dataset is 2,034.[19]

Table 5 shows that dividends are procyclical in the historical cross-country panel. The correlation between the cyclical components of annual dividends and output is on average 0.11 across the countries, ranging from −0.02 in Portugal to 0.47 in the United States. Only three out of 17 countries have negative correlations, all of which are small in magnitude. The relative volatility of dividends (the ratio of the dividend volatility over the output volatility) is 8.61 across the countries, varying from 3.06 in Portugal to 16.81 in the Netherlands (3.18 in the United States).[20] Time-aggregating annual observations into three- and five-year nonoverlapping observations raises the dividend-output correlation to 0.31 and 0.35 and lowers the relative volatility of dividends to 6.54 and 5.69, respectively. The evidence in the post-1950 sample is largely similar (Table S3 in the Internet Appendix).

The model explains procyclical dividends but overshoots the dividend-output correlation to 0.95. The model also underestimates the relative volatility of dividends at 2.82. Both differ significantly from their data moments. Time-aggregating does not affect the model's estimates. The dividend-output correlations are 0.96 and 0.95, and the relative volatility of dividends are 2.75 and 2.66 at the three- and five-year frequencies, respectively. In the historical data, there are likely measurement errors in dividends, which tend to average out over time, yielding higher dividend-output correlations at longer horizons. No such measurement errors exist in the model.

A possible reason why the model overshoots the dividend-output correlation is that dividends in the data refer only to cash dividends, but dividends in the model match conceptually to net payouts in the data. Net payouts include not only cash dividends but also share repurchases net of equity issuances (Boudoukh et al., 2007). Alas, to our knowledge, a historical sample of net payouts is not available. More important, our model has only one shock, which drives the high dividend-output correlation, but there exist most likely multiple shocks in the data.

### 3.4.2. Disaster dynamics

Petrosky-Nadeau et al. (2018) show that the search model of equilibrium unemployment gives rise to endogenous disasters. To explain the equity premium, we formulate a more general model by incorporating recursive utility and capital accumulation simultaneously. Disaster risks in consumption play a key role in yielding the equity premium in our model.

To characterize disasters in the data, we apply the Barro and Ursúa (2008) peak-to-trough method on the Jordà–Schularick–Taylor cross-country panel. Disasters are identified as episodes, in which the cumulative fractional decline in consumption or output exceeds a predetermined hurdle rate. We adopt two such hurdle rates, 10% and 15%.[21] We adjust for trend growth in the data because our model abstracts from growth. We subtract the mean log annual consumption growth of 1.62% from each consumption growth observation and subtract the mean log annual output growth of 1.78% from each output growth in the data (Table 1).

Table 6 shows that with a hurdle rate of 10%, the consumption disaster probability is 6.4%, and the output disaster probability is 5.78% in the cross-country panel. With a hurdle rate of 15%, the probabilities drop to 3.51% and 2.62%, respectively. The disaster size is 23.2% and 22.3% for consumption and output with a hurdle rate of 10%, but higher, 30.4% and 32.9%, respectively, with a hurdle rate of 15%. The duration for consumption and output disasters lasts 4.2 and 4.1 years with a hurdle rate of 10%, but 4.5 and 5 years with a hurdle rate of 15%, respectively.

[19] Germany, Portugal, and Spain have in total seven zero-dividend observations. For Switzerland, the capital gain series runs from 1900 to 2015, with 1926–1959 missing. We start its dividends series in 1960. For the Netherlands, both the capital gain and dividend-to-price series are missing from 1918 to 1949. We start its dividends series in 1950. For Canada, the capital gain series from the Jordà–Schularick–Taylor dataset seems incompatible with the total return series from the Dimson–Marsh–Staunton database. The implied dividend series are frequently negative, unlike the other countries, all of which have mostly nonnegative dividends. As a result, we drop Canada from our analysis.

[20] Due to the few zero-dividend observations (seven out of 2034), we detrend dividend and output series with HP-filtered proportional deviations from the mean. Using HP-filtered log deviations after discarding the seven observations yields a higher dividend-output correlation of 0.24 and a relative dividend volatility of 7.92 averaged across the countries.

[21] Suppose there are two states, normalcy and disaster, in a given period. 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 the likelihood with which the economy switches from normalcy to disaster in a given year. We calculate this probability as the ratio of the number of disasters over the number of normalcy years. For each disaster event, the disaster size is the cumulative fractional decline in consumption or output from peak to trough. Duration is the number of years from peak to trough.

**Table 5**
Dividend dynamics in the historical sample.

Real output and dividends are from the Jordà–Schularick–Taylor macrohistory database. "Prop. dev." is HP-filtered proportional deviations from the mean, and "Log dev." is log deviations from the HP-trend. $\rho_{DY}$ is the correlation between the cyclical components of dividends and output, and $\sigma_D/\sigma_Y$ is the volatility of the cyclical component of dividends divided by that of output. We examine three frequencies: annual, three-year, and five-year. For the three-year frequency, we sum up the three annual observations within a given three-year interval. The three-year intervals are nonoverlapping. The five-year series are constructed analogously. The smoothing parameters for the one-, three-, and five-year series are $1600/4^4 = 6.25$, $1600/12^4 = 0.077$, and $1600/20^4 = 0.01$, respectively, all of which match 1600 in the quarterly frequency. The column "Sample" indicates the starting year of a country. For Japan, the annual observations from 1946 and 1947 are missing. When calculating log deviations, we discard zero-dividend observations.

| | | One-year frequency | | | | Three-year frequency | | | | Five-year frequency | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Prop. dev. | | Log dev. | | Prop. dev. | | Log dev. | | Prop. dev. | | Log dev. | |
| | Sample | $\rho_{DY}$ | $\sigma_D/\sigma_Y$ | $\rho_{DY}$ | $\sigma_D/\sigma_Y$ | $\rho_{DY}$ | $\sigma_D/\sigma_Y$ | $\rho_{DY}$ | $\sigma_D/\sigma_Y$ | $\rho_{DY}$ | $\sigma_D/\sigma_Y$ | $\rho_{DY}$ | $\sigma_D/\sigma_Y$ |
| Australia | 1870 | 0.11 | 6.94 | 0.12 | 3.43 | 0.23 | 5.14 | 0.30 | 2.57 | 0.55 | 4.60 | 0.63 | 2.59 |
| Belgium | 1870 | 0.18 | 8.50 | 0.50 | 4.71 | 0.42 | 9.80 | 0.83 | 5.72 | 0.77 | 5.62 | 0.92 | 2.83 |
| Denmark | 1872 | 0.19 | 14.89 | 0.18 | 6.84 | 0.26 | 12.07 | 0.23 | 6.51 | 0.03 | 10.58 | 0.09 | 6.03 |
| Finland | 1912 | 0.08 | 10.14 | 0.31 | 6.88 | 0.67 | 8.46 | 0.50 | 5.75 | 0.82 | 4.23 | 0.44 | 5.48 |
| France | 1870 | 0.17 | 5.59 | 0.12 | 2.66 | 0.23 | 5.31 | −0.03 | 3.56 | 0.48 | 4.44 | −0.20 | 3.23 |
| Germany | 1870 | 0.02 | 6.05 | 0.21 | 20.32 | 0.11 | 3.82 | 0.55 | 2.92 | 0.24 | 1.95 | 0.89 | 3.65 |
| Italy | 1870 | 0.04 | 5.10 | 0.40 | 6.37 | 0.26 | 5.93 | 0.85 | 10.57 | 0.57 | 5.60 | 0.76 | 7.34 |
| Japan | 1886 (46–47) | 0.03 | 10.67 | 0.61 | 8.95 | 0.06 | 6.35 | 0.81 | 10.51 | 0.11 | 7.11 | 0.88 | 7.47 |
| Netherlands | 1950 | −0.00 | 16.81 | 0.20 | 14.90 | 0.55 | 13.77 | 0.39 | 13.04 | 0.37 | 18.40 | 0.26 | 13.53 |
| Norway | 1880 | 0.22 | 10.52 | 0.21 | 8.52 | 0.35 | 5.64 | 0.44 | 6.57 | 0.34 | 5.41 | 0.66 | 5.58 |
| Portugal | 1870 | −0.02 | 3.06 | 0.01 | 7.76 | 0.04 | 1.57 | 0.60 | 12.34 | 0.11 | 1.57 | 0.45 | 14.63 |
| Spain | 1899 | 0.04 | 11.60 | 0.27 | 8.87 | 0.18 | 6.01 | 0.56 | 11.54 | 0.27 | 4.14 | 0.63 | 5.04 |
| Sweden | 1871 | −0.02 | 9.31 | 0.15 | 5.66 | 0.09 | 5.76 | 0.44 | 5.11 | 0.57 | 4.62 | 0.70 | 5.63 |
| Switzerland | 1960 | 0.03 | 11.06 | 0.05 | 13.17 | 0.43 | 8.66 | 0.34 | 7.73 | 0.03 | 7.99 | 0.01 | 9.19 |
| UK | 1871 | 0.27 | 4.31 | 0.09 | 5.07 | 0.57 | 3.00 | 0.40 | 2.79 | 0.11 | 2.74 | 0.04 | 2.54 |
| USA | 1871 | 0.47 | 3.18 | 0.42 | 2.63 | 0.53 | 3.37 | 0.42 | 2.68 | 0.31 | 2.10 | 0.46 | 2.12 |
| Mean | | 0.11 | 8.61 | 0.24 | 7.92 | 0.31 | 6.54 | 0.48 | 6.87 | 0.35 | 5.69 | 0.48 | 6.06 |
| Median | | 0.06 | 8.91 | 0.21 | 6.86 | 0.26 | 5.84 | 0.44 | 6.13 | 0.33 | 4.61 | 0.54 | 5.53 |

**Table 6**
Disaster moments.

We obtain the data moments by applying the Barro and Ursúa (2008) peak-to-trough method on the Jordà–Schularick–Taylor cross-country panel. To adjust for trend growth in the data (because of no growth in our model), we subtract each log annual consumption growth observation with its mean of 1.62% and subtract each log annual output growth with the mean of 1.78% in the historical panel. We simulate 10,000 artificial samples from the model's stationary distribution under the benchmark calibration, each with 1740 months, matching the number of years, 145, from 1871 to 2015. On each artificial sample, we time-aggregate consumption and output into annual observations and apply the peak-to-trough method to identify disasters as cumulative fractional declines of consumption or output of at least 10% or 15%. We report the mean, 5th, 50th, and 95th percentiles across the simulations. If no disaster appears in an artificial sample, we set its disaster probability to zero and calculate the model's disaster probability moments across all the 10,000 simulations. However, we calculate disaster size and duration across samples with at least one disaster. The disaster probability and size are in percent, and duration is in the number of years.

| | Data | Mean | 5th | 50th | 95th | $p$ | Data | Mean | 5th | 50th | 95th | $p$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Disaster hurdle = 10% | | | | | | Disaster hurdle = 15% | | | | | |
| | Panel A: Consumption disasters | | | | | | | | | | | |
| Probability | 6.40 | 6.66 | 2.29 | 6.14 | 12.50 | 0.47 | 3.51 | 4.08 | 0.72 | 3.91 | 8.49 | 0.52 |
| Size | 23.16 | 23.70 | 14.89 | 23.10 | 34.27 | 0.49 | 30.36 | 30.11 | 19.23 | 29.02 | 44.12 | 0.42 |
| Duration | 4.19 | 4.10 | 2.90 | 4.00 | 5.67 | 0.41 | 4.50 | 4.49 | 3.00 | 4.33 | 6.50 | 0.40 |
| | Panel B: Output disasters | | | | | | | | | | | |
| Probability | 5.78 | 11.45 | 6.67 | 11.11 | 17.24 | 0.98 | 2.62 | 6.52 | 3.01 | 6.14 | 11.34 | 0.95 |
| Size | 22.34 | 22.85 | 16.20 | 22.38 | 31.01 | 0.50 | 32.9 | 29.04 | 20.43 | 28.38 | 39.75 | 0.23 |
| Duration | 4.14 | 3.72 | 2.89 | 3.67 | 4.73 | 0.21 | 5.04 | 4.25 | 3.11 | 4.17 | 5.67 | 0.14 |

The model-implied consumption disaster dynamics, which are crucial for the equity premium, are empirically plausible. We simulate 10,000 artificial samples from the model's stationary distribution, each with 1740 months, matching the 1871–2015 sample length. On each sample, we time-aggregate monthly into annual consumption and apply the exact peak-to-trough method as in the data. From Panel A of Table 6, the disaster probabilities are 6.66% and 4.08%, which are close to 6.4% and 3.51% in the data, with the hurdle rates of 10% and 15%, respectively. The size and duration of consumption disasters are also close to those in the data: 23.7% versus 23.2% for size and 4.1 versus 4.2 years for duration, with a hurdle rate of 10%. The $p$-values indicate that the differences between the model and data moments are all insignificant.

As noted, consumption is more volatile than output in the cross-country panel, likely due to government purchases during wartime (Barro and Ursúa, 2008). In contrast, consumption is naturally less volatile than output in production economies because of consumption smoothing. We focus on matching consumption dynamics because of their importance for the equity premium. Consequently, the model overshoots output disasters. From Panel B, the output disaster probability is 11.45%, which is higher than 5.78% in the data ($p = 0.98$), with a hurdle rate of 10%. With a higher hurdle of 15%, the disaster probability is 6.52% in the model, which is higher than 2.62% in the data ($p = 0.95$). However, disaster size and duration are relatively close to their data moments.

#### 3.4.3. Consumption dynamics

We dig deeper by comparing consumption dynamics in the search economy with those specified in the long-run risks literature (Bansal and Yaron, 2004). Kaltenbrunner and Lochstoer (2010) show that long-run risks (high persistence in expected consumption growth) arise endogenously in production economies with frictionless labor markets via consumption smoothing. Because of persistent aggregate productivity and consumption smoothing, long-run risks might also arise in our model. What is the relative role of long-run risks compared with disaster risks in our model? This economic question is important because different specifications of consumption dynamics can largely accord with observed moments of consumption growth, such as volatilities and autocorrelations, in the data. However, different specifications imply vastly different economic mechanisms.

We calculate the expected consumption growth, $E_t[g_{Ct+1}]$, and conditional consumption growth volatility, $\sigma_{Ct}$, in the model's state space. Using their solutions, we simulate one million months from the stationary distribution. Fitting the Bansal–Yaron process on the simulated data yields:

$$E_{t+1}[g_{Ct+2}] = 0.3527\, E_t[g_{Ct+1}] + 0.0092\, \epsilon^e_{t+1} \tag{21}$$

$$\sigma^2_{Ct+1} = 0.0078^2 + 0.9498\, (\sigma^2_{Ct} - 0.0078^2) + 0.4381 \times 10^{-5}\, \epsilon^V_{t+1}, \tag{22}$$

in which $\epsilon^e_{t+1}$ and $\epsilon^V_{t+1}$ are i.i.d. standard normal shocks.

Eq. (21) shows that the persistence in expected consumption growth is only 0.353 in our model, which is substantially lower than 0.979 in Bansal and Yaron (2004). Our persistence of the expected consumption growth is also much lower than that implied by the stochastic growth model in Kaltenbrunner and Lochstoer (2010).[22] As such, despite recursive utility and autoregressive productivity shocks, long-run risks (in the sense of highly persistent expected consumption growth) do not play an important role in our economy that features endogenous disasters.

Eq. (22) shows that the search economy also implies endogenously time-varying volatilities (Bloom, 2009). The consumption conditional variance appears "stochastic" in our model. Its persistence is 0.95, which is lower than 0.987 calibrated in Bansal and Yaron (2004) and 0.999 in Bansal et al. (2012). The time-variation of volatilities is another important dimension along which our search economy differs from stochastic growth models. These models with frictionless labor markets yield largely constant volatilities (Kaltenbrunner and Lochstoer, 2010). More important, Eq. (22) suggests that long-run risks in consumption volatility can be observationally equivalent to consumption disaster risks.

### 3.5. Time-varying risks and risk premiums

Our model gives rise endogenously to time-varying risks and risk premiums.

#### 3.5.1. Equilibrium properties

We first evaluate qualitative properties of the model's competitive equilibrium. From its stationary distribution (after a burn-in period of 1200 months), we simulate a long sample of one million months. Fig. 2 shows the heatmaps of key moments against productivity. From Panel A, the price-to-consumption ratio, $P_t/C_t$, increases with productivity. In the one-million-month sample, the correlations of $P_t/C_t$ with productivity, output, unemployment, vacancy, and the investment rate are 0.98, 0.78, −0.47, 0.91, and 0.6, respectively. Clearly, $P_t/C_t$ is procyclical.

Panel B shows that the expected equity premium, $E_t[r_{St+1}] - r_{ft+1}$, is countercyclical. Its correlations with productivity, output, unemployment, vacancy, and the investment rate are 0.85, 0.85, 0.64, 0.88, and 0.37, respectively. In addition, the correlation between the expected equity premium and price-to-consumption is −0.9. Stock market volatility, $\sigma_{St}$, is also countercyclical (Panel C). Its correlations with productivity, output, unemployment, vacancy, and the investment rate are −0.92, −0.82, 0.55, −0.94, and −0.44, respectively. Its correlations with the expected equity premium and price-to-consumption are 0.97 and −0.96, respectively.

The riskfree rate, $r_{ft+1}$, is weakly procyclical in the model (Panel D). Its correlations with productivity, output, unemployment, vacancy, and the investment rate are 0.22, 0.18, −0.14, 0.11, and 0.26, and those with the expected equity premium, stock market volatility, and price-to-consumption are −0.17, −0.16, and 0.26, respectively. Panel E shows that expected consumption growth, $E_t[g_{Ct+1}]$, behaves similarly as the risk-free rate. The correlation between $E_t[g_{Ct+1}]$ and $r_{ft+1}$ is 0.997. From Panel F, consumption volatility, $\sigma_{Ct}$, is largely acyclical. Its correlation with productivity is 0.52, which indicates procyclical dynamics, but its correlation with unemployment is 0.23, which suggests countercyclical dynamics. In addition, its correlations with output and investment rate are low, 0.14 and 0.07, respectively, which signal overall acyclical dynamics.[23]

In all, the model implies strong predictability for stock market excess return and volatility, some predictability for consumption volatility, and weak to no predictability for consumption growth and the interest rate. Intuitively, wage

[22] Kaltenbrunner and Lochstoer (2010, Table 6) show that the consumption growth follows $E_{t+1}[g_{Ct+2}] = 0.986\, E_t[g_{Ct+1}] + 0.093\, \sigma_{Ct}\, \epsilon^e_{t+1}$ and $g_{Ct+1} = 0.0013 + E_t[g_{Ct+1}] + \sigma_{Ct}\, \epsilon^g_{t+1}$, with transitory productivity shocks. With permanent shocks, $E_{t+1}[g_{Ct+2}] = 0.99\, E_t[g_{Ct+1}] + 0.247\, \sigma_{Ct} \epsilon^e_{t+1}$. But $\sigma_{Ct}$ is largely constant in both models.

[23] Because employment is an endogenous state variable in addition to the exogenous state of productivity, for completeness, Fig. S1 in the Internet Appendix reports the heatmaps of the key moments from Fig. 2 but against unemployment. Capital is another endogenous state variable. Fig. S2 in the Internet Appendix shows the heatmaps of the key moments against capital. The patterns all largely accord with those in Fig. 2.

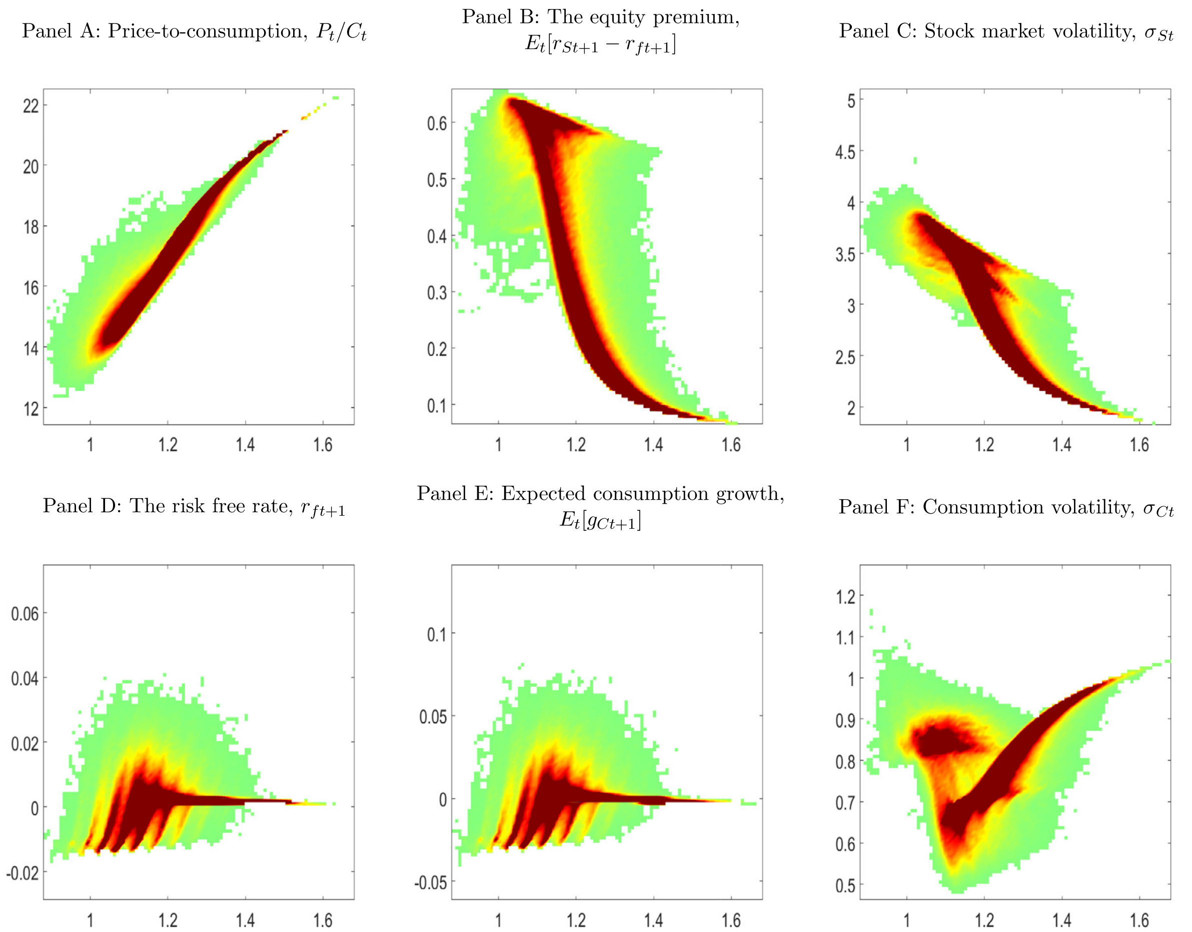


**Fig. 2.** Heatmaps of key moments against productivity. From the model's stationary distribution with the benchmark calibration (after a burn-in period of 1200 monthly periods), we simulate a long sample path with one million months. The equity premium, stock market volatility, and consumption volatility are in monthly percent. In each heatmap, dark red indicates high density, whereas light green indicates low density. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

inertia gives rise to operating leverage. In bad times, output falls, but wage inertia causes profits to drop disproportionately more than output, thereby magnifying the procyclical dynamics of profits and dividends, and causing the expected equity premium to rise.

The impact of wage inertia is also stronger in bad times, when the profits are even smaller because of low productivity (Fig. 1). This time-varying wage inertia amplifies the risks and risk premiums, making the expected equity premium and stock market volatility countercyclical.[24] In contrast, consumption growth and consumption volatility are less predictable because of consumption smoothing via capital investment. Despite adjustment costs, investment absorbs a large amount of shocks to render the first two moments of consumption growth less predictable.

### *3.5.2. Data*

Before quantifying the model's implications, Table 7 shows long-horizon regressions of stock market excess returns and log consumption growth on log price-to-consumption in the historical data. We follow Beeler and Campbell (2012) but implement the tests on the Jordà–Schularick–Taylor historical cross-country panel. We perform the regressions on log price-to-consumption, as opposed to log price-to-dividend, because dividends (net payouts) can be negative in the model. To align the data moments with the model moments, we adjust excess returns in the data for financial leverage (by multiplying unadjusted excess returns with 0.71).[25]

[24] Relatedly, Favilukis and Lin (2016) study a similar mechanism in a general equilibrium production economy with (exogenously specified) infrequent wage renegotiation, long-run risks, and labor adjustment costs. In contrast, wage inertia arises endogenously in our economy, and the equity premium arises from endogenous disaster risks.

[25] We again exclude Canada from our analysis because its capital gain series from the Jordà–Schularick–Taylor dataset is incompatible with its total return series from the Dimson–Marsh–Staunton database (footnote [19]).

**Table 7**
Predicting excess returns and consumption growth with log price-to-consumption in the historical sample.

The cross-country panel is from the Jordà–Schularick–Taylor macrohistory database, except for Canada. The annual series start as early as 1870 and end in 2015. Panel A performs predictive regressions of stock market excess returns on log price-to-consumption, $\sum_{h=1}^{H}\left[\log(r_{St+h})-\log(r_{ft+h})\right]=a+b\log(P_t/C_t)+u_{t+H}$, in which $H$ is the forecast horizon, $r_{St+1}$ is the real stock market return, $r_{ft+1}$ is the real interest rate, $P_t$ is the real stock market index, and $C_t$ is the real consumption. $r_{St+1}$ and $r_{ft+1}$ are over the course of period $t$, and $P_t$ and $C_t$ are at the beginning of period $t$ (the end of period $t-1$). Excess returns are adjusted for a financial leverage ratio of 0.29. Panel B performs long-horizon predictive regressions of log consumption growth on $\log(P_t/C_t)$, $\sum_{h=1}^{H}\log(C_{t+h}/C_t)=c+d\log(P_t/C_t)+v_{t+H}$. In both regressions, $\log(P_t/C_t)$ is standardized to have a mean of zero and a standard deviation of one. $H$ ranges from one year (1y) to five years (5y). The $t$-values of the slopes are adjusted for heteroscedasticity and autocorrelations of $2(H-1)$ lags. The slopes and $R$-squares are in percent.

| | Slopes | | | | | $t$-values | | | | | $R$-squares | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1y | 2y | 3y | 4y | 5y | 1y | 2y | 3y | 4y | 5y | 1y | 2y | 3y | 4y | 5y |
| Panel A: Predicting stock market excess returns | | | | | | | | | | | | | | | |
| Australia | −1.42 | −2.49 | −2.92 | −3.53 | −3.77 | −1.97 | −1.96 | −1.80 | −1.74 | −1.62 | 1.80 | 3.14 | 3.56 | 4.20 | 4.29 |
| Belgium | −1.30 | −3.26 | −4.79 | −5.48 | −5.16 | −0.82 | −0.98 | −1.00 | −0.91 | −0.76 | 0.58 | 1.62 | 2.47 | 2.58 | 2.01 |
| Denmark | −0.81 | −1.94 | −2.87 | −3.74 | −4.24 | −0.85 | −1.18 | −1.43 | −1.81 | −2.14 | 0.50 | 1.35 | 2.13 | 3.04 | 3.76 |
| Finland | −1.38 | −3.79 | −5.40 | −6.40 | −7.36 | −0.77 | −1.05 | −1.06 | −1.07 | −1.22 | 0.55 | 1.78 | 2.55 | 3.05 | 3.78 |
| France | −0.12 | −0.34 | −0.52 | −0.63 | −0.43 | −0.11 | −0.18 | −0.21 | −0.20 | −0.11 | 0.01 | 0.03 | 0.05 | 0.05 | 0.02 |
| Germany | −1.04 | −2.11 | −2.06 | −1.54 | 0.13 | −0.75 | −0.91 | −0.54 | −0.28 | 0.02 | 0.19 | 0.34 | 0.21 | 0.08 | 0.00 |
| Italy | −0.36 | −0.58 | −0.36 | −0.07 | 0.38 | −0.25 | −0.22 | −0.10 | −0.01 | 0.07 | 0.04 | 0.05 | 0.01 | 0.00 | 0.01 |
| Japan | −0.70 | −1.40 | −1.60 | −1.73 | −1.77 | −0.45 | −0.56 | −0.45 | −0.41 | −0.36 | 0.19 | 0.36 | 0.35 | 0.30 | 0.24 |
| Netherlands | −3.03 | −6.45 | −8.88 | −11.06 | −13.35 | −1.68 | −1.88 | −2.11 | −2.48 | −2.98 | 4.15 | 9.00 | 12.73 | 16.34 | 20.25 |
| Norway | −1.77 | −3.59 | −5.13 | −6.52 | −7.92 | −1.55 | −2.07 | −2.41 | −2.76 | −3.24 | 1.75 | 3.61 | 5.60 | 7.68 | 9.84 |
| Portugal | −0.24 | −2.39 | −3.87 | −3.41 | 0.53 | −0.08 | −0.39 | −0.50 | −0.37 | 0.06 | 0.02 | 0.55 | 0.83 | 0.48 | 0.01 |
| Spain | −1.02 | −2.77 | −4.90 | −6.80 | −8.13 | −0.74 | −0.92 | −1.21 | −1.66 | −2.38 | 0.59 | 1.68 | 3.13 | 4.42 | 5.25 |
| Sweden | −1.56 | −3.81 | −6.04 | −8.31 | −10.50 | −1.63 | −2.29 | −2.91 | −3.19 | −3.20 | 1.42 | 3.74 | 6.47 | 9.64 | 13.08 |
| Switzerland | −3.09 | −6.51 | −8.50 | −10.67 | −12.95 | −1.70 | −2.30 | −2.85 | −3.89 | −4.17 | 4.02 | 8.50 | 11.76 | 15.72 | 20.05 |
| UK | −2.95 | −5.64 | −7.62 | −8.91 | −10.51 | −2.33 | −4.92 | −5.43 | −5.84 | −5.92 | 6.35 | 12.49 | 18.14 | 23.18 | 28.03 |
| USA | −3.50 | −7.45 | −9.89 | −12.98 | −15.75 | −3.83 | −4.50 | −4.35 | −4.59 | −5.16 | 7.71 | 16.13 | 21.01 | 27.48 | 33.59 |
| Mean | −1.52 | −3.41 | −4.71 | −5.74 | −6.30 | −1.22 | −1.64 | −1.77 | −1.95 | −2.07 | 1.87 | 4.02 | 5.69 | 7.39 | 9.01 |
| Median | −1.34 | −3.01 | −4.84 | −5.94 | −6.26 | −0.83 | −1.11 | −1.32 | −1.70 | −1.88 | 0.59 | 1.73 | 2.84 | 3.63 | 4.03 |
| Panel B: Predicting consumption growth | | | | | | | | | | | | | | | |
| Australia | 0.75 | 0.98 | 1.14 | 1.50 | 1.85 | 1.40 | 0.88 | 0.65 | 0.67 | 0.71 | 1.69 | 1.52 | 1.21 | 1.49 | 1.75 |
| Belgium | −1.03 | −1.38 | −0.94 | −0.68 | −0.10 | −0.91 | −0.73 | −0.41 | −0.26 | −0.04 | 1.41 | 1.05 | 0.30 | 0.11 | 0.00 |
| Denmark | 0.23 | 0.32 | 0.28 | 0.24 | 0.20 | 0.71 | 0.73 | 0.52 | 0.40 | 0.29 | 0.18 | 0.18 | 0.13 | 0.08 | 0.05 |
| Finland | −0.91 | −2.10 | −2.90 | −3.62 | −4.07 | −1.14 | −1.46 | −1.54 | −1.67 | −1.68 | 2.30 | 5.20 | 6.56 | 7.56 | 7.66 |
| France | −0.84 | −1.47 | −2.02 | −2.55 | −3.18 | −2.12 | −1.81 | −1.81 | −1.85 | −1.95 | 1.64 | 1.79 | 1.89 | 2.11 | 2.67 |
| Germany | −0.95 | −1.87 | −2.88 | −3.79 | −4.70 | −2.15 | −1.85 | −1.81 | −1.74 | −1.74 | 2.97 | 4.64 | 6.17 | 6.84 | 7.79 |
| Italy | −0.60 | −1.22 | −1.74 | −2.28 | −2.91 | −2.71 | −2.21 | −1.96 | −1.87 | −1.89 | 2.74 | 4.02 | 4.32 | 4.84 | 5.79 |
| Japan | −1.76 | −3.59 | −5.38 | −7.12 | −8.78 | −4.04 | −3.35 | −2.89 | −2.60 | −2.40 | 8.22 | 11.84 | 14.23 | 15.81 | 16.95 |
| Netherlands | 0.66 | 1.10 | 1.43 | 1.83 | 2.32 | 2.41 | 1.47 | 1.22 | 1.17 | 1.14 | 7.27 | 6.03 | 5.50 | 6.17 | 7.48 |
| Norway | −0.35 | −0.77 | −1.21 | −1.68 | −2.10 | −1.36 | −1.80 | −2.11 | −2.40 | −2.54 | 0.91 | 2.40 | 5.58 | 8.09 | 9.68 |
| Portugal | −1.05 | −2.20 | −3.26 | −4.08 | −4.95 | −2.18 | −1.72 | −1.67 | −1.61 | −1.53 | 4.82 | 8.98 | 10.91 | 11.55 | 11.55 |
| Spain | −0.10 | −0.18 | −0.41 | −0.67 | −1.10 | −0.14 | −0.14 | −0.27 | −0.38 | −0.55 | 0.02 | 0.02 | 0.08 | 0.17 | 0.40 |
| Sweden | 0.18 | 0.22 | 0.20 | 0.02 | −0.17 | 0.56 | 0.44 | 0.28 | 0.02 | −0.17 | 0.18 | 0.15 | 0.10 | 0.00 | 0.05 |
| Switzerland | 0.22 | 0.31 | 0.36 | 0.35 | 0.34 | 1.32 | 0.84 | 0.61 | 0.43 | 0.33 | 2.52 | 1.40 | 1.00 | 0.64 | 0.44 |
| UK | −0.33 | −0.89 | −1.53 | −2.32 | −3.15 | −1.78 | −2.22 | −2.77 | −3.53 | −4.16 | 1.44 | 3.94 | 7.06 | 11.86 | 17.32 |
| USA | 0.48 | −0.09 | −0.64 | −1.05 | −1.40 | 1.86 | −0.18 | −0.85 | −1.08 | −1.23 | 1.89 | 0.03 | 0.94 | 1.92 | 2.70 |
| Mean | −0.34 | −0.80 | −1.22 | −1.62 | −1.99 | −0.64 | −0.82 | −0.93 | −1.02 | −1.09 | 2.51 | 3.32 | 4.12 | 4.95 | 5.77 |
| Median | −0.34 | −0.83 | −1.07 | −1.36 | −1.75 | −1.02 | −1.09 | −1.20 | −1.35 | −1.38 | 1.79 | 2.09 | 3.10 | 3.48 | 4.25 |

Panel A shows long-horizon predictive regressions of market excess returns:

$$\sum_{h=1}^{H}\left[\log(r_{St+h})-\log(r_{ft+h})\right]=a+b\log(P_t/C_t)+u_{t+H}, \tag{23}$$

in which $H$ is the forecast horizon, $P_t$ is the real market index, $C_t$ is the real consumption at the beginning of period $t$, and $u_{t+H}$ the residual. Panel B shows long-horizon regressions of log consumption growth:

$$\sum_{h=1}^{H}\log(C_{t+h}/C_t)=a+b\log(P_t/C_t)+v_{t+H}, \tag{24}$$

in which $v_{t+H}$ is the residual. In both long-horizon regressions, $\log(P_t/C_t)$ is standardized to have a mean of zero and a volatility of one. $H$ ranges from one to five years. Finally, the $t$-values are adjusted for heteroscedasticity and autocorrelations of $2(H-1)$ lags.

Panel A shows some evidence of predictability of market excess returns. The slopes are largely negative across the countries and forecast horizons from one to five years, and their $t$-values are often significant, especially at the longer horizons. The $R$-squares averaged across the countries vary from 1.87% to 9% as the forecast horizon goes from one to five years. The prior asset pricing literature has mostly focused on the U.S. sample, which is an outlier in Panel A. In particular, the U.S. features the strongest evidence of predictability in terms of the $t$-values of slopes and $R$-squares. For example, in the five-year horizon, the $R^2$ is 33.6% in the U.S. and 28% in the U.K., in contrast to 0% in Germany, 1% in Italy and Portugal, and 2% in France.

In the Internet Appendix (Table S4, Panel A), we document stronger stock market return predictability in the post-1950 sample. The slopes are all negative and mostly significant across the countries and forecast horizons. On average, the slopes are significant for all horizons except year one. The $R$-squares range from 4.9% in year one to 17.8% in year five.

Panel B of Table 7 shows that consumption growth is largely unpredictable. In the historical sample, the slopes averaged across the countries are all negative but insignificant. Even at the five-year horizon, the $R^2$ is only 5.77% on average. In the post-1950 sample, the average slopes all flip to positive but remain insignificant, although the average $R$-squares increase somewhat (to 9.1% in year five, for example) (Table S4, Panel B, the Internet Appendix).

Table 8 shows long-horizon regressions of excess return and consumption growth volatilities on log price-to-consumption. For a given forecast horizon, $H$, we measure excess return volatility as $\sigma_{St,t+H-1} = \sum_{h=0}^{H-1} |\epsilon_{St+h}|$, in which $\epsilon_{St+h}$ is the $h$-period-ahead residual from the first-order autoregression of log excess returns, $\log(r_{St+1}) - \log(r_{ft+1})$ (again adjusted for financial leverage). Panel A performs long-horizon predictive regressions of excess return volatilities:

$$\log \sigma_{St+1,t+H} = a + b \log(P_t/C_t) + u^{\sigma}_{t+H}. \tag{25}$$

In Panel B, the consumption volatility is $\sigma_{Ct,t+H-1} = \sum_{h=0}^{H-1} |\epsilon_{Ct+h}|$, in which $\epsilon_{Ct+h}$ is the $h$-period-ahead residual from the first-order autoregression of log consumption growth, $\log(C_{t+1}/C_t)$. We then perform long-horizon predictive regressions of consumption volatilities:

$$\log \sigma_{Ct+1,t+H} = a + b \log(P_t/C_t) + v^{\sigma}_{t+H}. \tag{26}$$

Panel A of Table 8 shows weak predictability for excess return volatilities. The average slopes are all negative and marginally significant in the first two years. The average $R$-squares range from 6.3% in year one to 19% in year five. However, in the post-1950 sample, the average slopes are all insignificant, with mixed signs (Table S5, Panel A, the Internet Appendix). Consumption volatilities are essentially unpredictable with log price-to-consumption. In the historical sample, the average slopes are all positive and, in long horizons, marginally significant. However, in the post-1950 sample, the slopes all flip to negative and insignificant.

#### 3.5.3. *The model's performance*

We simulate 10,000 samples from the model's stationary distribution, each with 1740 months. On each sample, we time-aggregate monthly returns and consumption into annual observations and implement the same procedures as in the data. Overall, the model succeeds in explaining stock market predictability but overstates consumption growth predictability, especially its volatility.

Table 9 shows the details. From Panel A, market excess returns are predictable in the model. The slopes are all significantly negative, and the $R$-squares range from 2.6% in year one to 9.2% in year five. None of the $p$-values for the slopes, their $t$-values, and $R$-squares are significant. From Panel B, the model overstates somewhat the consumption growth predictability. The slopes are all significantly negative. However, except for year one, the $p$-values for the slopes and their $t$-values indicate only insignificant differences between the model and data moments.

Panel C shows that stock market volatility is weakly predictable with log price-to-consumption in the model. As in the data, the slopes are all negative but insignificant. None of the $p$-values for slopes and their $t$-values suggest that the model moments deviate significantly from their data counterparts. However, the $R$-squares in the model are significantly lower than those in the data. More important, from Panel D, the model overstates the predictability of consumption growth volatility. While the slopes are mostly insignificant and positive in the data, the slopes in the model are significantly negative, and the $p$-values for the slopes and their $t$-values are significant.

Without capital, Petrosky-Nadeau et al. (2018, Table D3, Online Appendix) show that the baseline search model implies a similar amount of predictability for stock market excess returns with log price-to-consumption but a substantially higher amount for consumption growth. The $R$-square from predicting consumption growth reaches 23.32% in year five in contrast to only 11.11% in our model. The role of consumption smoothing via investment in reducing the predictability in consumption growth in our model is in the same spirit as in Hall (1978).

### 3.6. *Comparative statics*

We conduct comparative statics to shed light on the inner workings of our model. In each experiment, we vary one parameter only, while keeping all the other parameters identical to those in the benchmark calibration. (For log utility, we set both the risk aversion and elasticity of intertemporal substitution to one.) In all experiments, we recalibrate the capital scalar, $K_0$, to ensure that the average labor share is unchanged from the benchmark calibration. Otherwise, the impact from changing a given parameter would be confounded with the impact of changing the labor share. The only exception is the $\alpha = 0.3$ experiment, in which we recalibrate $K_0$ to match the average labor share of 0.7. The simulations follow the same design as in the benchmark model.

#### 3.6.1. *Preference parameters*

Table 10 details the comparative statics. Not surprisingly, the risk aversion, $\gamma$, has a quantitatively important impact on the equity premium. Reducing $\gamma$ from ten to 7.5 and further to five lowers the equity premium from 4.27% per annum in the benchmark calibration to 1.57% and further to 0.45%. Stock market volatility also falls from 12.4% to 10.1% and further to 8.2%.

Most important, risk aversion affects quantities. Lowering $\gamma$ from ten to 7.5 and to five reduces consumption volatility from 5.43% to 4.44% and further to 4.03%. The probability of consumption disasters falls from 6.66% to 5.02% and further to 4.41%, and the disaster size also drops somewhat. A lower discount rate (the equity premium plus the interest rate) raises the marginal benefit of hiring to

**Table 8**
Predicting volatilities of stock market excess returns and consumption growth with log price-to-consumption in the historical sample.
The cross-country panel is from the Jordà–Schularick–Taylor macrohistory database, except for Canada. The annual series start in 1870 and end in 2015. For a given forecast horizon, $H$, we measure excess return volatility as $\sigma_{St,t+H-1} = \sum_{h=0}^{H-1} |\epsilon_{St+h}|$, in which $\epsilon_{St+h}$ is the $h$-period-ahead residual from the first-order autoregression of excess returns, $\log(r_{St+1}) - \log(r_{ft+1})$. Excess returns are adjusted for a financial leverage ratio of 0.29. Panel A performs long-horizon predictive regressions of excess return volatilities, $\log\sigma_{St+1,t+H} = a + b\log(P_t/C_t) + u^{\sigma}_{t+H}$. Consumption growth volatility is $\sigma_{Ct,t+H-1} = \sum_{h=0}^{H-1} |\epsilon_{Ct+h}|$, in which $\epsilon_{Ct+h}$ is the $h$-period-ahead residual from the first-order autoregression of log consumption growth, $\log(C_{t+1}/C_t)$. Panel B performs long-horizon predictive regressions of consumption growth volatilities, $\log\sigma_{Ct+1,t+H} = c + d\log(P_t/C_t) + v^{\sigma}_{t+H}$. $\log(P_t/C_t)$ is standardized to have a mean of zero and a standard deviation of one. $H$ ranges from one year (1y) to five years (5y). The $t$-values are adjusted for heteroscedasticity and autocorrelations of $2(H-1)$ lags. The slopes and $R$-squares are in percent.

| | Slopes | | | | | $t$-values | | | | | $R$-squares | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1y | 2y | 3y | 4y | 5y | 1y | 2y | 3y | 4y | 5y | 1y | 2y | 3y | 4y | 5y |
| Panel A: Predicting stock market volatility | | | | | | | | | | | | | | | |
| Australia | 20.04 | 16.84 | 15.73 | 16.20 | 15.82 | 1.89 | 1.91 | 1.81 | 1.81 | 1.80 | 2.15 | 3.55 | 4.28 | 5.51 | 6.55 |
| Belgium | 11.85 | 12.70 | 12.20 | 11.69 | 11.61 | 1.28 | 2.11 | 2.05 | 1.99 | 2.21 | 1.42 | 5.12 | 7.26 | 8.84 | 10.71 |
| Denmark | −35.30 | −37.64 | −38.17 | −37.40 | −36.44 | −3.70 | −4.02 | −3.95 | −3.74 | −3.43 | 7.90 | 16.11 | 21.11 | 24.13 | 25.79 |
| Finland | 6.94 | 3.22 | 5.56 | 5.49 | 3.54 | 0.66 | 0.45 | 0.97 | 1.02 | 0.65 | 0.42 | 0.23 | 1.26 | 1.56 | 0.76 |
| France | −58.81 | −60.73 | −60.03 | −58.54 | −57.57 | −6.19 | −6.50 | −5.93 | −5.51 | −5.17 | 20.49 | 37.29 | 42.82 | 45.17 | 46.37 |
| Germany | −31.59 | −35.33 | −35.20 | −34.06 | −32.90 | −2.89 | −3.61 | −3.42 | −3.02 | −2.67 | 5.44 | 12.60 | 16.61 | 17.96 | 18.71 |
| Italy | −17.60 | −23.51 | −24.80 | −24.34 | −24.27 | −1.92 | −2.94 | −2.86 | −2.59 | −2.41 | 2.45 | 8.22 | 12.62 | 15.43 | 17.69 |
| Japan | 8.99 | 7.32 | 9.12 | 10.91 | 11.75 | 0.80 | 0.74 | 0.94 | 1.15 | 1.26 | 0.48 | 0.72 | 1.89 | 3.41 | 4.74 |
| Netherlands | 7.49 | 8.46 | 11.28 | 10.93 | 8.97 | 0.50 | 0.67 | −1.03 | 1.18 | 1.15 | 0.48 | 1.43 | 4.60 | 5.52 | 5.30 |
| Norway | −51.27 | −54.63 | −54.25 | −53.32 | −52.54 | −5.44 | −7.48 | −7.26 | −7.41 | −7.81 | 20.22 | 39.57 | 51.02 | 56.54 | 60.54 |
| Portugal | −50.20 | −45.97 | −44.35 | −43.46 | −39.43 | −4.10 | −3.57 | −3.50 | −3.56 | −3.39 | 14.11 | 23.07 | 27.71 | 28.72 | 25.37 |
| Spain | −37.40 | −34.97 | −34.23 | −33.42 | −32.51 | −4.00 | −5.24 | −4.81 | −4.51 | −3.96 | 10.86 | 18.97 | 26.06 | 30.91 | 33.48 |
| Sweden | −23.98 | −22.89 | −21.83 | −21.84 | −21.98 | −2.75 | −2.62 | −2.16 | −1.93 | −1.79 | 4.88 | 8.45 | 9.78 | 10.82 | 11.85 |
| Switzerland | 7.05 | 11.57 | 9.51 | 11.11 | 11.03 | 0.39 | 0.87 | 0.90 | 1.18 | 1.30 | 0.27 | 2.01 | 3.01 | 5.79 | 7.64 |
| UK | −35.31 | −34.28 | −33.22 | −32.10 | −31.62 | −4.99 | −4.69 | −4.10 | −3.58 | −3.23 | 9.59 | 18.29 | 21.60 | 22.69 | 23.91 |
| USA | 0.30 | 5.54 | 6.58 | 7.08 | 8.06 | 0.03 | 0.87 | 1.57 | 2.13 | 2.51 | 0.00 | 0.65 | 1.77 | 2.89 | 4.86 |
| Mean | −17.43 | −17.77 | −17.26 | −16.57 | −16.16 | −1.90 | −2.07 | −1.80 | −1.59 | −1.44 | 6.32 | 12.27 | 15.84 | 17.87 | 19.02 |
| Median | −20.79 | −23.20 | −23.32 | −23.09 | −23.12 | −2.34 | −2.78 | −2.51 | −2.26 | −2.10 | 3.67 | 8.34 | 11.20 | 13.12 | 14.77 |
| Panel B: Predicting consumption growth volatility | | | | | | | | | | | | | | | |
| Australia | 3.23 | −3.95 | −3.07 | −4.13 | −5.52 | 0.28 | −0.39 | −0.27 | −0.32 | −0.40 | 0.06 | 0.18 | 0.14 | 0.28 | 0.55 |
| Belgium | 48.77 | 54.27 | 55.42 | 58.66 | 59.15 | 2.88 | 3.74 | 3.41 | 3.50 | 3.50 | 11.11 | 23.57 | 29.61 | 36.63 | 40.03 |
| Denmark | −2.11 | −1.62 | 0.21 | 0.64 | 1.13 | −0.17 | −0.15 | 0.02 | 0.05 | 0.09 | 0.02 | 0.03 | 0.00 | 0.01 | 0.03 |
| Finland | 32.87 | 35.10 | 38.93 | 40.82 | 41.42 | 2.38 | 2.84 | 3.27 | 3.61 | 3.79 | 6.84 | 16.21 | 25.65 | 30.35 | 33.31 |
| France | 84.04 | 78.92 | 77.39 | 76.70 | 76.69 | 9.11 | 9.59 | 9.25 | 8.72 | 8.35 | 37.34 | 53.32 | 60.94 | 65.91 | 68.76 |
| Germany | 11.37 | 11.62 | 13.29 | 14.96 | 16.28 | 1.14 | 0.98 | 0.95 | 0.96 | 0.95 | 0.77 | 1.42 | 2.15 | 3.01 | 3.75 |
| Italy | 6.73 | 7.80 | 8.51 | 9.88 | 11.70 | 0.78 | 1.01 | 1.06 | 1.15 | 1.30 | 0.36 | 0.89 | 1.60 | 2.71 | 4.48 |
| Japan | 37.88 | 39.76 | 39.78 | 39.88 | 39.93 | 3.66 | 3.72 | 3.54 | 3.26 | 3.07 | 8.50 | 15.96 | 21.30 | 23.11 | 24.82 |
| Netherlands | 7.04 | 7.92 | 9.68 | 9.26 | 8.42 | 0.60 | 0.73 | 0.85 | 0.89 | 0.90 | 0.58 | 1.51 | 3.20 | 3.47 | 3.56 |
| Norway | 3.69 | 5.69 | 4.34 | 3.81 | 3.63 | 0.34 | 0.50 | 0.37 | 0.33 | 0.32 | 0.09 | 0.38 | 0.28 | 0.27 | 0.29 |
| Portugal | 13.68 | 15.62 | 16.08 | 18.09 | 19.63 | 1.43 | 2.51 | 3.57 | 5.20 | 5.93 | 2.03 | 6.49 | 10.05 | 15.19 | 18.62 |
| Spain | 64.78 | 61.73 | 59.39 | 57.46 | 56.29 | 6.29 | 6.16 | 5.80 | 5.51 | 5.46 | 25.68 | 40.34 | 49.05 | 51.18 | 54.04 |
| Sweden | −1.44 | 1.56 | 3.93 | 6.22 | 7.43 | −0.14 | 0.17 | 0.39 | 0.57 | 0.64 | 0.01 | 0.03 | 0.26 | 0.79 | 1.32 |
| Switzerland | −13.49 | −13.67 | −13.37 | −9.64 | −6.97 | −1.01 | −1.06 | −1.11 | −0.84 | −0.69 | 1.40 | 2.71 | 3.78 | 2.63 | 1.61 |
| UK | 0.76 | 0.75 | 1.50 | 2.03 | 2.31 | 0.07 | 0.11 | 0.22 | 0.27 | 0.30 | 0.00 | 0.01 | 0.06 | 0.14 | 0.23 |
| USA | −18.05 | −19.66 | −18.25 | −17.46 | −15.82 | −1.89 | −2.05 | −1.87 | −1.71 | −1.45 | 2.44 | 5.14 | 6.30 | 6.70 | 6.07 |
| Mean | 17.49 | 17.62 | 18.36 | 19.20 | 19.73 | 1.61 | 1.78 | 1.84 | 1.95 | 2.00 | 6.08 | 10.51 | 13.40 | 15.15 | 16.34 |
| Median | 6.88 | 7.86 | 9.10 | 9.57 | 10.06 | 0.69 | 0.85 | 0.90 | 0.93 | 0.92 | 1.09 | 2.11 | 3.49 | 3.24 | 4.12 |

stimulate employment. Consequently, the mean unemployment rate falls from 9.4% to 5.73% and further to 4.29%. The unemployment volatility rises somewhat, but the vacancy and labor market tightness volatilities both fall. In short, echoing Gourio (2012) and Hall (2017) but differing from Tallarini (2000), our results indicate that it is imperative to study macro quantities and asset prices simultaneously. Quantities are not determined separately from prices.[26]

The intertemporal elasticity of substitution, $\psi$, governs the willingness of the representative investor to substitute consumption over time. A lower elasticity indicates stronger incentives for consumption smoothing. Consequently, reducing $\psi$ from two to 1.5 and further to one lowers the consumption volatility from 5.43% per annum to 5.15% and further to 4.8%. The consumption disaster probability falls from 6.66% to 6.17% and further to 5.61%. The lower consumption risks reduce the equity premium

[26] The breakdown of the Tallarini separation proposition is another important difference between our work and Petrosky-Nadeau et al. (2018). The prior work reports a mostly small impact of risk aversion on quantities in a baseline search model without capital and concludes that "echoing Tallarini (2000), although critical for asset prices, the risk aversion seems unimportant for quantities (p. 2241)." In particular, in the prior work, lowering risk aversion from ten to 7.5 reduces the mean unemployment rate from 6.25% to 5.88% (with a difference of only 0.37%). In contrast, in our model, the mean unemployment rate falls from 9.4% to 5.73% (with a difference of 3.67%). In all, capital plays a critical role in breaking down the Tallarini separation.

**Table 9**
Predicting excess returns, consumption growth, and their volatilities with log price-to-consumption in the model.

Data moments are the means in Tables 7 and 8 on the Jordà–Schularick–Taylor database. We simulate 10,000 artificial samples from the model's stationary distribution (with a burn-in of 1200 months), each with 1740 months. On each sample, we time-aggregate monthly market excess returns and consumption growth into annual observations and implement the exact same procedures as in Tables 7 and 8. For each moment, we report the cross-simulation mean and the $p$-value (the fraction of simulations with which the model moment is higher than its data moment). The log price-to-consumption ratio, $\log(P_t/C_t)$, is standardized to have a mean of zero and a standard deviation of one. The forecast horizon, $H$, ranges from one year (1y) to five years (5y). The $t$-values of the slopes are adjusted for heteroscedasticity and autocorrelations of $2(H-1)$ lags. The slopes and $R$-squares are in percent.

| | 1y | 2y | 3y | 4y | 5y | 1y | 2y | 3y | 4y | 5y | 1y | 2y | 3y | 4y | 5y |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Panel A: Predicting stock market excess returns | | | | | | | | | | | | | | | |
| | Data | | | | | Mean | | | | | $p$ | | | | |
| $b$ | −1.52 | −3.41 | −4.71 | −5.74 | −6.30 | −1.44 | −2.72 | −3.86 | −4.87 | −5.78 | 0.55 | 0.72 | 0.71 | 0.67 | 0.59 |
| $t$ | −1.22 | −1.64 | −1.77 | −1.95 | −2.07 | −1.78 | −2.19 | −2.42 | −2.59 | −2.75 | 0.27 | 0.30 | 0.29 | 0.31 | 0.31 |
| $R^2$ | 1.87 | 4.02 | 5.69 | 7.39 | 9.01 | 2.62 | 4.61 | 6.32 | 7.82 | 9.16 | 0.55 | 0.49 | 0.50 | 0.48 | 0.46 |
| Panel B: Predicting consumption growth | | | | | | | | | | | | | | | |
| | Data | | | | | Mean | | | | | $p$ | | | | |
| $b$ | −0.34 | −0.80 | −1.22 | −1.62 | −1.99 | −1.37 | −1.97 | −2.56 | −3.12 | −3.65 | 0.01 | 0.07 | 0.10 | 0.12 | 0.13 |
| $t$ | −0.64 | −0.82 | −0.93 | −1.02 | −1.09 | −2.91 | −2.43 | −2.45 | −2.58 | −2.72 | 0.01 | 0.07 | 0.12 | 0.14 | 0.16 |
| $R^2$ | 2.51 | 3.32 | 4.12 | 4.95 | 5.77 | 7.59 | 7.31 | 8.44 | 9.78 | 11.11 | 0.88 | 0.74 | 0.69 | 0.67 | 0.66 |
| Panel C: Predicting excess return volatilities | | | | | | | | | | | | | | | |
| | Data | | | | | Mean | | | | | $p$ | | | | |
| $b$ | −17.43 | −17.77 | −17.26 | −16.57 | −16.16 | −12.85 | −11.30 | −10.24 | −9.43 | −8.72 | 0.65 | 0.76 | 0.81 | 0.84 | 0.86 |
| $t$ | −1.90 | −2.07 | −1.80 | −1.59 | −1.44 | −1.22 | −1.45 | −1.57 | −1.64 | −1.64 | 0.73 | 0.70 | 0.58 | 0.50 | 0.45 |
| $R^2$ | 6.32 | 12.27 | 15.84 | 17.87 | 19.02 | 1.54 | 2.49 | 3.61 | 4.62 | 5.35 | 0.03 | 0.01 | 0.01 | 0.02 | 0.03 |
| Panel D: Predicting consumption growth volatilities | | | | | | | | | | | | | | | |
| | Data | | | | | Mean | | | | | $p$ | | | | |
| $b$ | 17.49 | 17.72 | 18.36 | 19.20 | 19.73 | −35.07 | −33.16 | −31.56 | −30.10 | −28.72 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| $t$ | 1.61 | 1.78 | 1.84 | 1.95 | 2.00 | −3.54 | −4.29 | −4.31 | −4.19 | −4.03 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| $R^2$ | 6.08 | 10.51 | 13.40 | 15.15 | 16.34 | 8.00 | 13.99 | 17.00 | 18.40 | 18.95 | 0.62 | 0.66 | 0.64 | 0.62 | 0.59 |

from 4.27% to 3.74% and to 3.23%. The lower discount rate again raises the marginal benefit of hiring to reduce the unemployment rate to 8.47% and to 7.45%. However, labor market volatilities remain largely unchanged.

Finally, the log utility ($\gamma = \psi = 1$) implies lower consumption, output, and investment volatilities, 3.93%, 5.21%, and 5.21% per annum, than the benchmark calibration with recursive utility, 5.43%, 6.64%, and 8.83%, respectively. Although the unemployment volatility rises slightly, the vacancy and labor market tightness volatilities fall by about one-third. The equity premium drops from 4.27% to only 0.32%, and stock market volatility from 12.42% to 8.96%.

*3.6.2. Labor market parameters*

The flow value of unemployment, $b$, plays a key role. Lowering its value from 0.91 to 0.88 is sufficient to reduce the unemployment rate from 9.4% to 3.45% and the unemployment volatility from 0.31 to 0.24. Intuitively, a lower $b$ reduces wages and raises profits to stimulate hiring. A lower $b$ also enlarges the fundamental surplus allocated to the firm, dampening the unemployment volatility (Hagedorn and Manovskii, 2008; Ljungqvist and Sargent, 2017). This mechanism reduces the consumption volatility from 5.43% per annum to 3.24% and the consumption disaster probability from 6.66% to 3.37%. The lower consumption risks then reduce the equity premium to only 0.64% and stock market volatility to only 7.94%. As such, our results show that the small surplus mechanism behind the unemployment volatility puzzle in the labor market highlighted by Ljungqvist and Sargent also underpins the equity premium puzzle in the financial market.

The bargaining weight of workers, $\eta$, also plays an important role. Raising $\eta$ from 0.015 to 0.025 makes wages more sensitive to shocks. The wage elasticity to labor productivity rises from 0.28 to 0.39. Because wages become more procyclical, profits and dividends become less procyclical. Consequently, the equity premium falls from 4.27% to 3.95% per annum, and stock market volatility from 12.42% to 11.6%. However, business cycle and labor market volatilities are largely unchanged. Increasing the separation rate, $s$, from 3% to 3.5% raises the unemployment rate from 9.4% to 9.97%. However, its impact on macro and labor market volatilities is small. The equity premium declines slightly from 4.27% per annum to 4.16%, and stock market volatility from 12.42% to 12.35%.

Reducing the curvature parameter in the matching function, $\iota$, from 0.9 to 0.6 induces more severe search and matching frictions. Consequently, the mean unemployment rate rises from 9.4% to 10.58%. Macro volatilities all rise, with consumption volatility from 5.43% to 5.54% per annum, in particular. Disaster dynamics also strengthen somewhat. The equity premium rises to 4.35%, and stock market volatility to 12.77%. However, labor market volatilities remain mostly insensitive.

Raising the proportional cost of vacancy posting, $\kappa_0$, from 0.05 to 0.075 increases the marginal cost of hiring, causing the unemployment rate to rise from 9.4% to 9.75%. The consumption volatility rises to 5.49%. However, the equity premium falls slightly to 4.24% per annum. From Eq. (19), a higher $\kappa_0$ makes wages more sensitive to procyclical labor market tightness, $\theta_t$. Profits and dividends become less procyclical, dampening the equity premium.

**Table 10**
Comparative statics.
The first column shows the model moments from the benchmark calibration. In the remaining columns, $\gamma$ is relative risk aversion; $\psi$ the intertemporal elasticity of substitution; $b$ the flow value of unemployment; $\eta$ the bargaining weight for workers; $s$ the separation rate; $\iota$ the curvature of the matching function; $\kappa_0$ and $\kappa_1$ the proportional and fixed unit costs of vacancy posting, respectively; $\nu$ the adjustment cost parameter; $\delta$ the capital depreciation rate; $e$ the elasticity of capital-labor substitution; and $\alpha$ the distribution parameter. In each experiment, all other parameters are identical to those in the benchmark calibration. $\sigma_C$ is the consumption growth volatility (per annum). $\rho_{C1}$ is the first-order autocorrelation of consumption growth. Prob$_C$, Size$_C$, and Dur$_C$ are the probability, size, and duration of consumption disasters with a cumulative decline hurdle rate of 10%, respectively. $\sigma_Y$ is the output growth volatility. $\rho_{Y1}$ is the first-order autocorrelation of output growth. Prob$_Y$, Size$_Y$, and Dur$_Y$ are the probability, size, and duration of output disasters with a cumulative decline hurdle rate of 10%, respectively. $\sigma_I$ is the investment growth volatility, $\rho_{I1}$ is the first-order autocorrelation of investment growth. The consumption, output, and investment volatilities, and the probability and size of consumption and output disasters are in percent. Their durations are in years. $E[U]$ is mean unemployment rate. $\sigma_U, \sigma_V$, and $\sigma_\theta$ are the quarterly volatilities of unemployment, vacancy, and labor market tightness, respectively. $\rho_{UV}$ is the cross-correlation of unemployment and vacancy. $e_{w,y/n}$ is the wage elasticity to labor productivity. Finally, $E[r_S - r_f]$ is the mean equity premium, $E[r_f]$ is mean interest rate, $\sigma_S$ is stock market volatility, and $\sigma_f$ is interest rate volatility, all of which are in annual percent. Model moments are the cross-simulation means across 10,000 samples from the stationary distribution (with a burn-in of 1200 months), each with 1740 months.

| | | $\gamma$ | $\gamma$ | $\psi$ | $\psi$ | $\gamma, \psi$ | $b$ | $\eta$ | $s$ | $\iota$ | $\kappa_0$ | $\kappa_1$ | $\nu$ | $\delta$ | $e$ | $\alpha$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 7.5 | 5 | 1.5 | 1 | 1 | 0.88 | 0.025 | 0.035 | 0.6 | 0.075 | 0.05 | 1.5 | 0.01 | 0.5 | 0.3 |
| $\sigma_C$ | 5.43 | 4.44 | 4.03 | 5.15 | 4.80 | 3.93 | 3.24 | 5.42 | 5.45 | 5.54 | 5.49 | 5.48 | 5.23 | 4.87 | 5.96 | 4.62 |
| $\rho_{C1}$ | 0.23 | 0.19 | 0.16 | 0.22 | 0.21 | 0.17 | 0.15 | 0.23 | 0.23 | 0.24 | 0.23 | 0.23 | 0.25 | 0.18 | 0.21 | 0.22 |
| Prob$_C$ | 6.66 | 5.02 | 4.41 | 6.17 | 5.61 | 4.11 | 3.37 | 7.29 | 6.51 | 7.11 | 6.91 | 6.78 | 6.16 | 5.92 | 7.00 | 6.13 |
| Size$_C$ | 23.70 | 20.51 | 18.85 | 22.97 | 22.00 | 19.02 | 16.03 | 22.73 | 24.00 | 23.75 | 23.65 | 23.74 | 24.08 | 21.16 | 24.88 | 20.74 |
| Dur$_C$ | 4.10 | 4.36 | 4.41 | 4.15 | 4.22 | 4.47 | 4.70 | 4.11 | 4.09 | 4.12 | 4.10 | 4.10 | 4.24 | 4.09 | 3.98 | 4.25 |
| $\sigma_Y$ | 6.64 | 5.70 | 5.15 | 6.41 | 6.11 | 5.21 | 4.53 | 6.51 | 6.71 | 6.78 | 6.70 | 6.67 | 6.64 | 6.05 | 7.06 | 5.86 |
| $\rho_{Y1}$ | 0.22 | 0.19 | 0.16 | 0.21 | 0.20 | 0.17 | 0.15 | 0.22 | 0.21 | 0.23 | 0.22 | 0.22 | 0.23 | 0.18 | 0.21 | 0.21 |
| Prob$_Y$ | 11.45 | 9.69 | 8.77 | 10.97 | 10.48 | 8.82 | 7.96 | 11.44 | 11.56 | 11.95 | 11.65 | 11.52 | 11.33 | 10.51 | 11.72 | 10.68 |
| Size$_Y$ | 22.85 | 20.38 | 18.90 | 22.32 | 21.57 | 19.14 | 17.21 | 22.49 | 22.95 | 23.16 | 22.97 | 22.92 | 23.04 | 21.01 | 23.66 | 20.88 |
| Dur$_Y$ | 3.72 | 3.82 | 3.87 | 3.75 | 3.77 | 3.88 | 3.95 | 3.73 | 3.71 | 3.71 | 3.71 | 3.72 | 3.76 | 3.71 | 3.66 | 3.79 |
| $\sigma_I$ | 8.83 | 6.44 | 4.41 | 8.35 | 7.72 | 5.21 | 3.46 | 8.54 | 8.92 | 9.12 | 8.93 | 8.85 | 9.85 | 7.34 | 8.84 | 7.14 |
| $\rho_{I1}$ | 0.16 | 0.14 | 0.11 | 0.16 | 0.16 | 0.12 | 0.10 | 0.16 | 0.16 | 0.17 | 0.17 | 0.16 | 0.16 | 0.15 | 0.17 | 0.16 |
| $E[U]$ | 9.40 | 5.73 | 4.29 | 8.47 | 7.45 | 4.59 | 3.45 | 9.38 | 9.97 | 10.58 | 9.75 | 9.50 | 9.22 | 6.96 | 9.27 | 8.18 |
| $\sigma_U$ | 0.31 | 0.36 | 0.36 | 0.32 | 0.33 | 0.35 | 0.24 | 0.30 | 0.29 | 0.27 | 0.30 | 0.31 | 0.31 | 0.35 | 0.36 | 0.29 |
| $\sigma_V$ | 0.33 | 0.26 | 0.23 | 0.32 | 0.30 | 0.23 | 0.19 | 0.33 | 0.33 | 0.33 | 0.33 | 0.34 | 0.33 | 0.30 | 0.33 | 0.32 |
| $\sigma_\theta$ | 0.35 | 0.27 | 0.24 | 0.33 | 0.31 | 0.24 | 0.20 | 0.35 | 0.35 | 0.37 | 0.36 | 0.36 | 0.34 | 0.31 | 0.35 | 0.33 |
| $\rho_{UV}$ | −0.11 | −0.12 | −0.14 | −0.11 | −0.11 | −0.13 | −0.21 | −0.11 | −0.11 | −0.16 | −0.12 | −0.11 | −0.10 | −0.12 | −0.11 | −0.11 |
| $e_{w,y/n}$ | 0.28 | 0.28 | 0.28 | 0.28 | 0.29 | 0.28 | 0.29 | 0.39 | 0.26 | 0.26 | 0.28 | 0.28 | 0.28 | 0.28 | 0.27 | 0.28 |
| $E[r_S - r_f]$ | 4.27 | 1.57 | 0.45 | 3.74 | 3.23 | 0.32 | 0.64 | 3.95 | 4.16 | 4.35 | 4.24 | 4.25 | 3.99 | 2.68 | 4.29 | 2.94 |
| $E[r_f]$ | 1.97 | 2.63 | 2.86 | 1.99 | 1.90 | 2.91 | 2.81 | 1.96 | 2.03 | 2.06 | 2.01 | 1.98 | 1.97 | 2.36 | 1.96 | 2.18 |
| $\sigma_S$ | 12.42 | 10.08 | 8.22 | 11.95 | 11.36 | 8.96 | 7.94 | 11.60 | 12.35 | 12.77 | 12.48 | 12.40 | 11.51 | 10.46 | 12.51 | 9.92 |
| $\sigma_f$ | 2.47 | 1.93 | 1.56 | 2.98 | 3.84 | 2.94 | 1.05 | 2.35 | 2.52 | 2.46 | 2.49 | 2.52 | 2.44 | 2.07 | 2.81 | 1.86 |

The mechanism of the fixed cost of vacancy, $\kappa_1$, works in the same direction as $\kappa_0$. In particular, $\kappa_1$ enters the wage rule in the form of $\kappa_1 q(\theta_t)\theta_t = \kappa_1 f(\theta_t)$, in which the job finding rate, $f(\theta_t)$, is still procyclical. However, the impact of $\kappa_1$ on the equity premium is dampened by the countercyclical $q(\theta_t)$ (Panel D, Fig. 1). Consequently, although the experiment of raising $\kappa_1$ from 0.025 to 0.05 has a slightly lower consumption volatility and a lower consumption disaster probability than the $\kappa_0$ experiment, the $\kappa_1$ experiment yields a slightly higher equity premium.

### 3.6.3. Technology parameters

The supply elasticity of capital, $\nu$, governs the magnitude of capital adjustment costs. Raising $\nu$ from 1.2 to 1.5 reduces adjustment costs and strengthens consumption smoothing via investment. Consequently, the consumption volatility falls from 5.43% per annum to 5.23%, and the consumption disaster probability from 6.66% to 6.16%. However, the investment volatility rises from 8.83% to 9.85%, even though the output volatility remains virtually unchanged at 6.64%. The lower consumption risks then imply a lower equity premium, 3.99%, echoing Jermann (1998). A lower discount rate raises the marginal benefit of hiring, reducing the unemployment rate to 9.22%. However, similar to the output volatility, labor market volatilities are also largely unchanged.

Lowering the depreciation rate, $\delta$, from 1.25% to 1% reduces the consumption volatility from 5.43% to 4.87% and the consumption disaster probability from 6.66% to 5.92%. The output volatility falls to 6.05%, and the investment volatility drops to 7.34%. The lower consumption risks reduce the equity premium to 2.68%. The lower discount rate stimulates hiring and reduces the unemployment rate to 6.96%. Intuitively, a lower $\delta$ gives rise to a larger stochastic steady state capital and helps stabilize the economy in the presence of shocks. This $\delta$ effect on capital is distinct from the capital share, which, as noted, we keep unchanged by recalibrating the capital scalar, $K_0$.

Raising the elasticity of capital-labor substitution, $e = 1/(1-\omega)$, from 0.4 to 0.5 increases macro and labor market volatilities. The consumption volatility rises from 5.43% to 5.96%, and the consumption disaster probability increases from 6.66% to 7%. From the CES production function in Eq. (4), $\partial Y_t/\partial X_t$ increases with the elasticity. However, the equity premium only rises slightly, to 4.29%. Raising $e$ further to 0.6 and 0.7 increases the consumption volatility to 6.44% and 6.87% but the equity premium only to 4.3% and 4.33%, respectively (untabulated). As such, the CES production with a relatively low elasticity of capital-labor substitution might be necessary for explaining the equity premium without overshooting consumption volatility.

**Table 11**
Moments of investment and hiring returns.
The first column of numbers shows the model moments from the benchmark calibration. The remaining columns show the moments from 15 comparative statics. $\gamma$ is relative risk aversion; $\psi$ the intertemporal elasticity of substitution; $b$ the flow value of unemployment; $\eta$ the bargaining weight for workers; $s$ the separation rate; $\iota$ the curvature of the matching function; $\kappa_0$ and $\kappa_1$ the proportional and fixed unit costs of vacancy posting, respectively; $\nu$ the adjustment cost parameter; $\delta$ the capital depreciation rate; $e$ the elasticity of capital-labor substitution; and $\alpha$ the distribution parameter. In each experiment, all other parameters are identical to those in the benchmark economy. $E[r_K]$ is the mean investment return, $\sigma_K$ is investment return volatility, $E[r_N]$ is the mean hiring return, $\sigma_N$ is hiring return volatility, $w_K$ is the value weight of the investment return in the stock return, $\rho_{KN}$ is the cross-correlation between investment and hiring returns, $\rho_{KS}$ is the cross-correlation between investment and stock returns, and $\rho_{NS}$ is the cross-correlation between hiring and stock returns. The return means and volatilities are annualized, and all moments except for cross-correlations are in percent. All moments are cross-simulation *medians* across 10,000 samples from the model's stationary distribution (with a burn-in of 1200 months), each with 1740 months. We report cross-simulation medians instead of means because of large finite-sample variations in the moments of hiring returns.

| | | $\gamma$ 7.5 | $\gamma$ 5 | $\psi$ 1.5 | $\psi$ 1 | $\gamma,\psi$ 1 | $b$ 0.88 | $\eta$ 0.025 | $s$ 0.035 | $\iota$ 0.6 | $\kappa_0$ 0.075 | $\kappa_1$ 0.05 | $\nu$ 1.5 | $\delta$ 0.01 | $e$ 0.5 | $\alpha$ 0.3 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $w_K$ | 92.58 | 90.11 | 89.03 | 92.01 | 91.34 | 88.91 | 85.09 | 93.85 | 92.99 | 92.35 | 92.52 | 92.55 | 92.30 | 92.84 | 92.51 | 93.96 |
| $E[r_K]$ | 5.28 | 3.74 | 3.14 | 4.78 | 4.13 | 3.09 | 3.12 | 5.13 | 5.31 | 5.39 | 5.30 | 5.28 | 4.96 | 4.38 | 5.20 | 4.49 |
| $\sigma_K$ | 9.97 | 6.99 | 4.63 | 9.36 | 8.60 | 5.54 | 3.45 | 9.61 | 10.08 | 10.23 | 10.06 | 9.99 | 8.95 | 8.11 | 9.89 | 7.97 |
| $E[r_N]$ | 41.56 | 15.47 | 7.37 | 38.44 | 37.01 | 6.20 | 7.40 | 39.54 | 39.79 | 40.77 | 36.42 | 36.22 | 42.48 | 29.38 | 47.02 | 32.59 |
| $\sigma_N$ | 186.07 | 120.67 | 85.52 | 177.21 | 168.22 | 82.92 | 56.16 | 164.05 | 160.81 | 155.19 | 138.93 | 143.74 | 188.91 | 151.87 | 283.14 | 145.14 |
| $\rho_{KN}$ | 0.71 | 0.68 | 0.69 | 0.71 | 0.71 | 0.68 | 0.79 | 0.74 | 0.75 | 0.79 | 0.76 | 0.73 | 0.70 | 0.72 | 0.57 | 0.74 |
| $\rho_{KS}$ | 0.97 | 0.95 | 0.94 | 0.96 | 0.96 | 0.95 | 0.96 | 0.97 | 0.97 | 0.97 | 0.97 | 0.97 | 0.96 | 0.97 | 0.97 | 0.97 |
| $\rho_{NS}$ | 0.72 | 0.71 | 0.73 | 0.72 | 0.72 | 0.73 | 0.80 | 0.76 | 0.76 | 0.80 | 0.78 | 0.76 | 0.71 | 0.73 | 0.58 | 0.75 |

Finally, raising the capital share, $\alpha$, from 0.25 to 0.3 means that labor market frictions play a less prominent role in the economy. Macro and labor market volatilities all fall. The consumption volatility drops to 4.62%, and the consumption disaster probability decreases to 6.13%. Accordingly, the equity premium falls to 2.94%, and stock market volatility drops to 9.92%. The lower discount rate raises the marginal benefit of hiring to reduce the unemployment rate to 8.18%.

## 4. Additional predictions

We explore several additional issues, including investment versus hiring returns (Section 4.1), the timing premium (Section 4.2), the welfare cost of business cycles (Section 4.3), the equity term structure (Section 4.4), and the representativeness of the postwar U.S. sample (Section 4.5).

### *4.1. Investment versus hiring returns*

Eq. (18) decomposes the stock return as the value-weighted average of the investment and hiring returns. Table 11 shows the key moments from this decomposition in our benchmark economy as well as their comparative statics. Perhaps surprisingly, the value weight of the investment return, $w_{Kt}$, is on average 92.6% in the benchmark economy, in which the labor share in output, $W_tN_t/Y_t$, is calibrated to be on average 74.6%. As such, although labor contributes almost three quarters to output, capital accounts for a vast proportion of the market equity.

This seemingly high fraction of 92.6% is in fact intuitive. The market equity is the present value of future dividends. From Eq. (11), dividends are given by output minus wage expenses minus total investment costs. The high labor costs in producing output, $W_tN_t$, which are expensed as payments to workers, do not contribute to dividends. In contrast, as residual claimants, the only payments to shareholders are in the form of dividends. Nevertheless, because adjusting labor is not costless, labor still accounts for a fraction of the market equity, albeit a small one.

Panel A of Fig. 3 shows that the capital share in value, $w_{Kt}$, exhibits countercyclical dynamics. The correlation between $w_{Kt}$ and output is −0.8 in simulations. From Panel B, the labor share in output is also countercyclical. Its correlation with output is −0.83. This pattern reflects the impact of wage inertia (Panel D, Fig. 1) on labor share dynamics (Gomme and Greenwood, 1995). The pattern also arises in part from the CES production (Choi and Ríos-Rull, 2009). Specifically, Panel C shows that $(\partial Y_t/\partial N_t)N_t/Y_t$, the labor share in frictionless labor markets, in which wages equal the marginal product of labor, is weakly countercylical. Its correlation is −0.08 with output. In the Cobb–Douglas production, this labor share would be exactly constant. This result shows why in comparative statics a relatively low elasticity of capital-labor substitution in the CES production helps explain the equity premium with a plausible level of consumption volatility.[27]

Because of the high capital share in value, labor market frictions affect the stock return more via their indirect impact on the investment return than via their direct impact on the hiring return. From Table 11, the average investment return is 5.28% per annum in the benchmark economy, which accounts for 84.6% of the average stock return of 6.24% (the equity premium plus the interest rate in Table 4). The investment return volatility is 9.97%, which

[27] A remark on a technical issue is in order. In Panel A of Fig. 3, $w_{Kt}$ can wander above 100% with a tiny probability (0.28%) in our simulations. For comparison, the $V_t \geq 0$ constraint binds at a rate of 3.26%. Intuitively, with the $V_t \geq 0$ constraint binding, the firm is prevented from cutting labor at a rate higher than the exogenous separation rate, $s$. With our small-surplus, high-$b$ calibration, when the productivity is sufficiently low, the shadow value of labor, $\mu_{Nt}$, can turn negative. As discussed in Petrosky-Nadeau and Zhang (2017, p. 616–617), a similar issue also arises in Hagedorn and Manovskii (2008), in which the firm wishes to exit the economy. With capital in our model, the firm does not want to exit because the market equity is always positive (Panel A, Fig. 2). Modeling endogenous separation without the $V_t \geq 0$ constraint is likely to resolve the technical issue but is left for future work.

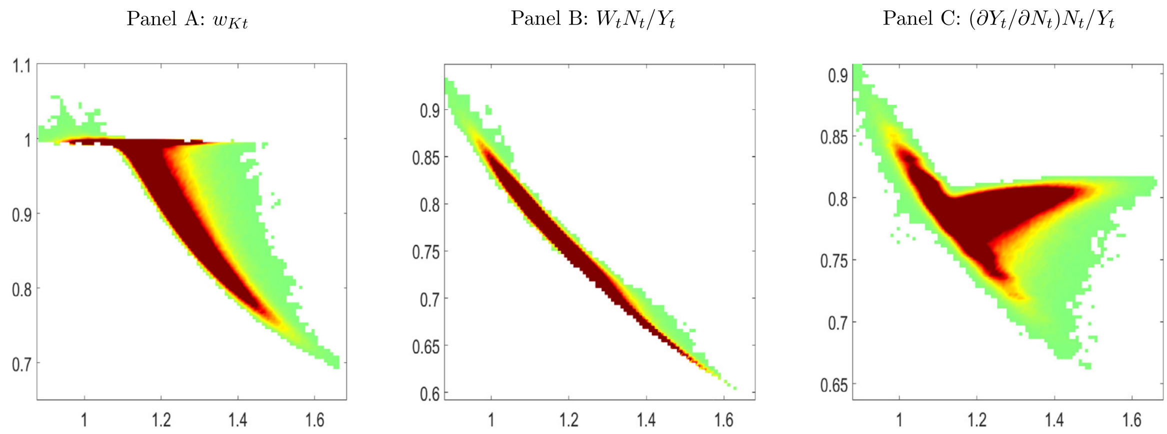


**Fig. 3.** Heatmaps of the value weight of the investment return and the labor shares against productivity. From the model's stationary distribution with the benchmark calibration (after a burn-in period of 1200 monthly periods), we simulate a long sample path with one million months. Panel A shows the value weight of the investment return in the stock return, $w_{Kt} \equiv \mu_{Kt}K_{t+1}/(\mu_{Kt}K_{t+1} + \mu_{Nt}N_{t+1})$, in which $\mu_{Kt}$ equals the marginal cost of investment, $(1/a_2)(I_t/K_t)^{(1/\nu)}$, and $\mu_{Nt}$ equals the marginal cost of hiring, $\kappa_t/q(\theta_t) - \lambda_t$. Panel B shows the labor share, which is the fraction of wage expenses, $W_tN_t$, in the output, $Y_t$. Panel C shows an alternative definition of labor share, in which wages are equal to the marginal product of labor, $\partial Y_t/\partial N_t$, as in frictionless labor markets. In each heatmap, dark red indicates high density, whereas light green indicates low density. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

accounts for 80.3% of stock market volatility, 12.42%. The correlation between investment and stock returns is 0.97.

The hiring return exhibits dramatic dynamics, with a mean of 41.56% and a volatility of 186.1% per annum! The dynamics are an order of magnitude more powerful than investment return dynamics, powerful enough to affect finite-sample cross-simulation means across 10,000 simulations (even 100,000 runs in practice). As such, in Table 11 we opt to report cross-simulation medians, which are stable. (For all the moments other than the first two moments of the hiring return, cross-simulation means are close to medians.) Despite the striking dynamics, their impact on stock return moments is muted because of the small labor share of value, 7.4%. Also, the hiring return turns more extreme in bad times precisely when its value weight goes to zero (Panel A, Fig. 3).

The remainder of Table 11 shows comparative statics that are mostly aligned with Table 10. Reducing the risk aversion, $\gamma$, to 7.5 and further to five lowers the average investment return to 3.74% and 3.14% and its volatility to 6.99% and 4.63% per annum, respectively. The mean hiring return falls more drastically, to 15.47% and 7.37%, and its volatility drops to 120.7% and 85.5%, respectively. As the discount rate falls, the marginal benefit of hiring (which equals the shadow value of labor) rises, reducing the capital share in value to 90.1% and 89%, respectively. Reducing $\psi$ to 1.5 and further to one has qualitatively similar effects as reducing $\gamma$. However, its impact on the first two moments of investment and hiring returns is smaller.

More important, labor market frictions affect the investment return. Reducing the flow value of unemployment, $b$, to 0.88 lowers the mean investment return to 3.12% and its volatility to 3.45% per annum. The mean and volatility of the hiring return also fall drastically, to 7.4% and 56.2%, respectively. By increasing the marginal benefit of hiring, the lower $b$ value also raises the labor share in value to 15%. Raising the bargaining power for workers, $\eta$, or the separation rate, $s$, makes labor less valuable to the firm, increasing the capital share in value. However, the return moments are mostly insensitive. Finally, by strengthening search and matching frictions, a lower curvature in the matching function, $\iota$, and higher proportional and fixed unit costs of vacancy posting, $\kappa_0$ and $\kappa_1$, make matched workers more valuable to the firm to reduce the capital share in value. The first two moments of the investment return rise, but those of the hiring return fall.

By reducing adjustment costs, a higher installation function curvature, $\nu$, lowers the capital share in value. The mean and volatility of the investment return fall, but those of the hiring return rise slightly. A lower depreciation rate, $\delta$, and a higher capital share in output, $\alpha$, make capital more valuable to the firm, raising its value share. However, the first two moments of investment and hiring returns all fall. Finally, raising the elasticity of capital-labor substitution, $e$, decreases the first moments of the investment return but increases those of the hiring return. The investment-hiring return correlation drops to 0.57, while it is more stable for all the other experiments. Intuitively, a higher $e$ weakens the capital-labor complementarity and strengthens diversification between investment and hiring returns, making it harder to match the equity premium.

### 4.2. The timing premium

Epstein et al. (2014) show that the representative investor in the Bansal and Yaron (2004) model would give up an implausibly high fraction, 31%, of its consumption stream for the early resolution of consumption risks. In the Wachter (2013) model with time-varying disaster probabilities, this fraction is even higher, at 42%. Epstein et al. argue that the fractions (dubbed the timing premium) seem too high because the household cannot use the information from the early resolution to modify its risky consumption stream. Because we follow Bansal and Yaron when calibrating preferences, with risk aversion higher than the inverse of the elasticity of intertemporal substitution, it is natural to ask what the timing premium is in our model.

The timing premium is defined as $\pi \equiv 1 - J_0/J_0^\star$, in which $J_0$ is the household's utility with risks resolved gradually, and $J_0^\star$ is the utility with risks resolved in the next period. Formally,

$$J_0^\star = \left[(1-\beta)C_0^{1-\frac{1}{\psi}} + \beta\left(E_t\left[(J_1^\star)^{1-\gamma}\right]\right)^{\frac{1-1/\psi}{1-\gamma}}\right]^{\frac{1}{1-1/\psi}}, \tag{27}$$

in which the continuation utility $J_1^\star$ is given by

$$J_1^\star = \left[(1-\beta)\sum_{t=1}^{\infty}\beta^{t-1}C_t^{1-\frac{1}{\psi}}\right]^{\frac{1}{1-1/\psi}}. \tag{28}$$

Following Epstein et al. (2014), we calculate $J_0^\star$ via Monte Carlo simulations at the economy's stochastic steady state ($N_t = 0.906$, $K_t = 14.6595$, and $x_t = 0.1945$) as the initial condition. We simulate in total 100,000 sample paths, each with $T = 2500$ months, while pasting $J_0$ as the continuation value at $T$. $J_0$ is available from our projection algorithm. On each path, we calculate one realization of $J_1^\star$ using Eq. (28). The expectation in Eq. (27), $E_t\left[(J_1^\star)^{1-\gamma}\right]$, is calculated as the cross-simulation average.

The timing premium in our model is only 16.11%, which we view as empirically plausible. For comparison, Epstein et al. (2014) calculate the timing premium to be 9.5% with i.i.d. consumption growth, a risk aversion of ten, and an elasticity of intertemporal substitution of 1.5. In the Barro (2009) model with a constant disaster probability, a risk aversion of four, and an elasticity of intertemporal substitution of two, the timing premium is 18%.

Intuitively, the long-run risks model assumes extremely high persistence in expected consumption growth (Bansal and Yaron, 2004) or in conditional consumption volatility (Bansal et al., 2012). Analogously, the Wachter (2013) model assumes very high persistence in time-varying disaster probabilities. Because the risks are not resolved until much later, the investor that prefers early resolution of uncertainty would pay a high timing premium for the risks to be resolved early. In contrast, our expected consumption growth and conditional consumption volatility are much less persistent per Eqs. (21) and (22), yielding a low timing premium.

### 4.3. The welfare cost of business cycles

Lucas (1987, 2003) argues that the welfare cost of business cycles is negligible. Assuming log utility for the representative household and log-normal distribution for consumption growth, Lucas (2003) calculates that the agent would sacrifice a mere 0.05% of their consumption in perpetuity to eliminate consumption fluctuations. However, Lucas assumes log utility that fails to explain the equity premium. Atkeson and Phelan (1994), for example, argue that welfare cost calculations should be carried out within models that at least roughly replicate how capital markets price consumption risks. Because our model replicates the equity premium, we quantify its welfare cost.

Following Lucas (1987, 2003), we define the welfare cost of business cycles as the permanent percentage of the consumption stream that the representative household would sacrifice to eliminate aggregate consumption fluctuations. Formally, let ${}_tC \equiv \{C_t, C_{t+1}, \ldots\}$ be the consumption stream starting at time $t$. For a given state of the economy, $(N_t, K_t, x_t)$, at date $t$, we calculate the welfare cost, denoted $\chi_t \equiv \chi(N_t, K_t, x_t)$, implicitly from:

$$J({}_tC(1+\chi_t)) = \bar{J}, \tag{29}$$

in which $\bar{J}$ is the recursive utility derived from the constant consumption at the deterministic steady state, $\bar{C}$. We solve for $\bar{J}$ by iterating on $\bar{J} = [(1-\beta)\bar{C}^{1-\frac{1}{\psi}} + \beta\bar{J}^{1-\frac{1}{\psi}}]^{\frac{1}{1-1/\psi}}$. Because $J_t$ is linear homogeneous, $J({}_tC(1+\chi_t)) = (1+\chi_t)J({}_tC)$, solving for $\chi_t$ from Eq. (29) yields:

$$\chi_t = \frac{\bar{J}}{J_t} - 1. \tag{30}$$

We calculate the welfare cost, $\chi_t$, on the state space, $(N_t, K_t, x_t)$. To evaluate its magnitude, we simulate one million months of $\chi_t$ from the model's stationary distribution. The average welfare cost in simulations is 33.62%, which is more than 670 times the Lucas estimate of 0.05%. The consumption in the stochastic steady state is 2.6% lower than its deterministic steady state value.

Perhaps more important, the welfare cost is time-varying and strongly countercyclical. In simulation, its median is 28.95%, and the 5th and 25th percentiles are 21.26% and 24.89%, whereas the 75th and 95th percentiles are 36.92% and 63.29%, respectively. Fig. 4 shows the heatmaps of the welfare cost against productivity, unemployment, and capital in simulations. The welfare cost is clearly countercyclical. Its correlations with productivity, output, unemployment, vacancy, and the investment rate are −0.75, −0.97, 0.95, −0.66, and −0.46, respectively. The countercyclicality of the welfare cost implies that optimal fiscal and monetary policies that aim to dampen disaster risks are even more important than what the average welfare cost of 33.6% would suggest.

### 4.4. The equity term structure

Binsbergen et al. (2012) show that short-maturity dividend strips on the aggregate stock market have higher expected returns and volatilities than long-maturity dividend strips. This pattern seems difficult to reconcile with leading consumption-based models.[28]

[28] Intuitively, in the Campbell and Cochrane (1999) external habit model, the impact of shocks on slow-moving surplus consumption is more pronounced for long-maturity dividend strips than for short-maturity strips, giving rise to an upward-sloping term structure of equity returns. In the Bansal and Yaron (2004) long-run risks model, small shocks on highly persistent expected consumption growth and to stochastic consumption volatility gradually build up over longer horizons to make long-maturity dividend strips riskier than short-maturity strips, again yielding an upward-sloping equity term structure. In the Rietz–Barro baseline disaster model, dividend strips of all maturities are exposed to the same amount of disaster risks, which are specified to be i.i.d., yielding a flat equity term structure. Finally, in the Wachter (2013) model with time-varying but highly persistent disaster probabilities, small shocks on the disaster probabilities build up over time to yield an upward-sloping equity term structure.

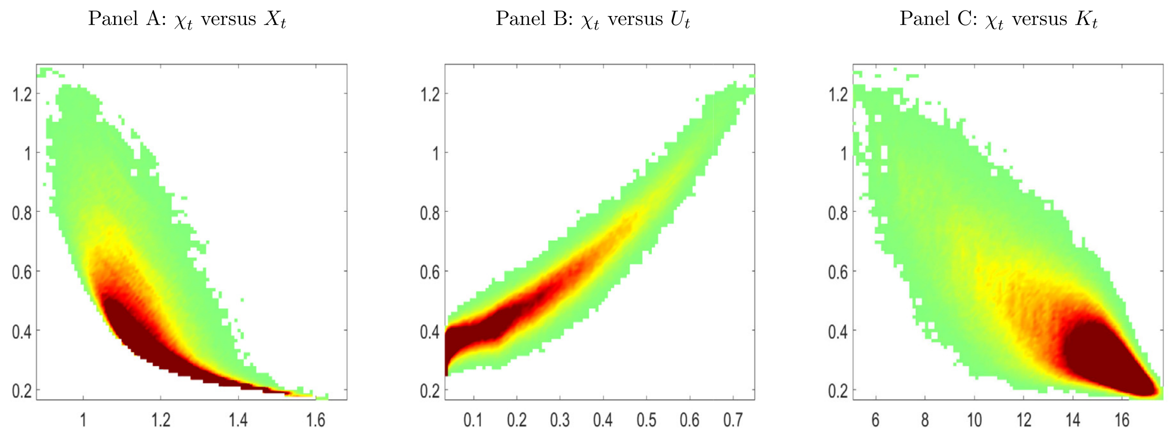


**Fig. 4.** Heatmaps of the welfare cost of business cycles against state variables. From the benchmark model's stationary distribution (after a burn-in period of 1200 months), we simulate a long sample with one million months. The vertical axis is the welfare cost, $\chi_t$. Dark red indicates high density, whereas light green indicates low density. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Our model yields a downward-sloping equity term structure. Let $P^D_{n,t}$ denote the price of an $n$-period dividend strip. For $n = 1$, $P^D_{1,t} = E_t[M_{t+1}D_{t+1}]$. For $n > 1$, we solve for $P^D_{n,t}$ recursively from $P^D_{n,t} = E_t[M_{t+1}P^D_{n-1,t+1}]$. We calculate $r^D_{n,t+1} \equiv P^D_{n-1,t+1}/P^D_{n,t}$ as the return of buying the $n$-period dividend strip at time $t$ and selling it at $t+1$. However, as noted, dividends in the model are net payouts, which can be negative in certain states of the world. Negative prices on these dividend strips then render their returns undefined. In practice, dividends are all positive when $n \geq 58$ months. As such, we calculate the equity term structure from year five to 40. Consumption in the model is always positive in all states of the world. Accordingly, we calculate the term structure of consumption strips from year one to 40. The definitions of price of an $n$-period consumption strip, $P^C_{n,t}$, and its return, $r^C_{n,t+1}$, are exactly analogous to those of the $n$-period dividend strip.

Fig. 5 shows that risk premiums, volatilities, and Sharpe ratios on dividend and consumption strips are largely downward-sloping in our model. From Panel A, the dividend risk premium falls from 8.01% per annum in year five to 6.13% in year ten and further to 0.88% in year 40. The volatility of the dividend strip falls from 22.7% in year five to 17.4% in year ten and further to 4% in year 40 (Panel B). The Sharpe ratio of the dividend strip starts at 0.35 in year five, remains at 0.35 in year ten, and then falls steadily to 0.22 in year 40 (Panel C).

For consumption strips, the risk premium starts at 2.1% in year one, rises to 2.28% in year six, then falls gradually to 0.46% in year 40 (Panel D). Volatility starts at 7.07% in year one, rises to 7.36% in year six, and drops to 3.09% in year 40 (Panel E). The Sharpe ratio starts at 0.3 in year one, rises slightly to 0.31 in year six, and falls to 0.15 in year 40 (Panel F). As for the wealth portfolio that pays the consumption stream as dividends, its risk premium is 1.76%, and its volatility is 4.19%.

Intuitively, short-maturity dividend and consumption strips are riskier in our model because of their higher exposures to disaster risks.[29] When the economy slides into a disaster, short-maturity dividends and consumption take a big hit because of inertial wages. Long-maturity dividend and consumption strips are less impacted because disasters are followed by recoveries.[30]

### 4.5. How representative is the postwar U.S. sample?

Following the Rietz–Barro exogenous disasters literature, we calibrate our model to a historical cross-country database, as opposed to the postwar U.S. sample. Brown et al. (1995) show that survivorship imparts a bias to ex post average returns. Jorion and Goetzmann (1999) show that the high U.S. equity premium appears to be the exception rather than the rule across countries. In the words of Dimson et al. (2002), the good fortune enjoyed by U.S. equity investors in the 20th century represents the "triumph of the optimists." Finally, Fama and French (2002) show that the average return estimate of the equity premium in the postwar U.S. sample is almost three times that of an ex ante estimate based on dividend growth rates.

[29] Nakamura et al. (2013) show that a model with (exogenous) multiperiod disasters and subsequent recoveries also yields a downward-sloping equity term structure. Our work differs in that disasters and recoveries are endogenous.

[30] The term structure of real interest rates is downward-sloping in our model (the Internet Appendix). The yield-to-maturity starts at 1.92% per annum for one-month zero-coupon bond but falls to 1.24% for one-year and to 0.59% for ten-year zero-coupon bond. The average yield spread is −1.33% for the ten-year zero-coupon bond relative to the one-month bond. The real term premium is also negative, −1.55%, for the ten-year zero-coupon bond. Intuitively, long-term bonds are hedges against disaster risks. Disasters stimulate precautionary savings, which drive down real interest rates and push up bond prices. Because long-term bond prices rise at the onset of disasters, these bonds provide hedges against disaster risks (Nakamura et al., 2013; Wachter, 2013).

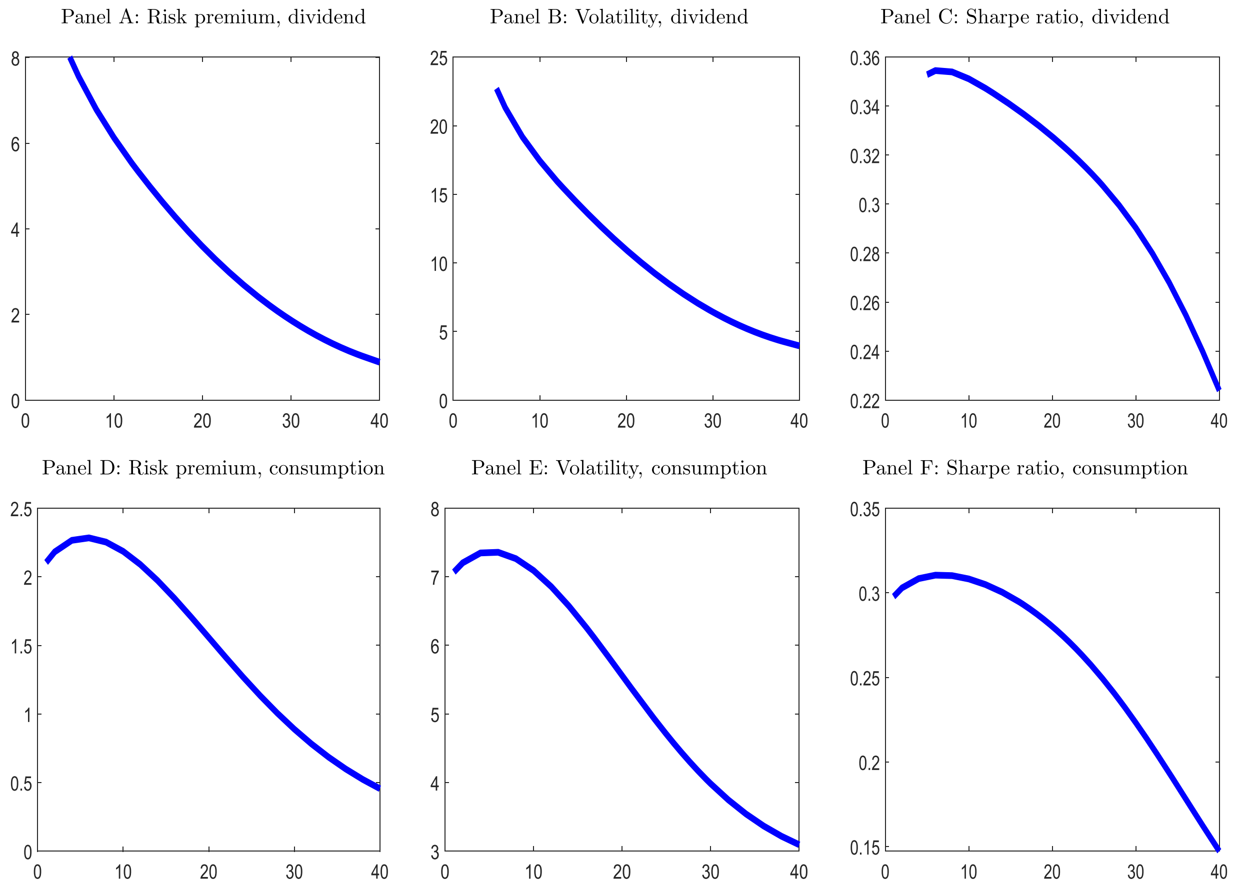


**Fig. 5.** The term structures of risk premium, volatility, and Sharpe ratio. From the model's stationary distribution with the benchmark calibration (after a burn-in of 1200 months), we simulate a long sample with one million months. In the vertical axis, risk premiums and volatilities are in annualized percentage. The Sharpe ratios are annualized. Maturity in the horizontal axis is in years.

Although the hurdle of explaining the equity premium given its consumption volatility in the historical cross-country sample is somewhat lower than that in the postwar U.S. sample, it still represents a significant challenge. In the Internet Appendix, we have recalibrated the Campbell and Cochrane (1999) model to the mean estimates of the equity premium and consumption volatility in the Jordà–Schularick–Taylor cross-country database. The model requires a steady state risk aversion of 15.47, which still seems high, to explain the equity premium.

However, how representative is the postwar U.S. sample from the perspective of our model? The answer, unfortunately, is not at all. We simulate 10,000 artificial economies from the model's stationary distribution, each with 792 months. The length matches the 1950–2015 postwar sample. The fraction of the economies in which the equity premium is no lower than 5.08% per annum and consumption volatility is no higher than 1.73% in the postwar U.S. sample, is zero. Even for the postwar cross-country estimates, the fraction is less than 0.01% for economies with the equity premium no lower than 5.38% and consumption volatility no higher than 2.4%.

Across the simulated economies, the correlation between the equity premium and consumption volatility is 0.3. Within the economies with consumption volatility no higher than 2.4%, the maximum equity premium is 5.88%. However, within the economies with consumption volatility no higher than 1.73%, the maximum equity premium is only 4.38%.

In short, it might be too ambitious to use a singular framework to explain the entire history. Key ingredients are likely missing but are responsible for the historical and postwar differences. Perhaps postwar macroeconomic policies have been extraordinarily successful in combating disasters. The 2007–2009 Great Recession notwithstanding, perhaps the postwar era is better described as the "Great Moderation" (Stock and Watson, 2003), signaling a regime change from the earlier period. Perhaps the ex post average equity premium is indeed a lot higher than the ex ante, expected equity premium in the postwar U.S. sample (Fama and French, 2002).

## 5. Conclusion

A dynamic stochastic general equilibrium framework with recursive utility, search frictions, and capital accumulation is a good start to forming a unified theory of asset prices and business cycles. The model yields a high equity premium (adjusted for financial leverage) of 4.27% per annum, a high stock market volatility of 12.42%, and a low average interest rate of 1.97%, while simultaneously retaining plausible quantity dynamics. The equity premium and stock market volatility are strongly countercyclical, whereas the real interest rate and consumption growth are largely unpredictable. The welfare cost of business cycles is huge, 33.6%. Wage inertia amplifies the procyclical dynamics of profits, which in turn overcome the procyclical dynamics of investment and vacancy costs to render dividends endogenously procyclical.

Several directions arise for future research. First, one can embed our model into a New Keynesian framework to analyze the nominal yield curve and the interaction between risk premiums and fiscal and monetary policies. Second, one can extend our model to a multi-country setting to study international asset prices and business cycles. Finally, one can incorporate heterogeneous firms to study how the cross-sectional distribution impacts on aggregate quantities and asset prices.

## Appendix

We adapt the Petrosky-Nadeau and Zhang (2017) globally nonlinear projection method with parameterized expectations to our setting. We discretize the $x_t$ process with the Rouwenhorst (1995) state space method with 17 grid points, which are sufficient to cover the $x_t$ values within four unconditional standard deviations from its unconditional mean, $\bar{x}$. The grid is symmetric around $\bar{x}$ and also even-spaced, with the distance between any two adjacent grid points, $d_x$, given by:

$$d_x \equiv 2\sigma/\sqrt{(1-\rho^2)(n_x-1)}, \tag{A.1}$$

in which $\rho$ is the persistence, $\sigma$ the conditional volatility of $x_t$, and $n_x = 17$. We still need to construct the transition matrix, $\Pi$, in which the $(i, j)$ element, $\Pi_{ij}$, is the probability of $x_{t+1} = x_j$ conditional on $x_t = x_i$. To this end, we set $p = (\rho + 1)/2$, and:

$$\Pi^{(3)} \equiv \begin{bmatrix} p^2 & 2p(1-p) & (1-p)^2 \\ p(1-p) & p^2+(1-p)^2 & p(1-p) \\ (1-p)^2 & 2p(1-p) & p^2 \end{bmatrix}, \tag{A.2}$$

which is the transition matrix for $n_x = 3$. To obtain $\Pi^{(17)}$, we use the following recursion:

$$p\begin{bmatrix} \Pi^{(n_x)} & \mathbf{0} \\ \mathbf{0}' & 0 \end{bmatrix} + (1-p)\begin{bmatrix} \mathbf{0} & \Pi^{(n_x)} \\ 0 & \mathbf{0}' \end{bmatrix} + (1-p)\begin{bmatrix} \mathbf{0}' & 0 \\ \Pi^{(n_x)} & \mathbf{0} \end{bmatrix} + p\begin{bmatrix} 0 & \mathbf{0}' \\ \mathbf{0} & \Pi^{(n_x)} \end{bmatrix}, \tag{A.3}$$

in which $\mathbf{0}$ is a $n_x \times 1$ column vector of zeros. We then divide all but the top and bottom rows by two to ensure that the conditional probabilities sum up to one in the resulting transition matrix, $\Pi^{(n_x+1)}$. Rouwenhorst (p 306–307; p 325–329) contains more details.

The state space consists of employment, capital, and productivity, $(N_t, K_t, x_t)$. We solve for the indirect utility function, $J(N_t, K_t, x_t)$, the optimal vacancy function, $V(N_t, K_t, x_t)$, the multiplier function, $\lambda(N_t, K_t, x_t)$, and the optimal investment function, $I(N_t, K_t, x_t)$, from:

$$J(N_t, K_t, x_t) = \left[(1-\beta)C(N_t, K_t, x_t)^{1-\frac{1}{\psi}} + \beta\left(E_t\left[J(N_{t+1}, K_{t+1}, x_{t+1})^{1-\gamma}\right]\right)^{\frac{1-1/\psi}{1-\gamma}}\right]^{\frac{1}{1-1/\psi}} \tag{A.4}$$

$$\begin{aligned}\frac{1}{a_2}\left(\frac{I(N_t, K_t, x_t)}{K_t}\right)^{1/\nu} = E_t\Bigg[M_{t+1}\Bigg[&\frac{Y(N_{t+1}, K_{t+1}, x_{t+1})}{K_{t+1}}\frac{\alpha(K_{t+1}/K_0)^{\omega}}{\alpha(K_{t+1}/K_0)^{\omega}+(1-\alpha)N_{t+1}^{\omega}} \\ &+\frac{1}{a_2}\left(\frac{I(N_{t+1}, K_{t+1}, x_{t+1})}{K_{t+1}}\right)^{1/\nu}(1-\delta+a_1) \\ &+\frac{1}{\nu-1}\frac{I(N_{t+1}, K_{t+1}, x_{t+1})}{K_{t+1}}\Bigg]\Bigg]\end{aligned} \tag{A.5}$$

$$\begin{aligned}\frac{\kappa}{q(\theta_t)} - \lambda(N_t, K_t, x_t) = E_t\Bigg[M_{t+1}\Bigg[&\frac{Y(N_{t+1}, K_{t+1}, x_{t+1})}{N_{t+1}}\frac{(1-\alpha)N_{t+1}^{\omega}}{\alpha(K_{t+1}/K_0)^{\omega}+(1-\alpha)N_{t+1}^{\omega}} - W_{t+1} \\ &+(1-s)\left[\frac{\kappa}{q(\theta(N_{t+1}, K_{t+1}, x_{t+1}))} - \lambda(N_{t+1}, K_{t+1}, x_{t+1})\right]\Bigg]\Bigg],\end{aligned} \tag{A.6}$$

in which

$$M_{t+1} = \beta\left[\frac{C(N_{t+1}, K_{t+1}, x_{t+1})}{C(N_t, K_t, x_t)}\right]^{-\frac{1}{\psi}} \times \left[\frac{J(N_{t+1}, K_{t+1}, x_{t+1})}{E_t[J(N_{t+1}, K_{t+1}, x_{t+1})^{1-\gamma}]^{\frac{1}{1-\gamma}}}\right]^{\frac{1}{\psi}-\gamma}. \tag{A.7}$$

Also, $V(N_t, K_t, x_t)$ and $\lambda(N_t, K_t, x_t)$ must satisfy the Kuhn–Tucker conditions.

Following Petrosky-Nadeau and Zhang (2017), we deal with $V_t \geq 0$ by exploiting a convenient mapping from the conditional expectation function, $\mathcal{E}_t \equiv \mathcal{E}(N_t, K_t, x_t)$, defined as the right-hand side of Eq. (A.6), to policy and multiplier functions to eliminate the need to parameterize the multiplier separately. After obtaining $\mathcal{E}_t$, we first calculate $\tilde{q}(\theta_t) = \kappa_0/(\mathcal{E}_t - \kappa_1)$. If $\tilde{q}(\theta_t) < 1$, the $V_t \geq 0$ constraint 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 $\tilde{q}(\theta_t) \geq 1$, the $V_t \geq 0$ constraint is binding, we set $V_t = 0$, $\theta_t = 0$, $q(\theta_t) = 1$, and $\lambda_t = \kappa_0 + \kappa_1 - \mathcal{E}_t$. An advantage of the installation function, $\Phi_t$, is that when investment goes to zero, the marginal benefit of investment, $\partial\Phi(I_t, K_t)/\partial I_t = a_2(I_t/K_t)^{-1/\nu}$, goes to infinity. As such, the optimal investment is always positive, with no need to impose the $I_t \geq 0$ constraint. We approximate $I(N_t, K_t, x_t)$ directly.

We approximate $J(N_t, K_t, x_t)$, $I(N_t, K_t, x_t)$, and $\mathcal{E}(N_t, K_t, x_t)$ on each grid point of $x_t$. We use the finite element method with cubic splines on 50 nodes on the $N_t$ space, [0.245, 0.975], and 50 nodes on the $K_t$ space, [5,20]. We experiment to ensure that the bounds are not binding at a frequency higher than 0.01% in the model's simulations. We take the tensor product of $N_t$ and $K_t$ for each grid point of $x_t$. We use the Miranda and Fackler (2002) CompEcon toolbox for function approximation and interpolation. With three functional equations on the 17-point $x_t$ grid, the 50-point $N_t$ grid, and the 50-point $K_t$ grid, we must solve a system of 127,500 nonlinear equations. We use such a large system to ensure the accuracy of our numerical solution. Following Judd et al. (2014), we use derivative-free fixed point iteration with a damping parameter of 0.00325. The convergence criterion is set to be $10^{-4}$ for the maximum absolute value of the errors across the nonlinear functional equations. We keep the same grid setup for all parameterizations, except for the comparative static with $\alpha = 0.3$, which implies a higher deterministic steady state capital of 22.17. We adjust the $K_t$ space to [7.5,25]. All other aspects remain identical.

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