Confidence Risk and Asset Prices

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Asset price movements in many cases seem de-linked from aggregate economic fundamentals. For example, Ravi Bansal and Ivan Shaliastovich (2008*a*) show that frequent large moves in asset prices, i.e. jumps, on average are not correlated with movements in macro-variables (see Table 1 below). Motivated by this, we present a general equilibrium model in which variation in investor confidence about expected growth determines risk premia and hence asset prices. This confidence risk channel can account for (i) the lack of connection between large asset-price moves and macro-variables such as consumption, (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. In essence, we present a model in which behaviorally motivated shifts in expectations play an important role for the asset prices.

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 fluctuations in confidence risk determines risk premia and asset prices.

We model investors as being recency-biased in their expectation formation, that is, they overweigh recent observations as in Werner De Bondt and Richard Thaler (1990). This is important, as in the standard Kalman-Filter based expectation formation, 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, 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-dividend ratios. Further, large moves in the confidence measure lead to large declines (negative jumps) in asset prices, though they are no large moves in consumption. Hence, our confidence risk 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 con-

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sumption stream C_t are described by the recursive utility function of Larry G. Epstein and Stanley Zin (1989):

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

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:

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

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 $x_{i,t}$,

$$x_{i,t} = x_t + \xi_{i,t}, \tag{1}$$

where each period the signal noise ξ_{it}, for $i = 1 \ldots n$, is drawn from a Normal distribution with zero mean and a time-varying variance, which reflects the fluctuations 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 $\bar{x}_t$:

$$\bar{x}_t \equiv \frac{1}{n} \sum x_{i,t} = x_t + \xi_t. \tag{2}$$

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

$$V_t = Var_t(\xi_t). \tag{3}$$

The uncertainty V_t determines the confidence of investors about their estimate of expected growth and is referred to as confidence measure. V_t fluctuates over time, and high V_t corresponds to periods of high confidence risk.

B. 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. This suppresses the effects of recent information and confidence risks on asset prices, particularly during periods of high confidence risk (high V_t). 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, investor's expectation formation can be expressed in the following way:

$$\Delta c_{t+1} = \mu + \hat{x}_t + a_{c,t+1}, \tag{4}$$

$$\bar{x}_{t+1} = \rho \hat{x}_t + a_{x,t+1}, \tag{5}$$

$$\hat{x}_{t+1} = \rho \hat{x}_t + K a_{x,t+1}, \tag{6}$$

where $a_{c,t+1}$ and $a_{x,t+1}$ are the observed innovations into the consumption growth and the average signal, respectively. The variance of the filtering error ω_t^2 is directly related to the confidence measure:

$$\omega_t^2 = K V_t. \tag{7}$$

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

C. Confidence Measure

The confidence measure in the model captures the uncertainty that investors face about expected growth. 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

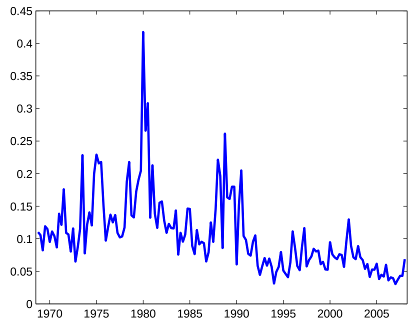

FIGURE 1. CONFIDENCE MEASURE $\sqrt{V_t}$

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 Possion jump,

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

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,

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

Positive value of the loading λ_1 implies that confidence jumps are more likely when the level of confidence measure V_t is high.

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 (1) we obtain

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

II. Model Solution

We solve the economy using a standard approach (see Bansal and Yaron 2004). The innovation in the log of the equilibrium intertemporal marginal rate of substitution is:

(12)
$$m_{t+1} - E_t m_{t+1} = -\gamma a_{c,t+1} - \lambda_x K a_{x,t+1}$$
$$- \lambda_v\left(\sigma_w\sqrt{V_t}w_{t+1} + Q_{t+1}\right) - \lambda_\sigma\varphi_w\sigma_t w_{c,t+1},$$

where the expressions for the market prices of risks are given in Bansal and Shaliastovich (2008*a*). 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.

The equilibrium price-dividend ratio is linear in the expected growth, consumption volatility and confidence measure:

$$(13)\qquad pd_t = H_0 + H_x\hat{x}_t + H_v V_t + H_\sigma\sigma_t^2.$$

The return beta to confidence measure is negative ($H_v < 0$) — 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 (2008*b*), 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

Table 1— Large Move Correlations

	0m	6m	12m
	Data:		
Consumption	-0.03	-0.03	0.09
	(0.02)	(0.03)	(0.12)
Confidence	0.34	-0.04	-0.04
Measure	(0.17)	(0.01)	(0.01)
	CR Model:		
Consumption	0.03	0.00	-0.01
	(0.10)	(0.08)	(0.07)
Confidence	0.39	0.00	0.00
Measure	(0.08)	(0.09)	(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: $\mu = 0.0017$, $\rho = 0.975$, $\sigma = 0.0064$, $\nu_c = 0.995$, $\varphi_w = 5.19 \times 10^{-4}$, $\varphi_e = 0.038$, $\phi = 2.75$, $\varphi_d = 3$. Confidence: $\sigma_v = 4.33 \times 10^{-4}$, $\nu = 0.91$, $\sigma_w = 0$, $\mu_j = 3.59 \times 10^{-7}$, $\lambda_0 = 0.18/3$, $\lambda_1 = 8 \times 10^5$

Table 2—Return Distribution

	Mean	Vol	Skew	Kurt
	Market return:			
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
	Risk-free rate:			
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, Confidence Risk (CR) Model and Gaussian Model.

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. In the estimation of the jump-diffusion model in (8), we find that Poisson jumps capture above 80% 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.

To evaluate the connection between large moves in returns and confidence measure, we construct a 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% of these moves are negative, which explains the reason for a negative skewness of returns in the data (see Table 2). 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 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 and consumption volatility are constant, and investors essentially use Kalman Filter to form expectations. The calibration of consumption and confidence dynamics, specified below Table 1, is designed to match their data counterparts; see Bansal and Shaliastovich (2008*a*) for additional details.

Fluctuating confidence plays a key role in accounting for the key features of the return dis-

TABLE 3—PREDICTABILITY EVIDENCE

	1y	3y	5y
Excess Returns:			
Data	0.03	0.13	0.26
Gaussian Model	0.01	0.01	0.02
CR Model	0.14	0.16	0.16
Consumption:			
Data	0.08	0.03	0.001
Gaussian Model	0.43	0.30	0.23
CR Model	0.14	0.09	0.07

Small-sample R^2 in projections of future excess returns and consumption growth on price-dividend ratio in the data, Confidence Risk (CR) Model and Gaussian Model.

tribution in the data. Large positive moves in the confidence measure endogenously translate into negative jumps in returns, even though consumption growth is Gaussian. Thus, our model can explain a puzzling evidence in the data for 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 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 and consumption by the price-dividend ratios, as shown in Table 3.

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 investor 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 (2008) shows that the confidence risk channel is also important to explain key dimensions of option prices in the data.

REFERENCES

Bansal, Ravi, and Amir Yaron. 2004. "Risks for the Long Run: A Potential Resolution of Asset Pricing Puzzles." *Journal of Finance*, 59(4): 1481–1509.

Bansal, Ravi, and Ivan Shaliastovich. 2008*a*. "Confidence Risks and Asset Prices." Working paper.

Bansal, Ravi, and Ivan Shaliastovich. 2008*b*. "Learning and Asset-Price Jumps." Working paper.

David, Alexander, and Pietro Veronesi. 2008. "Inflation and Earnings Uncertainty and Volatility Forecasts: A Structural Form Approach." Working paper.

De Bondt, Werner, and Richard Thaler. 1990. "Do security analysts overreact?" *Stock Market Volatility*, 80(2): 52–57.

Epstein, Larry G., and Stanley Zin. 1989. "Substitution, risk aversion and the temporal behavior of consumption and asset returns: A theoretical framework." *Econometrica*, 57: 937–969.

Hansen, Lars, and Thomas Sargent. 2006. "Fragile Beliefs and the Price of Model Uncertainty." Working paper.

Shaliastovich, Ivan. 2008. "Learning, Confidence and Option Prices." Working paper.

Veldkamp, Laura. 2006. "Slow Boom, Sudden Crash." *Journal of Economic Theory*, 124(2): 230–257.