

Confidence Risk and Asset Prices

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Aggregate stock price movements in many cases seem decoupled from movements in aggregate consumption and macroeconomic fundamentals. Ravi Bansal and Ivan Shaliastovich (2009a) show that large (above two-sigma) moves in asset prices average once every 18 months and are uncorrelated with concurrent or future moves in macro variables (see Table 1 below). To account for this data feature we present a general equilibrium model in which behaviorally motivated shifts in expectations play an important role in determining asset prices. In particular, fluctuations in investors' confidence about expected growth lead to variation in risk premia and asset-price jumps. This confidence risk channel can account for (i) the lack of connection between large asset-price moves and macro variables, (ii) large declines in asset prices, that is, the left tail of the return distribution, and (iii) observed predictability of equity returns and consumption growth by the price to dividend ratio.

Our economy set-up follows a standard long-run risks specification of Ravi Bansal and Amir Yaron (2004), and features Gaussian consumption growth process with time-varying expected growth and volatility; there are no large moves or jumps in the underlying consumption and dividend dynamics. Expected growth is not directly observable, and investors learn about it using the cross-section of signals. The time-varying cross-sectional variance of the signals determines the quality of the information, and therefore the confidence that investors place in their growth forecast. In the long-run risks framework, the fluctuation in confidence (i.e. confidence risk) determines risk premia and asset prices.

We model investors as being recency-biased in their expectation formation, that is, they overweight recent observations as in Werner De Bondt and Richard Thaler (1990). This is important, as in a standard Kalman-Filter based expectation forma-

tion, periods of low information quality get down-weighted, which diminishes the role of the confidence risk channel. Our behaviorally motivated approach also differs from Lars Hansen and Thomas Sargent (2006), who specify model-selection rules capturing investors' concerns for robustness in their expectation formation.

To give empirical content to the model, we directly measure confidence from the cross-section of forecasts from the Survey of Professional Forecasters. We show that there are frequent large moves in the confidence measure in the data. Moreover, in the data, these large moves are contemporaneously highly correlated with large moves in asset returns, highlighting the importance of confidence risk for asset prices. For our quantitative analysis, we calibrate the model to the observed confidence risk and consumption data. We find that the model can quantitatively account for the negatively skewed and heavy-tailed distribution of returns, even though consumption growth does not contain jumps. Exploiting the fluctuations in confidence risks, we show that the model can capture short and long-horizon predictability of excess returns and lack of consumption predictability by price to dividend ratio. Further, large moves in the confidence measure lead to large declines (negative jumps) in asset prices, though there are no large moves in consumption. Hence, our model provides a mechanism to account for the lack of connection between large asset-price moves and consumption fundamentals.

I. Model Setup

A. Real Economy

We consider a discrete-time real endowment economy. The agent's preferences over the consumption stream C_t are described by the recursive utility function of Larry G. Epstein and Stanley Zin (1989):

$$(1) \quad U_t = \left((1 - \delta) C_t^{\frac{1-\gamma}{\theta}} + \delta (E_t[U_{t+1}^{1-\gamma}])^{\frac{\theta}{\theta-1}} \right)^{\frac{\theta-1}{\theta}}$$

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where γ measures risk aversion of the agent, ψ is the intertemporal elasticity of substitution and δ is the subjective discount factor. For notational ease, we define $\theta = (1 - \gamma)/(1 - \frac{1}{\psi})$.

Following Bansal and Yaron (2004), log consumption growth Δc_{t+1} incorporates a time-varying mean x_t and stochastic volatility σ_t^2 :

$$\begin{aligned} (2) \quad \Delta c_{t+1} &= \mu + x_t + \sigma_t \eta_{t+1}, \\ (3) \quad x_{t+1} &= \rho x_t + \varphi_c \sigma_t \epsilon_{t+1}, \\ (4) \quad \sigma_{t+1}^2 &= \sigma^2 + \nu_c (\sigma_t^2 - \sigma^2) + \varphi_w \sigma_t w_{c,t+1}. \end{aligned}$$

All shocks are i.i.d. Normal, and we do not entertain jumps in the consumption process.

The agents know the structure and parameters of the model and observe consumption volatility σ_t^2 , however, the true expected growth factor x_t is not directly observable. They estimate it using the cross-section of signals $x_{i,t}$,

$$(5) \quad x_{i,t} = x_t + \xi_{i,t},$$

where each period the signal noise $\xi_{i,t}$, for $i = 1 \dots n$, is drawn from a Normal distribution with zero mean and a time-varying variance, which reflects the fluctuation in the quality of information about future growth. As the signals in the cross-section are ex-ante identical, investors need to rely only on the average signal \bar{x}_t :

$$(6) \quad \bar{x}_t \equiv \frac{1}{n} \sum x_{i,t} = x_t + \xi_t.$$

The average signal noise $\xi_t = \frac{1}{n} \sum \xi_{i,t}$ has a Normal distribution whose time-varying conditional variance is captured by V_t :

$$(7) \quad V_t = \text{Var}_t(\xi_t).$$

The uncertainty V_t determines the confidence of investors about their estimate of expected growth, and is referred to as confidence measure.

B. Confidence Measure

Confidence measure V_t fluctuates over time, and high V_t corresponds to periods of high confidence risk. Motivated by the empirical evidence and the theoretical model of Laura Veldkamp (2006), we specify a following discrete-time jump-diffusion model for the confidence measure, which features persistence

and jump-like confidence shocks:

$$(8) \quad V_{t+1} = \sigma_v^2 + \nu(V_t - \sigma_v^2) + \sigma_w \sqrt{V_t} w_{t+1} + Q_{t+1}.$$

The shock w_{t+1} is Gaussian, while Q_{t+1} is a Poisson jump,

$$(9) \quad Q_{t+1} = \sum_{i=1}^{N_{t+1}} J_{i,t+1} - \mu_j \lambda_t,$$

where N_{t+1} is a Poisson process with a stochastic intensity $\lambda_t \equiv E_t N_{t+1}$ and jump size $J_{i,t+1}$. In application, we assume that the jump size is exponential with a mean parameter μ_j , and the jump intensity λ_t is linear in V_t ,

$$(10) \quad \lambda_t = \lambda_0 + \lambda_1 V_t.$$

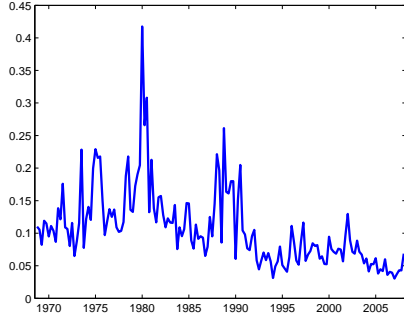
Positive value of the loading λ_1 implies that confidence jumps occur more frequently at times of high confidence risk.

In the model, confidence measure is assumed to be observable to investors. In the data, it can be estimated from the cross-sectional variation in the individual signals. Indeed, from (5) we obtain

$$(11) \quad V_t = \frac{1}{n} E \left(\frac{1}{n-1} \sum_{i=1}^n (x_{i,t} - \bar{x}_t)^2 \right).$$

C. Recency-Biased Learning

The agents use the history of signals to learn about the unobserved expected growth x_t . With a standard Kalman-Filter based expectation formation (see e.g. Alexander David and Pietro Veronesi (2008)), the weight to the recent information K_t is time-varying and falls as confidence risk rises – that is, as V rises. This suppresses the effects of recent information and confidence risks on asset prices, particularly during periods of high confidence risk. In contrast, empirical evidence in De Bondt and Thaler (1990) highlights recency-biased expectation formation, where more recent information is overweighed by investors. The evidence further suggests that the overweighing of recent news increases when the uncertainty is high. We operationalize the recency-biased expectation formation by setting the weight that investors give to recent news to a constant K . Under the recency bias specification, investors' expectation formation can be ex-

FIGURE 1. CONFIDENCE MEASURE $\sqrt{V_t}$

pressed in the following way:

$$(12) \quad \Delta c_{t+1} = \mu + \hat{x}_t + a_{c,t+1},$$

$$(13) \quad \bar{x}_{t+1} = \rho \hat{x}_t + a_{x,t+1},$$

$$(14) \quad \hat{x}_{t+1} = \rho \hat{x}_t + K a_{x,t+1},$$

where \hat{x}_t is investors' estimate of the true expected growth, and $a_{c,t+1}$ and $a_{x,t+1}$ are the observed consumption and signal innovations, respectively.

The variance of the estimation error between x_t and \hat{x}_t , ω_t^2 , is directly related to the confidence measure:

$$(15) \quad \omega_t^2 = K V_t.$$

The recency bias expectation formation ensures that the variance of the estimation error increases with V_t , as shown above.

II. Model Solution

Given the consumption dynamics based on investors' information (12), we solve for the equilibrium asset prices using a standard approach presented in Bansal and Yaron (2004). The innovation in the log of the equilibrium intertemporal marginal rate of substitution is:

$$(16) \quad \begin{aligned} m_{t+1} - E_t m_{t+1} &= -\lambda_c a_{c,t+1} \\ &\quad - \lambda_x K a_{x,t+1} - \lambda_\sigma \varphi_w \sigma_t w_{c,t+1} \\ &\quad - \lambda_v \left(\sigma_w \sqrt{V_t} w_{t+1} + Q_{t+1} \right), \end{aligned}$$

where the expressions for the market prices of risks are given in Bansal and Shaliastovich (2009a). In equilibrium, investors demand compensation for short-run, long-run, consumption volatility and confidence risks. The novel dimension of our paper is that the confidence risks ($\sigma_w \sqrt{V_t} w_{t+1} + Q_{t+1}$) are priced. Notably, confidence jump shocks Q_{t+1} are the source of the jump risk in the economy, even though there are no jump risks in the underlying consumption. When agents have preference for early resolution of uncertainty, the price of confidence risks λ_v is negative.

To evaluate model implications for equity markets, we specify a dividend process as a levered claim on consumption. The equilibrium log price to dividend ratio is linear in the expected growth, consumption volatility and confidence measure:

$$(17) \quad p d_t = H_0 + H_x \hat{x}_t + H_\sigma \sigma_t^2 + H_v V_t.$$

The return beta to confidence measure is negative ($H_v < 0$). Hence, when V rises sharply, investors lose confidence in their estimate of expected growth, which leads to a sharp reduction in asset prices. That is, positive jumps in V translate into negative jumps in asset prices. The negative return beta for confidence risk along with the negative λ_v ensures that the risk compensation for confidence risk is positive. A very different approach to model price jumps is presented in Ravi Bansal and Ivan Shaliastovich (2009b), who endogenize jumps in asset prices through optimal decisions of investors to learn about expected growth for a cost.

III. Model Output

A. Confidence and Jumps

We directly measure confidence using the cross-section of quarterly real GDP forecasts from the Survey of Professional Forecasters from 1969 to 2007. Figure 1 plots the square root of the confidence measure, $\sqrt{V_t}$, annualized. The confidence measure in the data fluctuates significantly over time, with frequent large positive jumps. The half-life of confidence shocks is about 6 months, which suggests that confidence fluctuations are very different from the persistent variations in expected growth and volatility of the underlying consumption. Our confidence risk measure highly correlates with the investor sentiment measure of Malcolm Baker and Jeffrey Wurgler (2006). This empirical dimension, and more gen-

TABLE 1—LARGE MOVE CORRELATIONS

	0m	6m	12m
<i>Data:</i>			
Consumption	-0.03 (0.02)	-0.03 (0.03)	0.09 (0.12)
Confidence Risk	0.34 (0.17)	-0.04 (0.01)	-0.04 (0.01)
<i>CR Model:</i>			
Consumption	0.03 (0.10)	0.00 (0.08)	-0.01 (0.07)
Confidence Risk	0.39 (0.08)	0.00 (0.09)	0.00 (0.07)

Correlations of large return move indicator with current and future macro-variable jump indicators 6 and 12 months ahead. Confidence Risk (CR) model calibration is as follows. Preferences: $\delta = 0.9992$, $\gamma = 10$, $\psi = 1.5$. Consumption and dividend: $\mu = 0.0017$, $\rho = 0.975$, $\sigma = 0.0064$, $\nu_c = 0.995$, $\varphi_w = 5.19 \times 10^{-4}$, $\varphi_e = 0.038$, $\phi = 2.75$, $\varphi_d = 3$. Confidence: $\sigma_v = 4.33 \times 10^{-4}$, $\nu = 0.91$, $\sigma_w = 0$, $\mu_j = 3.59 \times 10^{-7}$, $\lambda_0 = 0.06$, $\lambda_1 = 8 \times 10^5$.

erally our model provides a well-articulated equilibrium framework to analyze and interpret behaviorally-motivated investor sentiment.

In the estimation of the jump-diffusion model in (8), we find that Poisson jumps capture above 80 percent of the variation in the confidence measure. The jumps occur about once every 5 months, and the probability of jumps strongly and positively depends on the level of the confidence measure. We find that jump parameters are very significant, and a restricted specification with no confidence jumps is strongly rejected in the data.

To evaluate the connection between large moves in returns and confidence measure, we construct two standard deviation or above move indicators in the corresponding series. On a monthly frequency, we observe 54 two standard deviation or above moves in returns over the 80-year time-period, so that the frequency of large return moves is once every 18 months. 70 percent of these moves are negative, which explains the reason for a negative skewness of returns in the data. In the data, there is no persuasive link between the large moves in returns and current or future large moves in real consumption at the considered frequencies. Indeed, Table 1 shows that the correlations between the large move indicators in returns and contemporaneous or future large move indicators in consumption are essentially zero. However, the large moves in the confidence measure are

TABLE 2—RETURN DISTRIBUTION

	Mean	Vol	Skew	Kurt
<i>Market return:</i>				
Data	6.51	18.81	-0.44	9.68
Gaussian model	4.22	10.95	0.00	3.00
CR model	6.73	19.97	-0.85	8.64
<i>Risk-free rate:</i>				
Data	0.57	1.13	-0.80	6.91
Gaussian model	1.71	0.23	0.00	3.00
CR model	1.15	0.37	-1.35	6.82

Return distribution in the data, Gaussian model and Confidence Risk (CR) model.

significantly related to contemporaneous large moves in returns: the contemporaneous correlation of large move indicators in returns and in the confidence measure is 0.34 and is significant. Hence, large moves in the confidence measure contain important information about the asset-price jumps in the data, while significant asset-price moves appear disconnected from the real side of the economy.

B. Asset-Price Implications

We calibrate the model to evaluate its quantitative implications for the equity markets. Our Confidence Risk (CR) model, specified in Section I, includes fluctuating confidence risk, recency-biased learning and time-varying consumption volatility. For comparison, we also consider a Gaussian model, where confidence risk is absent and the time-varying consumption volatility channel is shut-off. In this Gaussian model investors use Kalman Filter to form expectations. Note that another variant of the model where we leave the time-varying consumption volatility channel open yields the results that are quantitatively quite similar to a simpler Gaussian model, and hence are not reported here. Our calibration of the model is specified below Table 1. The calibration of consumption growth is very similar to the long-run risks literature (see e.g. Bansal and Yaron 2004) and targets the key features of the consumption data. The volatility of consumption growth is 2.1 percent both in the model and in the long historical sample, and its autocorrelation is 0.42 in the model and 0.44 in the data. The model-implied dynamics of the confidence measure also matches very well its key properties in the data, in particular, a heavy right tail and the frequency and magnitude of large positive jumps from the jump-diffusion model in (8). Additional details are provided

TABLE 3—RETURN PREDICTABILITY

	1y	3y	5y
<i>Slope:</i>			
Data	-0.08 (0.05)	-0.25 (0.09)	-0.41 (0.11)
Gaussian model	-0.03	-0.10	-0.19
CR model	-0.39	-0.58	-0.68
<i>R²:</i>			
Data	0.03	0.13	0.26
Gaussian model	0.01	0.01	0.02
CR model	0.14	0.16	0.16

Small-sample slope coefficient and R^2 in projections of future excess returns on price-dividend ratio in the data, Gaussian model and the Confidence Risk model.

in Bansal and Shaliastovich (2009a).

Fluctuating confidence plays a key role in accounting for the key features of the return distribution in the data. Large positive moves in the confidence measure endogenously translate into negative jumps in returns, even though the consumption growth is Gaussian. Thus, our model can explain a puzzling evidence in the data for a significant link between large moves in returns and in the confidence measure, and lack of connection between large moves in returns and consumption. As shown in Table 1, the model-implied correlations of jump indicators are 0.39 for confidence and returns, and 0 for returns and consumption, which matches the data.

The model-implied distribution of returns is heavy-tailed and negatively skewed. Table 2 shows that the kurtosis of market returns is 8.6, and its skewness is -0.85; these values match the estimates in the data. The non-Gaussian features of returns are due to the fluctuations and large moves in the confidence measure: when the confidence measure and consumption volatility are constant, returns are Gaussian.

As shown in Table 2, the average return is 6.7 percent, and the mean risk-free rate is about 1 percent. Hence, the model can account for the level of the equity risk premium and the risk-free rate in the data. Confidence shocks contribute about one-third to the total premium. As the confidence measure is driven by jumps, the compensation for confidence risks thus determines the compensation for jump risks in the economy. The confidence risks provides a new channel for the variation in equity risk premium. Exploiting the fluctuations in confidence risks, we find that the model can capture predictability of excess returns by the price to dividend ratios, as shown in Table 3,

and a lack of predictability of consumption growth (see Bansal and Shaliastovich 2009a).

IV. Conclusion

We present a general equilibrium model in which behaviorally motivated shifts in expectations play an important role in determining asset prices. The model captures the intuition that time-varying investors' confidence about expected growth drives asset prices. This channel can explain the disconnect of significant moves in asset prices and the real economy, asset-price jumps and the left tail of returns, predictability of excess returns, and other key asset market facts. In a recent paper Ivan Shaliastovich (2009) shows that the confidence risk channel is also important to explain key dimensions of option prices in the data.

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