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U.S. credit-market sentiment and global business cycles

Ding Du *,[1]

The W. A. Franke College of Business, PO Box 15066 Northern Arizona University, Flagstaff, AZ 86011, United States

HIGHLIGHTS

- We study the international transmission of US credit-supply shocks.
- We use the methodology proposed by López-Salido et al. (2017).
- We find that US credit-supply shocks influence global business cycles.
- Economies more/less integrated with the U.S. are more/less impacted.

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ABSTRACT

There is a growing literature on the international transmission of US credit-supply shocks. In this paper, we identify changes in the US credit supply with the methodology proposed by López-Salido et al. (2017). Empirically, we find robust evidence suggesting that US credit-supply shocks influence real activities in economies that are more economically or geographically integrated with the US.

1. Introduction

The 2007–2009 global financial crisis that originated in the US credit market and precipitated recessions in almost all developed economies has motivated a growing literature on the international transmission of US credit-supply shocks. Previous studies use Global VAR (GVAR) (Eickmeier and Ng, 2015) and the factor-augmented VAR (FAVAR) (Helbling et al., 2011). As Eickmeier and Ng (2015) point out, GVAR has a number of econometrics advantages. However, even with GVAR, it is difficult to identify structural shocks, because of the "multiple models problem" associated with sign restrictions.

In this paper, we employ the methodology proposed by López-Salido et al. (2017) (LSSZ). LSSZ use the predicted reversal in US credit spreads to capture the change in the US credit supply associated with an unwinding of past investor sentiment. Although the LSSZ methodology does not constitute a formal identification strategy, the evidence from the US corporate financing mix suggests that this methodology does help identify certain changes in the US credit supply. With the LSSZ methodology, we find robust evidence that US credit-supply shocks forecast real activities in economies that are more economically or geographically integrated with the US.

2. Empirical methodology

LSSZ propose a two-step specification:

$$\Delta s_t = \theta_0 + \theta_1 \log(HYS_{t-2}) + \theta_2 s_{t-2} + e_t \tag{1}$$

$$\Delta y_t = \beta_0 + \beta_1 \Delta\hat{s}_t + \beta_2 \Delta y_{t-1} + \varepsilon_t \tag{2}$$

where Δs_t is the change in the US credit spread, HYS_{t-2} is the US high-yield bond issuance in year $t-2$ (expressed as a percentage of total bond issuance in the nonfinancial corporate sector), s_{t-2} is the US credit spread at the end of year $t-2$, Δy_t is the aggregate economic activity measure over year t, $\Delta\hat{s}_t$ is the predicted change in the credit spread from Eq. (1) that captures the change in the

* Fax: +928 523-7331.
E-mail address: ding.du@nau.edu.

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Table 1
G7 economies.

Panel A: Benchmark regressions							
	US	Canada	France	Germany	Italy	Japan	UK
$\Delta\hat{s}_t$	-2.869^{***}	-2.229^{**}	-1.395^{*}	-1.687^{*}	-1.770	-2.036	-2.197^{***}
	(0.84)	(1.07)	(0.90)	(1.19)	(1.45)	(1.66)	(0.85)
Δy_{t-1}	0.459^{***}	0.433^{***}	0.623^{***}	0.142	0.521^{***}	0.578^{***}	0.470^{***}
	(0.13)	(0.14)	(0.13)	(0.12)	(0.19)	(0.12)	(0.14)
R^2	0.208	0.182	0.355	0.054	0.277	0.289	0.201

Panel B: Additional controls							
	US	Canada	France	Germany	Italy	Japan	UK
$\Delta\hat{s}_t$	-2.722^{***}	-2.185^{**}	-1.045^{*}	-1.438^{*}	-1.459^{*}	-0.948	-1.800^{***}
	(0.77)	(1.00)	(0.72)	(0.97)	(1.02)	(1.11)	(0.65)
Δy_{t-1}	0.330^{**}	0.372^{***}	0.608^{***}	0.080	0.505^{***}	0.550^{***}	0.389^{***}
	(0.14)	(0.13)	(0.12)	(0.12)	(0.18)	(0.12)	(0.14)
R^2	0.280	0.225	0.352	0.061	0.280	0.276	0.213

Panel C: Fixed-effects panel regression			
	GDP per capita	Investment	Unemployment
$\Delta\hat{s}_t$	-1.589^{**}	-3.560^{**}	7.419
	(0.63)	(1.22)	(6.86)
Δy_{t-1}	0.469^{***}	0.450^{***}	0.288
	(0.10)	(0.10)	(0.17)
Observations	368	348	225
R^2 (within)	0.222	0.204	0.083

Robust standard errors in parentheses.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

US credit supply associated with an unwinding of past investor sentiment, and Δy_{t-1} the economic activity measure in year $t-1$. Following LSSZ, to account for the error-in-the-variable bias, the benchmark system of equations is estimated jointly by nonlinear least squares (NLLS). Heteroscedasticity- and autocorrelation-consistent asymptotic standard errors are computed according to Newey and West (1987) with the automatic lag selection method of Newey and West (1994).

We further discuss our methodology and data in Appendix A. Empirically, we first examine the G7 economies, then expand our analysis to all 186 economies in World Development Indicators. To save space, we do not report the first-step regression results, which are consistent with LSSZ and are available upon request. The significance of $\Delta\hat{s}_t$ is based on the one-sided test, because we expect that increases in the US credit spread (or decreases in the US credit supply) have negative impact on global economic activities.

3. Empirical results

3.1. G7 economies

In Panel A of Table 1, we forecast the GDP per capita growth for G7 countries individually with the benchmark specification over the sample period from 1960 to 2015. As can be seen, the predicted change in the US credit spread has significantly negative impact on the GDP per capita growth for not only the US but also Canada, France, Germany, and UK. The impact of $\Delta\hat{s}_t$ on Italy is economically large but statistically insignificant.

In Panel B, we add an additional sentiment indicator (identified by LSSZ) in the first-step regression, namely the US term spread at the end of year $t-2$. With this additional indicator in the first-step regression, the second-step results remain qualitatively unchanged in that the predicted change in the US credit spread negatively affects the GDP per capita growth for not only the US but also Canada, France, Germany, Italy, and UK.

To increase statistical power, inspired by Schularick and Taylor (2012), we estimate the second-step regression jointly for all seven countries with the fixed-effects panel regression (that accounts for time-invariant heterogeneity across countries). We cluster standard errors by both country and year to allow not only serial correlation within country but also spatial correlation across countries (calculating standard errors according to Driscoll and Kraay (1998) produces similar results). The results are presented in Column "GDP per capita" of Panel C, and are qualitatively similar as those in Panels A and B. We also explore other aggregate economic measures within our panel regression framework, namely investment growth and changes in unemployment, and report the results in the last two columns of Panel C. In general, the results are consistent. The results for unemployment growth are weaker. This may be due to that the definitions of unemployment differ across countries.

3.2. All countries

If the predicted change in the US credit spread causally affects other economies, we expect that economies more/less integrated with the US are more/less affected. In Panel A of Table 2, we report the results for three groups of economies based on the World Bank income classification.[2] In each column, the dependent variable in the second-step regression is the log-difference in the average GDP per capita for the group from year $t-1$ to t. Because high income countries are more integrated (e.g., Bekaert et al., 2011), we expect that high-income economies are more affected by changes in the US credit spread. The results in Panel A are in line with this expectation. For instance, while the predicted change in the US credit spread enters with a significantly negative coefficient in the high-income-group regression, it is not significant in the low-income-group regression.

[2] For the current 2017 fiscal year, low-income economies are defined as those with a GNI per capita, calculated using the World Bank Atlas method, of $1025 or less in 2015; middle-income economies are those with a GNI per capita between $1026 and $12,475; high-income economies are those with a GNI per capita of $12,476 or more.