# Identifying Firm-Level Financial Frictions Using Sign Restrictions.

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  - Distort investment, innovation, and export decisions. Cause misallocation of resources across firms, lower aggregate productivity.
  - Amplify business cycles.
  - Causes and consequences of financial crises.

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  - More difficult, in part because there are several different ways to model financial frictions (Higher interest rate? Quantity constraint? Asset based or earning based borrowing?)
- This paper proposes a new approach: identify  $\xi_t$  using model + panel data + a minimal set of identifying assumptions.
  - Advantage: identification consistent with broad range of financial friction models.

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- 3. Use information on  $\xi$  to identify financially constrained firms, with an empirical application on Compustat data
  - Compare with narrative approach
  - Natural experiment based on the Great Recession.

# The model

## The model

Simple model with one flexible input.

- Results hold in a more general model with additional inputs subject to adjustment costs.
- A firm lives many period and produces using the following production function:

$$y_t = z_t l_t^{\alpha} , \qquad (1)$$

With  $0 < \alpha < 1$ .

- It is the production input (call it labour)
- *z<sub>t</sub>* is stochastic (productivity shock)

# Timing

- 1. The firm observes the three shocks  $z_t$ ,  $\theta_t$  and  $\xi_t$ .
- 2. The firm decides  $l_t$ ,  $b_t$  to maximise net present value of dividends subject to the budget constraint:

$$V_{t}(s_{t}, z_{t}, \xi_{t}, \theta_{t}) = \max_{l_{t}, b_{t}} (1 + \phi_{t}) \, div_{t} + \frac{1}{1 + r} E_{t} \left[ V_{t+1}(s_{t+1}, z_{t+1}, \xi_{t+1}, \theta_{t+1}) \right]$$

$$div_{t} + wl_{t} = s_{t} - \theta_{t} + \frac{b_{t}}{1 + r} - c_{t}$$
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•  $s_t$  is savings from period t-1:

$$s_t = y_{t-1} - b_{t-1} \tag{3}$$

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- $\theta_t$  is a liquidity shock not directly related to the production process.
- $\phi$  is the shadow value of external finance
- c<sub>t</sub> is cost of financial frictions (next slide)
- 3. The firm produces  $y_t = z_t I_t^{\alpha}$

#### **Financial Frictions**

Budget constraint:

$$div_t + wl_t = s_t - \theta_t + \frac{b_t}{1+r} - c_t$$
(4)

Dividends div<sub>t</sub> cannot be negative, and the cost of debt is increased by an extra cost c<sub>t</sub> which is increasing in leverage.

$$c_t = \left\{ \begin{array}{c} \xi_t b_t^{\gamma} \text{ if } b_t > 0\\ 0 \text{ if } b_t \le 0 \end{array} \right\}$$
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With γ > 1. Results robust to adding capital and measuring leverage as b<sub>t</sub>/k<sub>t</sub>
 Results robust to a more general function:

$$c_{t} = \left\{ \begin{array}{c} \xi_{t} \left( b_{t} - p_{t} \right)^{\gamma} \text{ if } b_{t} > p_{t} \\ 0 \text{ if } b_{t} \leq p_{t} \end{array} \right\}$$
(6)

Where  $p_t = \lambda_t^1 a_t + \lambda_t^2 y_t$  is the borrowing capacity of the firm. With  $0 < \lambda_t^1 < 1$  and  $0 < \lambda_t^2 < 1$ 

#### The system

Log linearising the first order conditions and the production function we have:

$$\log b_t = C + \frac{1}{\gamma - 1} \log \psi_t - \frac{1}{\gamma - 1} \log \xi_t \tag{7}$$

$$\log n_t = C + \frac{1}{1-\alpha} \log z_t - \frac{1}{1-\alpha} \log \psi_t \tag{8}$$

$$\log y_t = \log z_t + \alpha \log I_t \tag{9}$$

Where  $\psi_t$  is the shadow value of external finance today relative to tomorrow:

$$\psi_t \equiv \frac{1 + \phi_t}{1 + \mathcal{E}_t(\phi_{t+1})}$$

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the model implies that  $\psi_t = \psi(\bar{s}_t, \theta_t, \bar{z}_t, \xi_t)$ . Log linearising:

$$\log \psi_t = C - \pi_1 s_t + \pi_2 \log \xi_t + \pi_3 \log \theta_t + \pi_4 \log z_t$$
(10)

#### The system

Substituting  $\log \psi_t$ :

$$\log b_t = C - \frac{\pi_1}{\gamma - 1} s_t - \frac{1}{\gamma - 1} (1 - \pi_2) \log \xi_t + \frac{\pi_3}{\gamma - 1} \log \theta_t + \frac{\pi_4}{\gamma - 1} \log z_t$$
(11)

$$\log n_t = C + \frac{\pi_1}{1 - \alpha} s_t - \frac{\pi_2}{1 - \alpha} \log \xi_t - \frac{\pi_3}{1 - \alpha} \log \theta_t + \frac{1 - \pi_4}{1 - \alpha} \log z_t$$
(12)

$$\log y_t = C + \frac{\alpha}{1-\alpha} \pi_1 s_t - \frac{\alpha \pi_2}{1-\alpha} \log \xi_t - \frac{\alpha \pi_3}{1-\alpha} \log \theta_t + \frac{1-\alpha \pi_4}{1-\alpha} \log z_t \quad (13)$$

>  $s_t$  is beginning of the period savings, so predetermined with respect to the 3 shocks.

## System in matrix form

$$Y_{t} = c + D \log s_{t} + B\varepsilon_{t}$$
(14)  
Where  $Y = \begin{bmatrix} \log b_{t} \\ \log l_{t} \\ \log y_{t} \end{bmatrix}$  and  $\varepsilon_{t} = \begin{bmatrix} \xi_{t} \\ \theta_{t} \\ z_{t} \end{bmatrix}$ 

Positive and decreasing marginal returns in I ( $0 < \alpha < 1$ ) and borrowing costs increasing in leverage ( $\gamma > 1$ ) imply the following restrictions on the B matrix:

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Positive and decreasing marginal returns in I ( $0 < \alpha < 1$ ) and borrowing costs increasing in leverage ( $\gamma > 1$ ) imply the following restrictions on the B matrix:

$$B = \begin{bmatrix} - & + & + \\ - & - & + \\ - & - & + \end{bmatrix}$$

$$rac{B_{31}}{B_{21}}\in [0,1]; \qquad rac{B_{32}}{B_{22}}\in [0,1]$$

- Restrictions very mild. Importantly, they are consistent with more general model and with shocks to either cost or quantity of credit.
- For empirical application we use  $0.4 < \alpha < 0.8$
- Next, we discuss recovering B and ε<sub>t</sub> using panel data and the above restrictions.

## Structural VAR

In general, a large class of structural models can be written as SVAR

$$Y_t = c + DW_t + A_1 Y_{t-1} + \ldots + A_p Y_{t-p} + \frac{B}{\varepsilon_t},$$

where

▶ *W<sub>t</sub>* includes the pre-determined variables: (in the model: financial savings from previous period. In the empirical applications also fixed capital)

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- ▶ *W<sub>t</sub>* includes the pre-determined variables: (in the model: financial savings from previous period. In the empirical applications also fixed capital)
- ▶ the lags  $Y_{t-1}, \ldots, Y_{t-p}$  capture the dynamics
- the reduced form parameters are given by

$$\mu \equiv (\operatorname{vec}(\Phi)', \operatorname{vech}(\Sigma)')'$$
,  $\Phi = (D, A_1, \dots, A_p)$ ,  $\Sigma = BB'$ .

• the sign restrictions on *B* together with estimates for  $\mu$  allow to recover structural elements.

## Structural VAR

In principle,

$$Y_t = c + DW_t + A_1 Y_{t-1} + \ldots + A_p Y_{t-p} + \mathbf{B}\varepsilon_t ,$$

can be studied for any single firm

- but T is often short, leading to large uncertainty and uninformative estimates
- instead we rely on repeated cross-sections of firms for inference

#### Structural Panel VAR

We consider Structural Panel VAR (SPVAR)

$$Y_{i,t} = c_i + DW_{i,t} + A_1Y_{i,t-1} + \ldots + A_pY_{i,t-p} + B\varepsilon_{i,t}$$

where  $i = 1, \ldots, N$  indexes firm.

Extend sign restriction based SVAR methods to short T panel data setting

- ▶ We estimate the reduced form parameters using Arellano-Bond.
- From the reduced form residuals u<sub>i,t</sub> and the sign restrictions we recover the sets of structural shocks

#### Reduced form inference

Let  $u_{i,t} = B\varepsilon_{i,t}$  reduced form shocks.

The model in first differences is given by

$$\Delta Y_{i,t} = D\Delta W_{i,t} + A_1 \Delta Y_{i,t-1} + \ldots + A_p \Delta Y_{i,t-p} + \Delta u_{i,t} ,$$

Arrelano-Bond type moment conditions

$$\mathbb{E}(\Delta u_{i,t}Y'_{i,t-1-l}) = 0 \qquad \mathbb{E}(\Delta u_{i,t}W'_{i,t-l}) = 0$$

enable GMM inference

#### Reduced form inference

#### Define

$$\Delta Y_{i} = \begin{bmatrix} \Delta Y_{i,1}' \\ \vdots \\ \Delta Y_{i,T}' \end{bmatrix} \Delta u_{i} = \begin{bmatrix} \Delta u_{i,1}' \\ \vdots \\ \Delta u_{i,T}' \end{bmatrix} \Delta X_{i,t} = \begin{bmatrix} \Delta W_{i,t} \\ \Delta Y_{i,t-1} \\ \vdots \\ \Delta Y_{i,t-p} \end{bmatrix} \Delta X_{i} = \begin{bmatrix} \Delta X_{i,1}' \\ \vdots \\ \Delta X_{i,T}' \end{bmatrix}$$

Model for  $\Delta Y_i$  is given by

$$\Delta Y_i = (I_K \otimes \Delta X_i) \operatorname{vec}(\Phi) + \Delta u_i$$
.

with  $\Phi = (D, A_1, \dots, A_p)$ , and we can used instruments

$$Z_{i} = \begin{bmatrix} \tilde{Z}_{i,1}' & 0 & \dots & 0 \\ 0 & \tilde{Z}_{i,2}' & 0 & \dots \\ \dots & \dots & \dots & \dots \\ 0 & 0 & \dots & \tilde{Z}_{i,T}' \end{bmatrix} = \begin{bmatrix} Z_{i,1}' \\ Z_{i,1}' \\ \vdots \\ Z_{i,T}' \end{bmatrix}$$

where  $\tilde{Z}_{i,t} = (W'_{i,-p+1}, \dots W'_{i,t-1}, Y'_{i,-p}, \dots Y'_{i,t-2})'$ 

#### Reduced form inference

The GMM estimator for  $\phi = \operatorname{vec}(\Phi)$  becomes

$$\hat{\phi} = \operatorname{vec}\left\{ \left[ S_{ZX}' S_{ZZ}^{-1} S_{ZX} \right]^{-1} S_{ZX}' S_{ZZ}^{-1} S_{ZY} \right\}$$

where  $S_{ZX} = \frac{1}{N} \sum_{i=1}^{N} Z'_i \Delta X_i$ ,  $S_{ZY} = \frac{1}{N} \sum_{i=1}^{N} Z'_i \Delta Y_i$  and  $S_{ZZ} = \frac{1}{N} \sum_{i=1}^{N} Z'_i GZ_i^1$ 

The reduced form variance matrix  $\Sigma = BB'$  is estimated by

$$\widehat{\Sigma} = \frac{1}{NT} \sum_{t=1}^{T} \sum_{i=1}^{N} \widehat{u}_{i,t} \widehat{u}'_{i,t} \qquad \widehat{u}_{i,t} = (y_{i,t} - y_{i,.}) - \widehat{\Phi}'(X_{i,t} - X_{i,.})$$

where  $y_{i,.}$  and  $X_{i,.}$  denote the time averages.

 $<sup>^{1}</sup>$ with G a tri-diagonal matrix with two on the main diagonal and minus one of the first sub-diagonals

#### Asymptotic results reduced form

Summarize reduced form estimates

$$\hat{\mu} \equiv (\operatorname{vec}(\widehat{\Phi})', \operatorname{vech}(\widehat{\Sigma})')'$$

It can be shown that

•  $\hat{\mu}$  is asymptotically normal for  $N \to \infty$ 

$$\sqrt{N}(\hat{\mu}-\mu)\stackrel{d}{
ightarrow} N(0,\Omega)$$
 .

• There exists  $\widehat{\Omega}$  such that

 $\widehat{\Omega} \stackrel{\textit{p}}{\to} \Omega$ 

Key difference wrt SVAR: Ω is not block-diagonal

#### Recovering structural shocks

• We recover sets of structural shocks  $\epsilon_{i,t}$ 

The lower and upper bounds are given by

$$\begin{split} \hat{\varepsilon}^{L}_{i,j,t} &= \inf_{B \in \mathbb{R}^{K \times K}} B_{j}^{-1} \hat{u}_{i,t} & s.t. \quad \widehat{\Sigma} = BB', \ B \in \mathcal{R}(\hat{\mu}) \\ \hat{\varepsilon}^{U}_{i,j,t} &= \sup_{B \in \mathbb{R}^{K \times K}} B_{j}^{-1} \hat{u}_{i,t} & s.t. \quad \widehat{\Sigma} = BB', \ B \in \mathcal{R}(\hat{\mu}) \ , \end{split}$$

▶ Note any element in  $[\hat{\varepsilon}_{i,j,t}^L, \hat{\varepsilon}_{i,j,t}^U]$  is equally likely

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- ▶ The output are set estimates of productivity shock *z*, liquidity shock  $\theta$  and financial frictions shock  $\xi$

 $\begin{matrix} \widehat{log\xi_{i,t}}^{LB}, \widehat{log\xi_{i,t}}^{UB} \\ \widehat{log\theta_{i,t}}^{LB}, \widehat{log\theta_{i,t}}^{UB} \\ \widehat{logt_{i,t}}^{LB}, \widehat{log\theta_{i,t}}^{UB} \\ \hline \begin{matrix} \widehat{logz_{i,t}}^{LB}, \widehat{logz_{i,t}}^{UB} \end{matrix} \end{matrix} \end{matrix}$ 

- Additionally, we can estimate the latent shadow value of finance  $\psi$ .
- Estimated shocks can be used directly to estimate impulse responses (not in this presentation).

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- Additionally, we can estimate the latent shadow value of finance  $\psi$ .
- Estimated shocks can be used directly to estimate impulse responses (not in this presentation).
- Next steps:
  - use simulated data to show admissible interval provides relevant information on true shock.
  - use [log \(\xi\_{i,t}\), log \(\xi\_{i,t}\)] to identify financially constrained firms on empirical data. Compare with narrative methods, and use Great recession as natural experiment.

#### Model based Evidence

- Solve the structural model and simulate a panel of 10000 firms for 10 periods
- Compare relation between shocks (true and estimated) and observables.

	(1)	(2)	(3)	(4)
VARIABLES	True Shock	Median shock	Lower bound shock	Upper bound shock
$log(\xi_t)$	-0.0034	-0.0040	-0.0037	-0.0060
$log(\theta_t)$	-0.0004	-0.0028	-0.0038	-0.0020
$log(z_t)$	0.0486	0.0429	0.0431	0.0429
Constant	3.4684	3.4646	3.4652	3.4642
Observations	80,000	80,000	80,000	80,000
R-squared	0.9992	0.7826	0.7819	0.7846
	2			

Dependent Variable:  $log(y_t)$ 

Robust standard errors in parentheses

#### Dependent Variable: log(debt<sub>t</sub>)

	(1)	(2)	(3)	(4)
VARIABLES	True Shock	Median shock	Lower bound shock	Upper bound shock
$log(\xi_t)$	-0.0485	-0.0629	-0.0658	-0.0602
$log(\theta_t)$	0.0235	0.0202	0.0223	0.0304
$log(z_t)$	0.1091	0.1029	0.1059	0.1005
Constant	2.3092	2.3006	2.2922	2.3033
Observations	80,000	80,000	80,000	80,000
R-squared	0.8024	0.8013	0.7908	0.7741

Robust standard errors in parentheses

#### Dependent Variable: log(debt<sub>t</sub>)

	(1)	(2)	(3)	(4)	(5)
VARIABLES	$\log(\psi_t^{ extsf{true}})$	$\log(\psi_t^{true})$	$\log(\psi_t^{true})$	$\log(\psi_t^{true})$	$\log(\psi_t^{ extsf{true}})$
$log(\xi_t)$	0.3734	0.3731			
$log(\theta_t)$	0.2847		0.2843		
$log(z_t)$	0.2618			0.2595	
$log(\psi_t)$					0.6383
Constant	-1.4024	-1.4028	-1.4027	-1.4035	-1.4030
Observations	80,000	80,000	80,000	80,000	80,000
R-squared	0.8782	0.4221	0.2463	0.2072	0.6347
% Correct					83.1%

- 1. Compare aggregate detrended  $\widehat{log\xi_t}$  With Gilchrist and Zakrajsek (2012) excess bond premium.
- Use financial shocks to construct dummy of likely financially constrained firms, and compare it to financial frictions estimated using narrative methods.
- 3. Great recession as a natural experiment.

# 1) Comparison with Excess Bond Premium



Average  $\xi$  shock and excess corporate bond spread from Gilchrist and Zakrajsek (2012)

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Average  $\xi$  shock and excess corporate bond spread from Gilchrist and Zakrajsek (2012)

Delayed effect in 2008-2009 perhaps because of firms using up credit lines.

2) Comparison with Financial frictions measure based on narrative approach

- We consider, as dependent variable, the *equitydelaycon* indicator proposed by Holberg and Maksimovic (2015).
- High value when firms indicate, in the "Capitalization and Liquidity" Subsection of the 10-K reports, delayed investment because of liquidity problems, which will be addressed by issuing equity.

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- High value when firms indicate, in the "Capitalization and Liquidity" Subsection of the 10-K reports, delayed investment because of liquidity problems, which will be addressed by issuing equity.
- Our main explanatory variable is *Dconstrained*, a dummy equal to one for the group of 25% firm-year observations with highest value of *ξ<sub>i</sub>*, and zero otherwise.
- We consider alternative dummies based on  $\widehat{\psi}$ ,  $\widehat{\theta}$ ,  $\widehat{z}$ .
- control variables: 2-digit sector-year dummies; size (measured as number of employees), leverage, and labour productivity (measured as output divided by number of employees).

#### Dependent Variable: equity delaycon

	(1)	(2)	(3)	(4)
VARIABLES	Dconstr. using $\theta$	Dconstr. using $\xi$	Dconstr. using $\psi$	Dconstr. using z
Dconstrained	0.012***	0.006***	0.007***	0.001
	(5.787)	(2.715)	(3.567)	(0.517)
log(fixedassets)	-0.009***	-0.009***	-0.009***	-0.009***
	(-7.070)	(-6.986)	(-7.151)	(-7.417)
leverage	0.000	0.001*	0.001*	0.001*
	(1.470)	(1.792)	(1.725)	(1.702)
labprod	-0.000***	-0.000***	-0.000***	-0.000***
	(-2.822)	(-3.000)	(-3.010)	(-2.976)
Dlarge	0.023***	0.024***	0.024***	0.024***
	(4.695)	(4.701)	(4.725)	(4.741)
Dhighlev	0.003	0.006	0.005	0.005
	(0.887)	(1.465)	(1.422)	(1.298)
Dhighprod	0.009*	0.009*	0.009*	0.009*
	(1.853)	(1.881)	(1.848)	(1.865)
Constant	-0.011	-0.010	-0.010	-0.008
	(-1.025)	(-0.881)	(-0.895)	(-0.758)
Observations	14,088	14,088	14,088	14,088
R-squared	0.104	0.102	0.102	0.101
Sector-Year FE	YES	YES	YES	YES
	Dobuo	+ + ctatictics in nava	nthecoc	

Robust t-statistics in parentheses

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

▶ We create a dummy variable  $D\hat{\xi}_{i,t-1}^{high}$ , equal to one if firm *i* in year t-1 was among the highest 25% values of  $\widehat{\log \xi_{i,t}}$ , and zero otherwise (estimated using only data up to 2007).

- ► We create a dummy variable D<sup>k</sup><sub>i,t-1</sub>, equal to one if firm *i* in year t 1 was among the highest 25% values of log ξ<sub>i,t</sub>, and zero otherwise (estimated using only data up to 2007).
- Intuition: Firms did not expect crisis, and firms facing financial frictions in 2007 were likely to suffer more in 2008 when crisis started.

- ► We create a dummy variable D<sup>k</sup><sub>i,t-1</sub>, equal to one if firm *i* in year t 1 was among the highest 25% values of log ξ<sub>i,t</sub>, and zero otherwise (estimated using only data up to 2007).
- Intuition: Firms did not expect crisis, and firms facing financial frictions in 2007 were likely to suffer more in 2008 when crisis started.
- Dependent variable is the log of employment in period t,  $log(l_t)$ .
- ► Regressors include log( $I_{t-1}$ ),  $D\hat{\xi}_{t-1}^{high}$  and several lagged control variables.

- ► We create a dummy variable D<sup>k</sup><sub>i,t-1</sub>, equal to one if firm *i* in year t 1 was among the highest 25% values of log ξ<sub>i,t</sub>, and zero otherwise (estimated using only data up to 2007).
- Intuition: Firms did not expect crisis, and firms facing financial frictions in 2007 were likely to suffer more in 2008 when crisis started.
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- ▶ Regressors include  $log(I_{t-1})$ ,  $D\hat{\xi}_{t-1}^{high}$  and several lagged control variables.
- All regressors are also interacted with the dummy Gr, equal to one for the year 2008.

- ► We create a dummy variable D<sup>khigh</sup><sub>i,t-1</sub>, equal to one if firm *i* in year t 1 was among the highest 25% values of log ξ<sub>i,t</sub>, and zero otherwise (estimated using only data up to 2007).
- Intuition: Firms did not expect crisis, and firms facing financial frictions in 2007 were likely to suffer more in 2008 when crisis started.
- Dependent variable is the log of employment in period t,  $log(l_t)$ .
- Regressors include log( $I_{t-1}$ ),  $D\hat{\xi}_{t-1}^{high}$  and several lagged control variables.
- All regressors are also interacted with the dummy Gr, equal to one for the year 2008.
- ► The coefficient of D\$\u03c6\$<sup>high</sup> \* Gr should be negative. Firms classified as constrained in t = 2007 should have reduced employment relative to unconstrained ones in the following year, more so than for t < 2007.</p>

	(1)	(2)	(3)	(4)
VARIABLES	$\log(l_{\star})$	$\log(I_{t})$	$\log(l_{\star})$	$\log(I_{\ell})$
	8(-1)	8(-1)	8(-1)	8(-1)
$log(I_{t-1})$	0.923***	0.923***	0.929***	0.927***
0(1-1)	(118.852)	(124.533)	(119.116)	(116.123)
$log(I_{t-1}) * Gr$	-0.001	0.000	0.002	0.002
-, ,	(-0.419)	(0.084)	(0.528)	(0.612)
$D\hat{\xi}_{t-1}^{high}$	0.006	0.004	0.001	. ,
<i>n</i> -1	(1.359)	(0.960)	(0.119)	
$D\hat{\mathcal{E}}_{+}^{high} * Gr$	-0.050***	-0.057***	-0.060***	
51-1	(-3.092)	(-3.506)	(-3.296)	
Small <sub>t-1</sub>	( )	0.094	0.085	0.086
		(1.500)	(1.473)	(1.496)
Small <sub>t-1</sub> * Gr		0.063*	0.076* <sup>*</sup>	0.073*
		(1.762)	(2.063)	(1.919)
$Highlev_{t-1}$		-0.015**	-0.009	-0.009
		(-2.242)	(-1.223)	(-1.160)
$Highlev_{t-1} * Gr$		-0.011	-0.019	-0.019
		(-0.672)	(-0.967)	(-0.953)
$Lowprod_{t-1}$		-0.016	-0.003	-0.003
		(-1.435)	(-0.219)	(-0.271)
$Lowprod_{t-1} * Gr$		-0.015	0.010	0.003
		(-0.742)	(0.427)	(0.119)
labp <sub>t-1</sub>			0.038**	0.038**
			(2.484)	(2.484)
$labp_{t-1} * GR$			0.027	0.023
			(1.572)	(1.372)
lev <sub>t-1</sub>			-0.006	-0.009**
			(-1.641)	(-2.128)
$lev_{t-1} * GR$			0.004	0.005
			(0.576)	(0.718)
$\xi_{t-1}$				-0.004
				(-1.241)
$\xi_{t-1} * Gr$				-0.028**
<b>c</b>	0.405***	0 400000		(-2.483)
Constant	0.105***	0.106***	-0.097	-0.093
	(7.895)	(7.680)	(-1.199)	(-1.159)
Observations	6 270	6 270	6 264	6 264
Diservations Diservations	0,570	0,570	0,504	0,504
Number of firm	0.094 420	420	420	420
Firm FE	439 VES	439 VES	439 VES	439 VES
Sector*Vear FE	VES	VES	VES	VES
Jector rear FE	163	163	163	163

Robust t-statistics in parentheses \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

#### Placebo experiment

VARIABLES	(1) 2008	(2) 2007	(3)	(4)	(5) 2004	(6) 2003	(7)	(8) 2001
$D\hat{\xi}_{t=1}^{high}$	0.001	-0.004	-0.002	-0.002	-0.001	-0.002	-0.002	-0.005
	(0.119)	(-0.877)	(-0.505)	(-0.403)	(-0.286)	(-0.336)	(-0.485)	(-1.051)
$D\hat{\xi}_{t-1}^{high} * Gr$	-0.060***	0.015	-0.018	-0.001	0.005	0.002	0.018	0.021
	(-3.296)	(0.827)	(-1.177)	(-0.060)	(0.312)	(0.096)	(0.880)	(0.994)
Constant	-0.097	-0.119	-0.232***	-0.224***	-0.208***	-0.160**	-0.182***	-0.236***
	(-1.199)	(-1.522)	(-3.246)	(-3.045)	(-3.085)	(-2.561)	(-2.886)	(-3.378)
Observations	6,364	6,680	7,131	7,523	7,372	7,400	7,523	7,699
R-squared	0.895	0.899	0.899	0.896	0.897	0.886	0.887	0.885
Number of firm	439	462	493	519	509	514	524	535
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Sector*Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	(4)	(0)	(2)	(4)	(5)	(6)	(7)	(0)
	(1)	(2)	(3)	(4)	(5)	(0)	$(\prime)$	(8)
VARIABLES	(1) 2008	(2) 2007	(3) 2006	(4) 2005	(5) 2004	(6) 2003	2002	(8) 2001
VARIABLES	(1) 2008	2007	2006	2005	2004	2003	2002	2001
VARIABLES $\xi_{t-1}$	(1) 2008 -0.004	(2) 2007 -0.006*	-0.006*	-0.005	-0.003	0.000	-0.001	-0.002
VARIABLES	(1) 2008 -0.004 (-1.241)	(2) 2007 -0.006* (-1.700)	(3) 2006 -0.006* (-1.741)	(4) 2005 -0.005 (-1.535)	-0.003 (-0.808)	(6) 2003 0.000 (0.001)	-0.001 (-0.165)	(8) 2001 -0.002 (-0.504)
VARIABLES $\xi_{t-1}$ $\xi_{t-1} * Gr$	(1) 2008 -0.004 (-1.241) -0.028** (2.402)	(2) 2007 -0.006* (-1.700) 0.007 (0.656)	(3) 2006 -0.006* (-1.741) -0.011 (1.022)	(4) 2005 -0.005 (-1.535) -0.015 (1.035)	(5) 2004 -0.003 (-0.808) -0.004 (0.0277)	(6) 2003 0.000 (0.001) -0.009 (0.772)	(7) 2002 -0.001 (-0.165) 0.007 (0.570)	(8) 2001 -0.002 (-0.504) 0.001 (0.112)
VARIABLES $\xi_{t-1}$ $\xi_{t-1} * Gr$	(1) 2008 -0.004 (-1.241) -0.028** (-2.483) (-2.483)	(2) 2007 -0.006* (-1.700) 0.007 (0.666) 0.116	(3) 2006 -0.006* (-1.741) -0.011 (-1.089)	(4) 2005 (-1.535) -0.015 (-1.275)	(5) 2004 -0.003 (-0.808) -0.004 (-0.377)	(6) 2003 0.000 (0.001) -0.009 (-0.773)	(7) 2002 -0.001 (-0.165) 0.007 (0.578)	(8) 2001 -0.002 (-0.504) 0.001 (0.113)
VARIABLES $\xi_{t-1}$ $\xi_{t-1} * Gr$ Constant	(1) 2008 -0.004 (-1.241) -0.028** (-2.483) -0.093 (1)150)	(2) 2007 -0.006* (-1.700) 0.007 (0.666) -0.116 (1.405)	(3) 2006 (-1.741) -0.011 (-1.089) -0.231***	(4) 2005 -0.005 (-1.535) -0.015 (-1.275) -0.223***	(5) 2004 -0.003 (-0.808) -0.004 (-0.377) -0.208***	(6) 2003 0.000 (0.001) -0.009 (-0.773) -0.159**	(7) 2002 -0.001 (-0.165) 0.007 (0.578) -0.182***	(8) 2001 -0.002 (-0.504) 0.001 (0.113) -0.238*** (2.200)
VARIABLES $\xi_{t-1}$ $\xi_{t-1} * Gr$ Constant	(1) 2008 -0.004 (-1.241) -0.028** (-2.483) -0.093 (-1.159)	(2) 2007 -0.006* (-1.700) 0.007 (0.666) -0.116 (-1.495)	(3) 2006 (-1.741) -0.011 (-1.089) -0.231*** (-3.260)	(4) 2005 (-1.535) -0.015 (-1.275) -0.223*** (-3.044)	(5) 2004 -0.003 (-0.808) -0.004 (-0.377) -0.208*** (-3.084)	(0) 2003 0.000 (0.001) -0.009 (-0.773) -0.159** (-2.552)	(7) 2002 -0.001 (-0.165) 0.007 (0.578) -0.182*** (-2.856)	(8) 2001 (-0.504) 0.001 (0.113) -0.238*** (-3.388)
VARIABLES $\xi_{t-1}$ $\xi_{t-1} * Gr$ Constant Observations	(1) 2008 -0.004 (-1.241) -0.028** (-2.483) -0.093 (-1.159) 6,364	(2) 2007 (-1.700) 0.007 (0.666) -0.116 (-1.495) 6,680	(3) 2006 (-1.741) -0.011 (-1.089) -0.231*** (-3.260) 7,131	(4) 2005 (-1.535) -0.015 (-1.275) -0.223*** (-3.044) 7,523	(5) 2004 -0.003 (-0.808) -0.004 (-0.377) -0.208*** (-3.084) 7,372	(0) 2003 0.000 (0.001) -0.009 (-0.773) -0.159** (-2.552) 7,400	(7) 2002 -0.001 (-0.165) 0.007 (0.578) -0.182*** (-2.856) 7,523	(8) 2001 -0.002 (-0.504) 0.001 (0.113) -0.238*** (-3.388) 7,699
VARIABLES $\xi_{t-1}$ $\xi_{t-1} * Gr$ Constant Observations R-squared	(1) 2008 -0.004 (-1.241) -0.028** (-2.483) -0.093 (-1.159) 6,364 0.895	(2) 2007 (-1.700) 0.007 (0.666) -0.116 (-1.495) 6,680 0.899	(3) 2006 -0.006* (-1.741) -0.011 (-1.089) -0.231*** (-3.260) 7,131 0.899	(4) 2005 -0.005 (-1.535) -0.015 (-1.275) -0.223*** (-3.044) 7,523 0.896	(5) 2004 -0.003 (-0.808) -0.004 (-0.377) -0.208*** (-3.084) 7,372 0.897	(0) 2003 0.000 (0.001) -0.009 (-0.773) -0.159** (-2.552) 7,400 0.886	(7) 2002 -0.001 (-0.165) 0.007 (0.578) -0.182*** (-2.856) 7,523 0.887	(8) 2001 -0.002 (-0.504) 0.001 (0.113) -0.238*** (-3.388) 7,699 0.885
VARIABLES $\xi_{t-1}$ $\xi_{t-1} * Gr$ Constant       Observations       R-squared       Number of firm	(1) 2008 -0.004 (-1.241) -0.028** (-2.483) -0.093 (-1.159) 6,364 0.895 439	(2) 2007 -0.006* (-1.700) 0.007 (0.666) -0.116 (-1.495) 6,680 0.899 462	(3) 2006 -0.006* (-1.741) -0.011 (-1.089) -0.231*** (-3.260) 7,131 0.899 493	(4) 2005 -0.005 (-1.535) -0.015 (-1.275) -0.223*** (-3.044) 7,523 0.896 519	(5) 2004 -0.003 (-0.808) -0.004 (-0.377) -0.208*** (-3.084) 7,372 0.897 509	(0) 2003 0.000 (0.001) -0.009 (-0.773) -0.159** (-2.552) 7,400 0.886 514	(7) 2002 -0.001 (-0.165) 0.007 (0.578) -0.182*** (-2.856) 7,523 0.887 524	(3) 2001 -0.002 (-0.504) 0.001 (0.113) -0.238*** (-3.388) 7,699 0.885 535
VARIABLES $\xi_{t-1}$ $\xi_{t-1} * Gr$ Constant Observations R-squared Number of firm Firm FE	(1) 2008 -0.004 (-1.241) -0.028** (-2.483) (-2.483) (-2.483) (-2.483) (-1.159) 6,364 0.895 439 YES	(2) 2007 -0.006* (-1.700) 0.007 (0.666) -0.116 (-1.495) 6,680 0.899 462 YES	(3) 2006 -0.006* (-1.741) -0.011 (-1.089) -0.231*** (-3.260) 7,131 0.899 493 YES	(4) 2005 -0.005 (-1.535) -0.015 (-1.275) -0.223*** (-3.044) 7,523 0.896 519 YES	(5) 2004 -0.003 (-0.808) -0.004 (-0.377) -0.208*** (-3.084) 7,372 0.897 509 YES	(0) 2003 0.000 (0.001) -0.009 (-0.773) -0.159** (-2.552) 7,400 0.886 514 YES	(7) 2002 -0.001 (-0.165) 0.007 (0.578) -0.182*** (-2.856) 7,523 0.887 524 YES	(8) 2001 -0.002 (-0.504) 0.001 (0.113) -0.238*** (-3.388) 7,699 0.885 535 YES
VARIABLES $\xi_{t-1}$ $\xi_{t-1} * Gr$ Constant       Observations       R-squared       Number of firm       Firm FE       Sector*Vear FE	(1) 2008 -0.004 (-1.241) -0.028** (-2.463) -0.093 (-1.159) 6,364 0.895 439 YES YES	(2) 2007 -0.006* (-1.700) 0.007 (0.666) -0.116 (-1.495) 6,680 0.899 462 YES YES	(3) 2006 -0.006* (-1.741) -0.011 (-1.089) -0.231*** (-3.260) 7,131 0.899 493 YES YES	(4) 2005 -0.005 (1.535) -0.015 (1.275) -0.223*** (-3.044) 7,523 0.896 519 YES YES	(5) 2004 -0.003 (-0.808) -0.004 (-0.377) -0.208*** (-3.084) 7,372 0.897 509 YES YES	(0) 2003 0.000 (0.001) -0.009 (-0.773) -0.159** (-2.552) 7,400 0.886 514 YES YES	(7) 2002 -0.001 (-0.165) 0.007 (0.578) -0.182*** (-2.856) 7,523 0.887 524 YES YES	(3) 2001 -0.002 (-0.504) 0.001 (0.113) -0.238*** (-3.388) 7,699 0.885 535 535 YES YES

Robust t-statistics in parentheses

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

#### Conclusions

- New method to estimate panel data SVAR with sign and inequality restrictions.
- Apply to a new identification strategy to estimate financial frictions at the firm level.
- Balance sheet data + mild restrictions allow us to generate useful information on ξ (the financial frictions shocks).
  - Key property: consistent with wide range of financial imperfections.
- Can also recover latent shadow value of finance:  $\psi_t = \psi(s_t, \theta_t, z_t, \xi_t)$ . (but mapping more model dependent)