Dissecting the Effect of Credit Supply on Trade: Evidence from Matched Credit-Export Data On Line Appendix

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August 19, 2014

A OLS Bias

In this appendix we expand the explanation in Subsection 4.3.1. The IV estimate of the export elasticity to finance is 7.8 times larger than the OLS estimate. We expect the attenuation bias of the OLS estimator to be of the such order of magnitude. This is why.

We are interested in the following model of supply-induced variation in exports —demand variation is absorbed by the product-destination dummies, α_{pd}— on variations in credit supply:

$$\Delta \ln (X_{ipd}) = \beta \Delta \ln \left(d_i^S\right) + \alpha_{pd} + \varepsilon_i \tag{A.2}$$

However, the OLS estimates this variation in supply of exports on *total* credit variations:

$$\Delta \ln (X_{ipd}) = \beta \Delta \ln (D_i) + \alpha_{pd} + \varepsilon_i$$

where total credit variation includes changes in both demand and supply of credit:

$$\Delta \ln (D_i) = \Delta \ln \left(d_i^S\right) + \Delta \ln \left(d_i^D\right). \tag{A.3}$$

Variations in total credit are given by demand and supply factors. If these factors are orthogonal, the bias of OLS in this setting corresponds to the classical attenuation bias. The magnitude of the attenuation bias increases with the fraction of the total credit variation that is explained by credit demand factors. Moreover, when the independent variable (i.e., the supply of credit) exhibits serial correlation, first-differencing increases the magnitude of the attenuation bias (see Arellano, 2003).

With no serial correlation in credit supply, demand variation must explain around 87% of the total variation in credit to obtain a bias of $\frac{\beta}{\beta_{OLS}}$ above 7. Using the classic measurement error bias formula:

$$\frac{\beta}{\beta_{OLS}} = 1 + \frac{\sigma_D^2}{\sigma_S^2} = 1 + \frac{.87}{.13} = 7.69$$

Adding reasonable magnitudes of serial correlation in credit supply —for example, through firm time-invariant heterogeneity— we show in Monte-Carlo simulations that the bias can be 7 to 10 times when demand explains 60% of the variation in total credit. Table **??** in this

letter shows the results of that simulation. The coefficients in columns 1 and 2 correspond to the true model in equation (A.2) and the naive OLS estimation on total credit in equation (A.3), respectively. In column 3, we report the results of the IV regression, where credit supply is instrumented with a supply shifter. The code of the simulation is attached to this appendix.

In our simulation, the magnitude of the OLS bias required demand factors to explain around 60% of the variation in credit. This number is close to the R^2 of 62% obtained in the within-firm credit specification (5) in the body of the paper, estimated with firm-time dummies only, which capture firms' changes in credit demand. That is:

$$\ln\left(C_{ibPost}\right) - \ln\left(C_{ibPre}\right) = \mu_i^{'} + \nu_{ib}$$

The firm dummies $\mu_i^{'}$ absorb all changes in credit demand by the firm. This is our best approximation of the minimum amount of variation in total credit explained by demand.

We can conclude from the comparison of the OLS and IV estimates that supply side factors explain less than half of the variation in total credit during the crisis.

Table A.1: Monte-Carlo Simulations

Dep. Variable	$\Delta \ln X_i$		
	True Model (1)	OLS (2)	IV (3)
$\Delta \ln d^s$	0.199		
	(0.0292)		
$\Delta \ln D$		0.023	0.203
		(0.0107)	(0.0581)
Simulations	200	200	200

In this simulation the standard deviation of credit demand shocks is set to be 1.6 times the standard deviation of credit supply shocks. The resulting IV estimate of the elasticity is 8.65 times the OLS estimate.

Monte Carlo Simulation- Stata Code

1. Bootstrap clustered by Product-Destination (PD)

   use bootstrap_sample, clear

   Step 1 (Benchmark)

```
ivregress 2sls Dlpeso _I* (Dlsaldotot = fexposure_2006)
matrix observe = ( _b[Dlsaldotot] )
```

   Step 2 capture program drop myboot

```
program define myboot, rclass
preserve
bsample, cluster(pd)
ivregress 2sls Dlpeso _I* (Dlsaldotot = fexposure_2006)
return scalar beta = _b[Dlsaldotot]
restore
end
```

   Step 3 simulate beta=r(beta), reps(400): myboot

   Step 4 bstat , stat(observe) n(400)

2. Bootstrap clustered by Firm (RUC)

   use bootstrap_sample, clear

   Step 1 (Benchmark)

```
quietly ivregress 2sls Dlpeso _I* (Dlsaldotot = fexposure_2006)
matrix observe = ( _b[Dlsaldotot] )
```

   Step 2 capture program drop myboot

```
program define myboot, rclass
preserve
bsample, cluster(ruc)
ivregress 2sls Dlpeso _I* (Dlsaldotot = fexposure_2006)
return scalar beta = _b[Dlsaldotot]
restore
end
```

   Step 3 simulate beta=r(beta), reps(400): myboot

   Step 4 bstat , stat(observe) n(400)

```
*estat bootstrap, all
```

B Cross-Sectional Analysis

In this appendix we analyze how the (intensive margin) elasticity of exports to credit shocks varies according to observable characteristics of the export flow, the exporting firms, and the product. This analysis allows us to make inferences regarding the role of external financing in the activities of the firm.

B.1 Firm Heterogeneity in Access to Credit

Changes in a bank's supply of credit affect the outcomes of related firms to the the extent that these firms cannot find alternative sources of funding. Then, differences across firms in their access to finance translate into heterogeneous elasticity to bank credit. We analyze how the elasticity of exports to bank credit varies across two firm dimensions: membership of a multinational enterprise, which potentially provides the firm with access to funding from internal capital markets, and the number of banking relationships, which potentially allows the firm to substitute among bank funding sources at a lower cost.

In Table B.1 we report the results of estimating equation (11) augmented with an interaction between all the right-hand side variables with a dummy that equals one whenever the exporting firm is an affiliate of a foreign owned multinational (column 1) and a dummy that equals one when the exporter obtains credit from more than one bank in the Pre period (column 2). The point estimate of the elasticity on the intensive margin indicates that exports by foreign affiliates are not sensitive to local bank credit. Having multiple banking relationships, on the other hand, is not found to affect the elasticity.

B.2 Sectoral Heterogeneity in Credit Intensity

Since the seminal work by Rajan and Zingales (1998), heterogeneity in the degree of external finance dependence across sectors—measured according to the fraction of total capital expenditure not financed by internal cash flows based on cross sectoral data of U.S. firms—has been widely used to identify the effect of credit constraints on long-term growth and the cross country pattern of international trade. We showed in Subsection 5.3 that the elasticities of export to credit does not vary with this measure. That is, the factors that affect the sensitivity of exports to long-term finance do not predict the effect of short-term credit shocks.

In this appendix we expand the analysis in Subsection 5.3 to incorporate another sectoral indicators of credit intensity often used in this literature: the average usage of trade credit—i.e. the sector average ratio of the change in accounts payable over the change in total assets—. Column 3 of Table B.1 shows how the intensive margin elasticity varies for sectors with share of trade credit above the mean in our sample. The point estimate is not statistically significant.

Finally, we analyze how the sensitivity to credit varies for commodities and differentiated goods. World exports of these types of goods behave differently during the 2008 crisis. Although quantities exported drop for all products and countries, their unit values present interesting differences: world commodity prices collapse while prices of differentiated goods do not (see Haddad, Harrison and Hausman (2010)). Credit constraints in the differentiated

sector, by negatively affecting supply of exports, can rationalize this pattern. We explore this hypothesis by comparing the elasticity for homogeneous and differentiated goods, following the product classification in Rauch (1999). The point estimate in column 4 of Table B.1 is not statistically significant.

Table B.1: Cross-Sectional Heterogeneity in Export Elasticity to Credit

Dep. Variable	$\Delta \ln X_{ipd}$			
	(1)	(2)	(3)	(4)
$\Delta \ln C_i$	0.195***	0.206*	0.190***	0.183***
	(0.048)	(0.116)	(0.046)	(0.048)
$\Delta \ln C_i \times Multinational_i$	-0.172			
	(0.202)			
$\Delta \ln C_i \times ManyBanks_i$		0.208		
		(0.166)		
$\Delta \ln C_i \times TradeCredit_p$			-0.011	
			(0.063)	
$\Delta \ln C_i \times Differentiated_p$				-0.080
				(0.171)
Observations	14,208	14,208	12,652	13,537
Observations Multinational	6,763			
Observations ManyBanks		7,226		
Observations TradeCredit			5,619	
Observations Differentiated				5,448

IV estimation of equation (11). The (log of) credit, $\ln C_i$, is instrumented with $F_i = \sum_b \omega_{ib}\ D(FD_b > 10\%)$, where ω_{ib} is the share of bank b in overall credit of firm i and FD_b is the share of foreign funding of bank b. $Multinational_i$ is a dummy equal to one if the firm is owned by a foreign multinational. Information on foreign ownership is from *Top Peru*. $ManyBank_i$ in column 2 is a dummy equal to one if the firm i borrows from more than one bank. $TradeCredit_p$ in column 3 is a dummy equal to one if the product is considered to use trade credit above the median across sectors (source Chor and Manova, 2010). Classification of differentiated goods in column 4 follows Rauch (1999). Standard errors in parentheses, allowing for correlation at the product-destination level. $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.1$