Journal of Economic Dynamics & Control 51 (2015) 459–479

Contents lists available at ScienceDirect

Journal of Economic Dynamics & Control

journal homepage: www.elsevier.com/locate/jedc

News, disaster risk, and time-varying uncertainty ☆

Wenyi Shen [1]

Department of Economics and Legal Studies, Oklahoma State University, Stillwater, OK 74078, USA

A R T I C L E I N F O

Article history:
Received 12 July 2014
Received in revised form
10 November 2014
Accepted 19 November 2014
Available online 29 November 2014

Keywords:
Uncertainty
Information flows
Disaster risk
Regime switch

JEL classification:
E32
E22
C60

A B S T R A C T

Standard real business cycle models are often unable to replicate three empirical facts: positive output in response to good news, stochastic volatility of macro variables, and asymmetric business cycles. This paper proposes a unified basis for understanding these facts in a tractable dynamic stochastic general equilibrium (DSGE) model, in which the key is the interaction of information flows and disaster risk. Information flows fluctuate between two regimes with different precision levels for signals regarding future economic fundamentals. A shift in forecast precision changes the probability of entering an economic disaster. High disaster risk leads to low expected capital returns and a decline in hours, investment, and output. Changing information structures results in different volatility and skewness over the business cycle. Simple theory makes the two expectation effects through information flows and disaster risk transparent. Quantitatively, the model suggests that the interaction of the two expectation effects plays a significant role in accounting for the higher-order moments of the business cycle.

1. Introduction

In recent years there has been a surge of interest in the idea that economic fluctuations are largely driven by anticipated shocks, referred to as news-driven business cycles (Beaudry and Portier, 2004, 2006; Fujiwara et al., 2011; Schmitt-Grohe and Uribe, 2012). In these models the precision of signals about future economic fundamentals remains unchanged. Yet, the theory does not square with some common observations of the business cycle, particularly the Great Recession during which the U.S. economy experienced a significant rise in measured uncertainty (Bloom, 2009).

To address the gap, this paper investigates the interaction among uncertainty, information flows, and business cycle fluctuations. I develop a dynamic stochastic general equilibrium (DSGE) model with time-varying uncertainty, in which uncertainty arises from fluctuations in the precision of signals regarding future fundamentals. To approximate the precision of signals, Fig. 1 plots the absolute value of the median analyst forecast error from the Survey of Professional Forecasters along with the detrended real GDP.[2] The median forecast error varies over the business cycle – it is high in recessions and low in expansions. In the Great Recession, the forecast error rose to almost 6%. Furthermore, regression with detrended GDP

☆ I am grateful to Eric Leeper and Todd Walker for their constant encouragement and thoughtful advice. I thank Shu-Chun S. Yang for many helpful discussions. I also would like to thank Huixin Bi, Martin Boileau, Grey Gordon, Bulent Guler, Juan Carlos Hatchondo, Amanda Michaud, Joon Park, Alexander Richter, Nathaniel Throckmorton, an anonymous referee, and the editor for useful comments and suggestions. All errors are mine.

E-mail address: wenyi.shen@okstate.edu

[1] Tel.: +1 4057448763.

[2] The Survey of Professional Forecasters contains median and mean forecasts for 32 economic variables. The median forecast error is constructed by the log absolute deviation of the four-quarter-ahead median forecast of nominal GDP from the real-time data that is measured two quarters after the end of the quarter. Real GDP is detrended using the Hodrick–Prescott filter.

http://dx.doi.org/10.1016/j.jedc.2014.11.009
0165-1889/

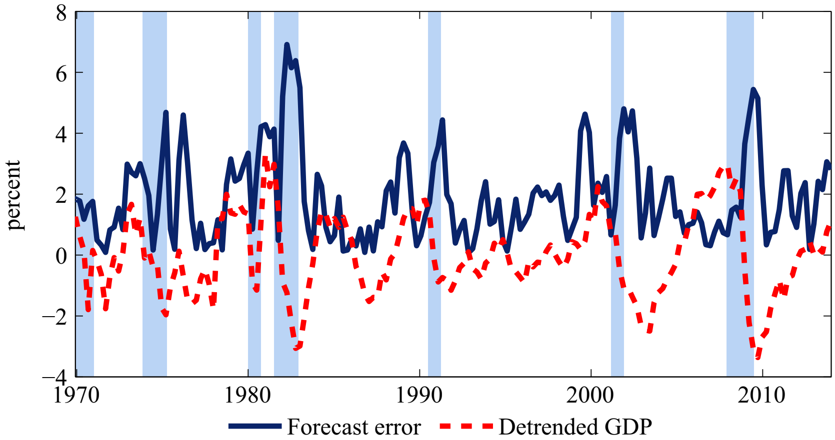

Fig. 1. 1-year forecast errors and detrended GDP.

as the independent variable and the forecast error as the dependent variable finds that the correlation between the two is negative and significant, implying counter-cyclical forecast errors. The countercyclicality of forecast errors is a robust result across different forecast surveys. Van Nieuwerburgh and Veldkamp (2006) show that the forecast precision is higher in expansions than in recessions based on the Survey of Professional Forecasters, and Jaimovich and Rebelo (2009) produce similar results using the Livingston survey of output forecasts. Motivated by these observations, this paper models time-varying uncertainty as a regime switch in information flows between "high precision" and "low precision" regimes. In "high precision" regimes, more anticipated shocks relative to unanticipated ones lower forecast errors and increase forecast precision. In "low precision" regimes, unanticipated shocks dominate the information flow, therefore reducing forecast precision. Unlike recent literature that assumes time-varying uncertainty as shocks to the variance of the exogenous innovations (Bloom, 2009; Bloom et al., 2012; Fernandez-Villaverde et al., 2012), this paper connects uncertainty with agents' information sets, which makes the source of uncertainty explicit.

By changing forecast precision, this paper generates three business cycle facts that standard real business cycle models are often unable to replicate. The first is positive co-movement between aggregate output and "news shocks" – anticipated shocks consisting of information that changes agents' expectations for future fundamentals but does not affect current fundamentals.[3] The second fact regards stochastic volatility: The volatility of investment, hours, and several other macroeconomic variables varies over the business cycle. Third, the model shows that the distribution of key macroeconomic variables is negatively skewed relative to the mean or trend, known as asymmetric business cycles.[4]

To understand these empirical observations, simple theory highlights two expectation effects–information flow and disaster risk–in an analytical example. The information flow channel changes agents' expectations about future productivity, which affects current hours, consumption, and investment decisions (Beaudry and Portier, 2004; Jaimovich and Rebelo, 2009). As people are more responsive to information when the precision of signals is sufficiently high, this expectation effect is larger in high precision regimes than in low precision regimes. Disaster risk refers to a small probability of disastrous events, such as wars or depressions. Following Gourio (2012), this paper defines an economic disaster as a combination of large negative technology shocks and capital quality shocks. In economic disasters, capital is not used effectively and the return on capital is low. Under rational expectations, only a small probability of those rare events can change the dynamics substantially. Even without the realization of negative shocks that trigger the disaster, the large weight on unanticipated shocks in low precision regimes makes the distribution of technology more dispersed relative to high precision regimes, increasing the probability of left-tail events (economic disasters). As capital is more risky, firms are cautious when investing, which makes investment decline sharply. In high precision regimes, fewer unanticipated shocks lowers disaster risk on average and the expectation effect from disaster risk becomes small relative to low precision regimes.[5]

Through the interaction of these two expectation effects, quantitative analysis generates business cycle moments that match the data. In a standard neoclassical setting, the wealth effect of good news about future productivity causes households to desire more consumption and leisure, leading to a decrease in hours, investment, and output. In other words,

[3] There are multiple ways to model "news shocks." For example, Blanchard et al. (2009) model permanent shocks to productivity as "news" and transitory shocks to productivity as "noise." Jaimovich and Rebelo (2009) and Schmitt-Grohe and Uribe (2012) model anticipated shocks as news shocks. This paper takes the second approach.

[4] The literature on business cycle asymmetries measures and models three different types of asymmetry: level asymmetries (deepness), growth rate asymmetries (steepness), and delays. Van Nieuwerburgh and Veldkamp (2006) study growth asymmetry and this paper examines level asymmetry.

[5] In special cases, a sequence of extreme values of negative anticipated shocks may shift the distribution of technology to the left and increase disaster risk in high precision regimes, as shown in Section 5.2. As the probability of such events is very small, on average, disaster risk is lower in high precision regimes compared to low precision regimes.