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BEHAVIORAL THEORIES OF THE BUSINESS CYCLE

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ABSTRACT

We explore the business cycle implications of expectation shocks and of two well-known psychological biases, optimism and overconfidence. The expectations of optimistic agents are biased toward good outcomes, while overconfident agents overestimate the precision of the signals that they receive. Both expectation shocks and overconfidence can increase business-cycle volatility, while preserving the model's properties in terms of comovement, and relative volatilities. In contrast, optimism is not a useful source of volatility in our model.

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1. Introduction

In his book “Prosperity and Depression” published in 1937, Gottfried Haberler emphasizes the role of behavioral biases and shocks to expectations in generating and amplifying business cycles. His discussion draws on a large body of work, including contributions by Taussig (1911), Lavington (1922), Pigou (1929), and Keynes (1936). This emphasis on behavioral biases and expectation shocks, which has vanished from business cycle research, is making a comeback in microeconomics and in finance but remains very controversial in macroeconomics.¹ In this paper we set this controversy aside and ask the question: can behavioral biases or autonomous changes in expectations be useful building blocks for a theory of the business cycle?

As far as psychological biases, we focus our attention on the two biases emphasized in the behavioral finance literature: optimism and overconfidence.² The expectations of optimistic agents are biased toward good outcomes, while overconfident agents overestimate the precision of the signals that they receive.

Changes in expectation about the future, generated by behavioral biases or by exogenous shocks, cannot be an important source of business cycles in the standard neoclassical growth model. These changes engender a negative correlation between consumption and hours worked (see Beaudry and Portier (2004), Danthine, Donaldson and Johnsen (1998), and Christiano, Motto, and Rostagno (2005)). Our analysis is based on the model that we propose in Jaimovich and Rebelo (2006), which generates comovement between consumption and hours worked in response to expectation changes. This model introduces three elements into the neoclas-

¹Multiple equilibrium models emphasize shocks to expectations, but these “sunspot” shocks must be i.i.d. In addition, expectations are self-fulfilling, so these models do not generate scenarios in which expectations do not materialize.

²Brunnermeier and Parker (2005) discuss the literature on these biases and provide a model of the optimal level of optimism.

sical growth model: variable capital utilization, adjustment costs to investment, and preferences that imply a weak short-run wealth effect on the labor supply. The fundamental shock in our model is investment-specific technical change.

We find that overconfidence is a potentially useful amplification mechanism. This psychological bias generates overinvestment in booms and underinvestment in recessions. As a result, overall volatility is higher when agents are overconfident than when they are rational. At the same time, overconfidence preserves the model's properties in terms of comovement, persistence, and relative volatilities. However, in the context of our model, deviations from rationality must be large in order for overconfidence to generate substantial volatility.

Optimism is not a significant source of volatility in our model. The main effect of optimism is on the steady state level of the different variables. Optimistic agents expect an unrealistically high average rate of investment-specific technical change, and so they consistently overinvest. As a result, the steady-state levels of capital and output, normalized by the level of investment-specific technical change, are higher in the economy with optimistic agents than in the economy with rational agents.

We find that autonomous shocks to expectations can be a useful source of volatility. We calibrate these shocks using the Conference Board's consumer expectations index. This version of the model also preserves the comovement, persistence, and relative volatility properties. However, when we drive our model only with expectation shocks we do not obtain sufficient investment volatility.

We conclude that both overconfidence and expectations shocks can be potentially useful sources of volatility but are not, by themselves, sufficient to produce a successful theory of the business cycle.

2. Our Model

The lifetime utility of the representative agent is given by:

$$U = E_0 \sum_{t=0}^{\infty} \beta^t \frac{(C_t - \psi N_t^\theta X_t)^{1-\sigma} - 1}{1-\sigma}, \quad (2.1)$$

where

$$X_t = C_t^\gamma X_{t-1}^{1-\gamma}.$$

We assume that $0 < \beta < 1$, $\theta > 1$, $\psi > 0$, and $\sigma > 0$. These time-nonseparable preferences include as special cases the two classes of utility functions most common in the business cycle literature. Preferences in the class discussed in King, Plosser, and Rebelo (1988) and Greenwood, Hercowitz, and Huffman (1988) correspond to the case of $\gamma = 0$ and $\gamma = 1$, respectively.

Output is produced using capital services and labor,

$$Y_t = A (u_t K_t)^{1-\alpha} N_t^\alpha. \quad (2.2)$$

Capital services are the product of the stock of capital and the rate of capital utilization (u_t). Output can be used for consumption or investment,

$$Y_t = C_t + I_t/z_t, \quad (2.3)$$

where z_t represents the current state of the technology for producing capital goods. We interpret declines in z_t as resulting from investment-specific technological progress as in Greenwood, Hercowitz, and Krusell (2000). Capital accumulation is given by,

$$K_{t+1} = I_t \left[1 - \phi \left(\frac{I_t}{I_{t-1}} \right) \right] + [1 - \delta(u_t)] K_t. \quad (2.4)$$

The function $\phi(\cdot)$ represents adjustment costs to investment of the form proposed by Christiano, Eichenbaum, and Evans (2004). We assume that $\phi(1) = 0$, $\phi'(1) =$

0, and $\phi''(1) > 0$. These conditions imply that there are no adjustment costs in the steady state and that adjustment costs are incurred when the level of investment changes over time. The function $\delta(u_t)$ represents the rate of capital depreciation. We assume that depreciation is convex in the rate of utilization: $\delta'(u_t) > 0$, $\delta''(u_t) \geq 0$. The initial conditions of the model are $K_0 > 0$, I_{-1} , and $X_{-1} > 0$.

We solve the model by linearizing the equations that characterize the planner's problem around the steady state. We use the same parameters as in Jaimovich and Rebelo (2006).³

3. Model Simulations

We simulate a version of our model driven by stochastic, investment-specific technical progress. We assume that $\log(z_t)$ follows a random walk:

$$\log(z_t) = \log(z_{t-1}) + \varepsilon_t.$$

We use the two-point Markov chain for ε_t estimated in Jaimovich and Rebelo (2006) using data for the U.S. price of investment measured in units of consumption. The support of the estimated Markov chain is:

$$\varepsilon_t \in \{0.0000, 0.0115\}. \tag{3.1}$$

We refer to these two points on the support of the distribution as “high” and “low”. The transition matrix is:

$$\pi = \begin{bmatrix} p & 1-p \\ 1-q & q \end{bmatrix}. \tag{3.2}$$

The first-order serial correlation for ε_t implied by this transition matrix is $p+q-1$. We estimate $p = q = 0.74$, so the first-order serial correlation of ε_t is 0.48.

³We set $\gamma = 0.001$, $\sigma = 1$, $\theta = 1.4$, $\beta = 0.985$, $\alpha = 0.64$, $\phi''(1) = 1.3$, and $\delta''(u) = 0.15$, where u denotes the steady-state level of utilization.

We generate 1000 model simulations with 230 periods each. For each simulation we detrend the logarithm of the relevant time series with the Hodrick-Prescott filter using a smoothing parameter of 1600. We use the same method to detrend U.S. data. Table 1 reports variances, correlations with output, and serial correlations for the main macroeconomic aggregates in both the model and in U.S. data.

Rational Agents The second column of Table 1 displays key second moments for a version of our model populated by rational agents. This version of the model generates business cycle moments that are similar to those of postwar U.S. data reported in column 1. Consumption, investment, and hours worked are procyclical. Investment is more volatile than output, consumptions is less volatile than output, and the volatility of hours is similar to that of output. The model generates 69 percent of the output volatility observed in the data.

Optimistic Agents Next we study the effects of optimism. There are many ways to introduce optimism into the model with potentially different implications. To facilitate comparison with the economy populated by rational agents, we assume that the persistence of ε_t perceived by optimistic agents is the same as the true persistence of ε_t . So, optimistic agents assume that ε_t is generated by the transition matrix (3.2). However, they also assume that the support of the distribution is,

$$\varepsilon_t \in \{0.00, 0.0115 \times 1.20\}.$$

Optimists base their expectations on a distribution with an upper bound that is 20 percent higher than its real value. As a result, they see the world through rose-tinted glasses. Their conditional expectations of future values of ε_t are always higher than those of a rational agent.

The main effect of optimism is on the steady state of the model. Optimists expect higher average rates of technical progress, so in the steady state the value of K_t/z_t is higher than in the rational economy. Optimistic agents consistently overinvest.

In our linearized economy the effect of optimism on volatility is small. Optimistic agents expect a higher mean for ε_t . This higher mean affects the size of percentage deviations from the mean, which are relevant for the model's volatility. As a result, the overall impact of optimism is small. Column 3 of Table 1 shows that output volatility increases from 1.09 in the fully rational case to 1.11. The properties of the model in terms of comovement and relative volatility of the different variables are similar to those of the rational model.

Introducing News about the Future We now consider an economy with rational agents who receive signals that are useful to forecast future fundamentals. At time t agents receive signals about the value of ε_{t+2} . The signal can be high or low. The signal's precision, d_i , is the probability that ε_{t+2} will be high (low) given that the signal is high (low):

$$d_i = \Pr(\varepsilon_{t+2} = i | S = i), \quad i = \text{high, low.}$$

We choose the precision of the signal to be $d_H = d_L = 0.85$. Agents forecast ε_{t+2} by combining the signal S , taking into account its precision, and the current value of ε_t using Bayes' rule. For example:

$$\Pr(\varepsilon_{t+2} = H | S = i, \varepsilon_t) = \frac{\Pr(S = i | \varepsilon_{t+2} = H) \Pr(\varepsilon_{t+2} = H | \varepsilon_t)}{\sum_{j=H,L} \Pr(S = H | \varepsilon_{t+2} = j) \Pr(\varepsilon_{t+2} = j | \varepsilon_t)}. \quad (3.3)$$

Moments for this economy are reported in column 4 of Table 1. The presence of news about the future lowers output volatility relative to the economy without news since it makes ε_t more predictable.

Overconfidence Next we introduce overconfidence in the economy with signals. To study the impact of overconfidence we consider the case in which agents treat the signal discussed above as perfect ($d_H = d_L = 1.0$), even though its true precision is $d_H = d_L = 0.85$.⁴ To compare overconfidence with optimism we chose these two pair of values for d_H and d_L so that they generate the same mean-square-forecast error for ε_t as in the model with optimism.

As in the rational economy, agents forecast ε_{t+2} by combining the signal S and the current value of ε_t using Bayes' rule. Since agents assume that the signal is perfect, Bayes rule, implies that $\Pr(\varepsilon_{t+2} = H|S = H, \varepsilon_t) = 1$ and $\Pr(\varepsilon_{t+2} = L|S = L, \varepsilon_t) = 1$. Overconfidence amplifies the impact of a news shock. When agents receive a high signal they overestimate the expected value of ε_{t+2} and overinvest. When they receive a low signal they underestimate the expected value of ε_{t+2} and underinvest. Overconfidence amplifies agents' forecast errors increasing the volatility of the economy. The fifth column of Table 1 shows that output volatility increases from 1.06 in the fully rational case with signals (column 4) to 1.11 in the overconfidence case.

Expectation Shocks Finally, we study the effect of expectation shocks. To isolate the effect of these shocks we consider an exercise similar to that in Danthine, Donaldson, and Johnsen (1998). In this experiment there are no shocks to fundamentals; ε_t is always zero and so z_t is constant. However, agents form expectations about future values of ε_t according to the Markov chain

$$\pi^* = \begin{bmatrix} p^* & 1 - p^* \\ 1 - q^* & q^* \end{bmatrix}.$$

⁴Söderlind (2005) finds evidence of this type of over-confidence in the Survey of Professional Forecasters (SPF). The subjective variance reported by the SPF forecasters is 40 percent lower than the actual forecast error variance.

When the economy is in state one, agents expect $\varepsilon_{t+1} = 0.0115$ with probability $1 - p^*$ and $\varepsilon_{t+1} = 0.0000$, with probability p^* . When the economy is in state two, agents expect $\varepsilon_{t+1} = 0.0115$ with probability q^* and $\varepsilon_{t+1} = 0.0000$, with probability $1 - q^*$. Expectations about periods beyond $t + 1$ are also formed according to the Markov chain π^* .

To impose some discipline on this exercise we estimated the transition matrix π^* with the Tauchen and Hussey (1991) method, using the Conference Board's consumer expectations index for the period 1967.1 to 2005.9.⁵ We obtained $p^* = q^* = 0.82$.

Column 6 of Table 1 shows second moments for this economy. Changes in expectations can, in our model, be a significant source of volatility. The model generates 64 percent of the volatility of output in the data. At the same time, the model preserves the positive comovement between hours, investment, consumption, and output. However, the results in Table 1 also show that expectation shocks cannot, in our model, be the sole driver of business cycles. The volatility of investment generated by the model driven by expectation shocks is similar to the volatility of output.

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⁵The data is reported at a bimonthly frequency before 1977.6 and at a monthly frequency after this date. We constructed a quarterly index by averaging the information available for each quarter.

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Table 1

	U.S. Data	Rational No Signal	Optimism No Signal (Assume upper support is 20% higher)	Rational Signal (precision 0.85)	Overconfidence Signal (true precision=0.85, belief=1)	Expectations Shocks
Std. Dev. Output	1.57	1.09	1.11	1.06	1.11	0.70
Std. Dev. Hours	1.52	0.77	0.79	0.76	0.79	0.49
Std. Dev. Investment	4.81	3.38	3.37	3.42	3.42	0.80
Std. Dev. Consumption	1.18	0.80	0.85	0.78	0.88	0.74
Correlation Output and Hours	0.88	1.00	1.00	1.00	1.00	0.99
Correlation Output and Investment	0.91	0.97	0.96	0.95	0.89	0.73
Correlation Output and Consumption	0.8	0.94	0.94	0.93	0.93	0.98