Available online at www.sciencedirect.com
ScienceDirect
Economics Letters 99 (2008) 504–507
economics letters
www.elsevier.com/locate/econbase

A note on pitfalls of credit crunch regressions ☆

Ryo Kato *

Policy Development and Review Department, International Monetary Fund, 700 19th street, N.W. Washington DC 20431, United States

Received 22 September 2006; received in revised form 14 September 2007; accepted 26 September 2007
Available online 9 October 2007

Abstract

This note introduces an example where a typical credit crunch regression fails to detect significant effects of borrowing constraints embedded in a dynamic general equilibrium model. The failed estimation result remains robust even if the regression is based on a large sample.

Keywords: Credit crunch; Financial accelerator; Lost decade

JEL classification: E32; C2

1. Introduction

There is a large body of empirical studies on credit/capital crunch in the literature. Various econometric approaches have been proposed to test possible effects of borrowing constraints on output. While I do not investigate the massive literature entirely here, my focus in this note is a typical "credit crunch regression" á la Hayashi and Prescott (2002), which was originally introduced in Bernanke and Lown (1991). The credit crunch regression that I dub here is typically of the form

$$\Delta y_t = \beta_0 + \beta_1 \times \Delta b_t + \varepsilon_t, \tag{1}$$

where Δy_t and Δb_t denote growth rate of output and loans from banks. ε_t is an *i.i.d.* error term. The idea of the regression is simple. Whichever the shift matters, either loan demand or loan supply, the output should be affected, most likely truncated, if loan supply/demand is cut for any reason. A capital crunch is a view that such comovement of output and loan is supply-side driven, reflecting, for example, changes in bank balance-sheets that prompt shifts in loan supply curve. On the other hand, a credit crunch may include broader phenomena, where loan demand is reduced due to borrowers' balance-sheet problems. In either case, the credit crunch regression should detect statistically significant effect of Δb_t with a positive estimate of β_1, if there is any agency problem in the economy creating borrowing constraints, regardless of whether supply or demand side phenomena are driving forces.

Although the regression seems an adequate idea to measure the impact of agency problem, there is a pitfall in the approach. The main purpose of the note is to provide a counter-example where a typical credit crunch regression cannot properly detect significant effect of borrowing constraints. The results presented in the note may pose a question to some of the conclusions of such empirical studies, particularly for those that rejected a credit crunch hypothesis.

2. Main results

Several well-known dynamic general equilibrium (DGE) models, such as Bernanke and Gertler (1989) and Kiyotaki and Moore (1997), have been developed to study how agency problems play a critical role in creating business cycle dynamics. As a typical and indispensable feature in those model, there is a certain kind of borrowing constraints arising from agency problem. For example, in a DGE model presented by Kiyotaki and Moore (1997, denoted as KM hereafter), the borrowing constraint takes the form,

$$Rb_t \leq E_t q_{t+1} k_t, \tag{2}$$

where R, b, k and q denote gross interest rate, debt (which is equal to loan demand/supply), capital stock ("trees"), and price

☆ I thank Akihisa Shibata, Ketil Hviding, Keiichiro Kobayashi, Toshitaka Sekine, Wako Watanabe, and the anonymous referee for her helpful comments. All remaining errors are my own. The views expressed in this paper are those of the author and not of the International Monetary Fund.
* Tel.: +1 202 623 4997; fax: +1 202 589 4997.
E-mail address: rkato@imf.org.

0165-1765/$ - see front matter © 2007 Elsevier B.V. All rights reserved.
doi:10.1016/j.econlet.2007.09.042

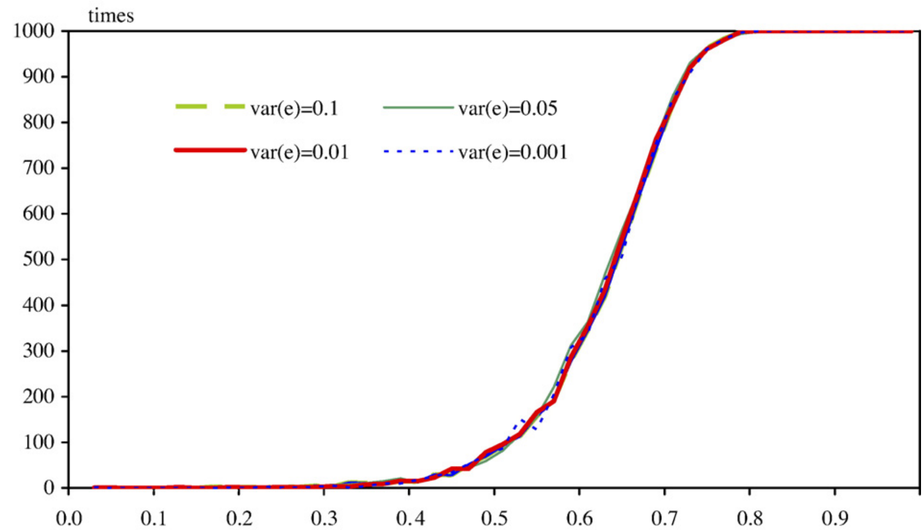

Fig. 1. Simulation results.

of capital. By several assumption specified in the paper, the borrowing constraint is always binding in the model.

Now taking KM's "full model" as an example, I can run Monte-Carlo simulations with stochastic technology shocks.[1] In the model, output is produced via a simple linear technology as follows.

$$y_t = (z + c)k_t, \tag{3}$$

where c and z denote the share of non-tradables and tradables, respectively. I assume that z is stochastic and time-variant, denoted as z_t. Due to the linear technology, growth of output (=Δy_t) can be written as,

$$\Delta y_t = \frac{1}{z^* + c}\Delta z_t + \Delta k_t, \tag{4}$$

where z^* is a steady state level of z_t, which is normalized at one, as handled in KM. The Monte-Carlo simulation generates series of artificially created data for each output and loan.[2] I run the credit crunch regression as shown in Eq. (1) using the data obtained in the simulation. In stochastic simulations, I assume AR(1) process for z_t, such that $z_t = \rho z_{t-1} + e_t$, where $\rho < 1$ and e_t is an *i.i.d*$\sim N(0, \sigma^2)$. For ρ, the parameter which does not appear in the original KM's work,[3] I tried various values ranging from 0.1 to 0.9 (Fig. 1). Other parameters were calibrated following the original KM model.[4] For each value of ρ, I ran regressions 1000 times for each value of ρ. Each simulation period was 240 interpreted as 60 years as the model was calibrated on quarterly data. Table 1 summarizes the results.

Each number in the Table 1 indicates times where β_1 is estimated significantly positive. The results are striking. The table indicates that the β_1 is quite often estimated insignificant under the broad range of ρ.[5] Particularly, for cases with smaller ρ, in other words, technology shocks are short-lived, β_I tends to be estimated negative rather than positive, which is contrary to the prediction by the credit crunch regression. Why do I obtain the results?

The major reason yielding the non-positive or insignificant estimates of β_I is neither small sample bias nor endogeneity bias. The clue to the puzzle can be found in Fig. 2 which displays the impulse responses of KM model to a technology shock (e_t=0.1). The left-side two panels show impulse responses to a positive technology shock which is highly persistent (ρ=0.9). In this case, both output and loan (denoted Y_t and B_t in the figure) move together roughly in the same direction all through the period. In contrast, the upper right-side panel that shows output and loan move in opposite directions for a while after the impact, which is the ultimate source of negative or insignificant estimates of β_1. Further investigation into the mechanism yielding the deviating impulse responses is provided as follows.

Suppose a positive technology shock is realized. First, consider the case that the current higher productivity is persistent and expected to be long-lived. Recall that capital stock is a function of a jump variable q_t, price of capital as well as state variables, k_t and b_t. Because q_t is, roughly speaking, a discounted present value of marginal products of capital held by lenders (*i.e.*, "gatherers" who are not subject to borrowing constraints), a rise in q_t tends to be larger when higher productivity is expected long-lasting over the future. When the price of capital is high, the borrowing constraint becomes

[1] "Stochastic" means that unanticipated shocks are consecutively hitting the economy. This type of uncertainty does not affect the design of the financial contract between borrowers and lenders and thus the structure of the dynamic model remains unchanged. See Calstron and Fuerst (1997) for this issue in more details.

[2] More details on the model and simulations are available from the author upon requests.

[3] In Kiyotaki and Moore (1997), they analyze transitory technology shock, assuming r = 0 implicitly.

[4] Fraction of farmers in the population, π is set at 0.1 as assumed in KM. While π does not appear in Eq. (4), a higher π alters the simulation results significantly creating a larger financial accelerator effects. As I will discuss later, larger amplification tends to allow the credit crunch regression to detect borrowing constraints more easily.

[5] More complete results are shown in Fig. 1.