

# Non-Linear Productivity and Investment Dynamics

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# Motivation

- ▶ Firms' productivity dynamics define
  1. expectation on the productivity evolution
  2. uncertainty on the productivity realization
- ▶ Key determinants of firm-level investment
- ▶ The resulting investment behavior contains information on
  1. the nature of economic frictions, e.g., adjustment costs
  2. the allocation of resources among firms, and
  3. the performance of the aggregate economy

## Motivation (cnt'd)

- ▶ Most dynamics models of investment behavior assume “canonical” AR(1) process for productivity
- ▶ The canonical process: AR(1) implies
  1. linear productivity dynamics, with
  2. normally distributed shocks
- ▶ Limitations that may bias existing qualitative and quantitative work

# This paper

- ▶ Uses the dataset *Central de Balances Integrada* from 1999 to 2017
- ▶ Estimates sector-specific production functions to extract **revenue** productivity
- ▶ Estimates two persistent + transitory productivity processes:
  1. *Canonical process*
    - ▶ Persistent: AR(1) with normally distributed shocks
  2. *Non-linear process*
    - ▶ Persistent: non-linear with flexible shock distributions
- ▶ Studies the implications on investment behavior through
  - ▶ Estimation of empirical policy functions
  - ▶ Structural investment model with adjustment costs

# Findings

- ▶ Firm-level productivity series from PF estimation display
  1. non-linearity
  2. non-normality
- ▶ The estimated non-linear (NL) productivity process captures those features well
- ▶ Estimated empirical policy functions under the NL process imply
  1. better fit of investment dynamics
  2. larger investment responses to persistent productivity shocks
  3. no investment responses to transitory productivity shock
- ▶ Structural model under the NL process
  1. fits data moments better
  2. different nature of adjustment costs → larger role for convex vs fixed

# Related literature

## **Non-linear processes**

Arellano et al. (2017); De Nardi et al. (2020); Guvenen et al. (2021); Ruiz-Garcia (2021)

► Depart from linearity in estimation of productivity process

## **Investment at the firm level**

Caballero and Engel (1999); Cooper and Haltiwanger (2006); Bazdresch et al. (2018); Gala et al. (2020)

► Importance of NL productivity for investment dynamics

## **Productivity dynamics in macro models**

Jaimovich et al. (2021); Ruiz-Garcia (2021); Pugsley et al. (2020); Asker et al. (2014); Bloom et al. (2007)

► Implications of NL productivity for the nature of adjustment costs and aggregate quantification

# Roadmap

1. Data and production function estimation
2. Firm productivity dynamics
3. Empirical investment policy functions
4. Structural firm dynamics model with capital adjustment costs

Data

Production Function Estimation



# Data

- ▶ *Central de Balances Integrada* hosted by *Banco de España*
- ▶ Firm-level data
  1. Balance sheet
  2. Earnings statement
  3. Annual report
- ▶ Quasi-universe of Spanish firms
- ▶ Time period: 1999 - 2017
- ▶ Focus on limited liability firms not controlled by the public sector
- ▶ Main variables: value-added, capital, labor, and materials
- ▶ After cleaning: 1.1 million firms, 7.5 million firm-year observations

# Production function estimation

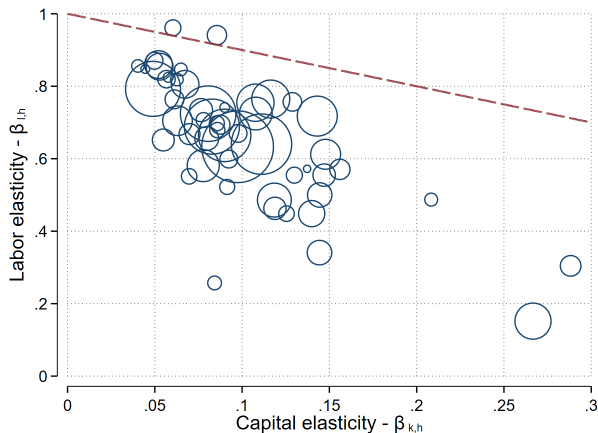
- ▶ Consider the following production function specification in logs:

$$y_{jht} = \beta_{h,t} + \beta_{k,h}k_{jht} + \beta_{l,h}l_{jht} + z_{jht} + \varepsilon_{jht}$$

- $y_{jht}$ : log of value-added
  - $k_{jht}$ : log of physical capital
  - $l_{jht}$ : log of labor – wage bill
  - $\beta_{h,t}$ : aggregate evolution of TFP in sector  $h$
  - $z_{jht}$ : firm productivity
  - $\varepsilon_{jht}$ : error term
- ▶ Modify Akerberg et al. (2015) estimation procedure to capture aggregate shocks as Hahn et al. (2020) [▶ More](#)
  - ▶ CUGMM for robustness to starting points as Kim et al. (2019)

# Production function estimates

## Sector-specific value-added elasticities



- ▶ Large heterogeneity in the production process across sectors
- ▶ Only two sectors display increasing returns to scale
- ▶ Large heterogeneity on firm-level productivity [▶ More](#)

# Production function estimates

## Aggregate value-added elasticities

Aggregation	Capital (90% CI)	Labor (90% CI)	RtS (90% CI)
Unweighted	0.101 (0.073, 0.131)	0.658 (0.508, 0.802)	0.759 (0.627, 0.884)
Weighted	0.101 (0.085, 0.124)	0.658 (0.565, 0.744)	0.759 (0.676, 0.834)

- ▶ Aggregate diminishing returns to scale in line with the literature
- ▶ Low elasticity wrt capital
- ▶ Tighter confidence intervals in the weighted aggregation  
—more precise estimates in sectors with high weight in the Economy—

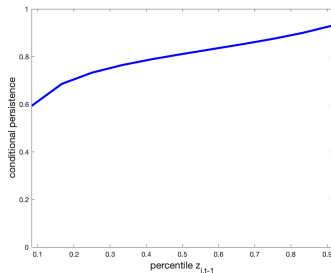
# Firm Productivity Dynamics

# Features of productivity data

Persistence and skewness [▶ More](#)

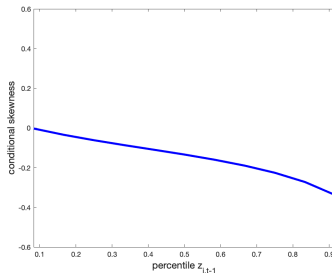
## Persistence

First order AR coefficient



## Skewness

$$S_K = \frac{(P90 - P50) - (P50 - P10)}{P90 - P10}$$



- ▶ Productivity persistence is larger for high-productivity firms
- ▶ Conditional productivity distribution displays negative skewness
- ▶ High-productivity firms face larger negative skewness

# Modelling productivity dynamics

- ▶ Typical AR(1) model of productivity dynamics:

$$z_{jt} = \rho z_{j,t-1} + v_{jt}, \quad v_{jt} \sim N(0, \sigma_v)$$

- ▶ Implies:

1. Linearity
2. Normality

- ▶ In the paper, we allow for:

- ▶ measurement error/different shock persistence (e.g., Gourio, 2008 ; Roys, 2016; Sterk et al., 2021)

$$z_{jt} = \eta_{jt} + \varepsilon_{jt}$$

with  $\eta$  : persistent component

- ▶ non-linearity in  $\eta_{jt}$  and non-normality

# Flexible productivity process [▶ More](#)

$$\begin{aligned}\eta_{it}(q^\eta) &= Q_\eta(q^\eta | \eta_{i,t-1}, age_{it}), & q^\eta &\sim U(0, 1) \\ \epsilon_{it}(q^\epsilon) &= Q(q^\epsilon | age_{it}), & q^\epsilon &\sim U(0, 1)\end{aligned}$$

Flexible, non-linear process:

- ▶ Both  $\eta$  and  $\epsilon$ :
  - ▶ Flexible + age-dependent distribution of shocks  $Q$
- ▶ Persistent component  $\eta$  :
  - ▶ Non-linear dependence between  $\eta_{jt}$  and  $\eta_{jt-1}$   
—different distributions of shocks for different type of firms—
  - ▶ Non-linear dependence between  $\eta_{jt}$  and  $q^\eta$   
—current shocks can wipe out memory of past shocks—



# Flexible productivity process [▶ More](#)

Canonical model

$$\begin{aligned}\eta_{it}(q^\eta) &= Q_\eta(q^\eta | \eta_{i,t-1}, age_{it}), & q^\eta &\sim U(0, 1) &= & \rho \eta_{i,t-1} + \sigma_v \phi^{-1}(q^\eta) \\ \epsilon_{it}(q^\epsilon) &= Q_\epsilon(q^\epsilon | age_{it}), & q^\epsilon &\sim U(0, 1) &= & \sigma_\epsilon \phi^{-1}(q^\epsilon)\end{aligned}$$

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# Flexible productivity process [▶ More](#)

Canonical model

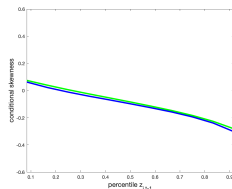
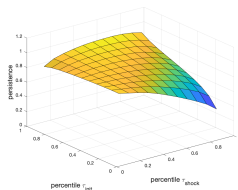
$$\begin{aligned}\eta_{it}(q^\eta) &= Q_\eta(q^\eta | \eta_{i,t-1}, age_{it}), & q^\eta &\sim U(0, 1) &= \rho \eta_{i,t-1} + \sigma_v \phi^{-1}(q^\eta) \\ \epsilon_{it}(q^\epsilon) &= Q(q^\epsilon | age_{it}), & q^\epsilon &\sim U(0, 1) &= \sigma_\epsilon \phi^{-1}(q^\epsilon)\end{aligned}$$

Flexible, non-linear process:

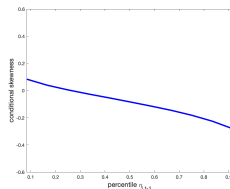
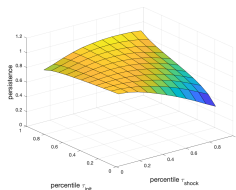
- ▶ Both  $\eta$  and  $\epsilon$ :
  - ▶ Flexible + age-dependent distribution of shocks  $Q$
- ▶ Persistent component  $\eta$  :
  - ▶ Non-linear dependence between  $\eta_{jt}$  and  $\eta_{jt-1}$   
—different distributions of shocks for different type of firms—
  - ▶ Non-linear dependence between  $\eta_{jt}$  and  $q^\eta$   
—current shocks can wipe out memory of past shocks—

# Data vs non-linear vs canonical productivity dynamics [▶ SE](#)

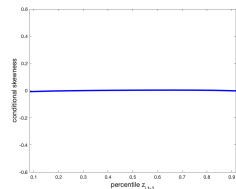
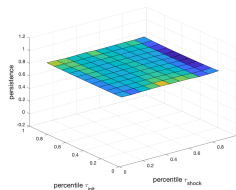
Data



Non-linear



Canonical



▶ Non-linear productivity process captures the data

1. Non-linearity
2. Non-normality

▶ The canonical process cannot capture these, by construction [▶ Results](#)

# But do they matter for investment?

## 1. Empirical exercise

- ▶ Estimate flexible investment policy function under the two processes
- ▶ Are the investment reactions –marginal propensities to invest– equivalent?

## 2. Structural model

- ▶ Calibrate the model with adjustment costs under the two processes
- ▶ Do they imply similar firm-level investment dynamics?
- ▶ What is the nature of capital adjustment costs?
- ▶ What are the implications for the aggregate Economy? - [not today]

# Empirical Investment Policy Functions

# Empirical investment policy functions

- ▶ Empirical investment policy function:

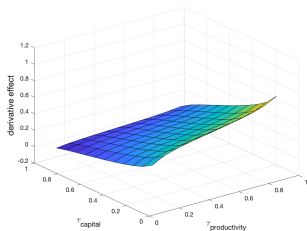
$$i_{jt+1} = g_t(k_{jt}, \eta_{jt}, \varepsilon_{jt}, u_{jt+1}), \quad t = 1, \dots, T$$

- ▶  $i_{jt}$  is firm net investment rate
- ▶  $u_{jt}$  are unobserved stochastic determinants of firm investment costs
- ▶  $\eta_{jt}$  and  $\varepsilon_{jt}$  as opposed to  $z_{jt}$  in Bazdresch et al. (2018) and Gala et al. (2020)  $\rightarrow$  latent variables
- ▶ Simulated EM based algorithm following ABB [▶ More](#)
- ▶ EIPF under both productivity process fit the investment distribution [▶ More](#)
- ▶ We define marginal propensities to invest

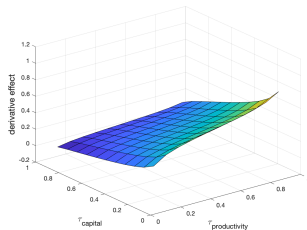
$$\phi_{\chi,t} = \mathbb{E} \left[ \frac{\partial g_t(k_{jt}, \eta_{jt}, \varepsilon_{jt}, u_{jt+1})}{\partial \chi_{jt}} \right], \quad \chi_{jt} = \eta_{jt}, \varepsilon_{jt}, k_{jt}$$

# Marginal propensities to invest ► Capital

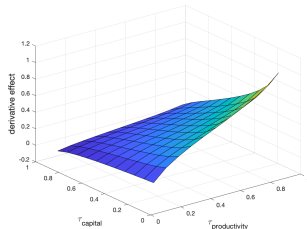
Productivity in real data vs. simulated data



Data



NL



Canonical

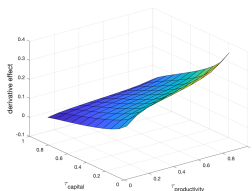
- MPI is increasing with productivity and decreasing with capital
- MPI under NL productivity dynamics are closer to the data ► SE

# Marginal propensities to invest ► SE

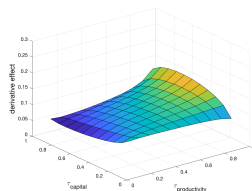
Persistent vs. transitory productivity

Non-linear

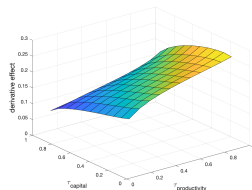
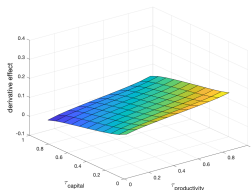
Persistent



Transitory



Canonical



- MPI under NL are mostly driven by the persistent component
- MPI under canonical are mostly driven by the transitory component



# Structural Firm Dynamics Model with Capital Adjustment Costs

# Model – Production

- ▶ Time is discrete with infinite horizon
- ▶ Production technology is Cobb-Douglas with DRS

$$f(z_{jt}, K_{jt}, L_{jt}) = \exp(z_{jt}) K_{jt}^{\beta_K} L_{jt}^{\beta_L} \quad \beta_K + \beta_L < 1.$$

- ▶ Idiosyncratic productivity evolves according to either
  1. estimated NL process
  2. canonical AR(1)
- ▶ Labor decision is
  1. static
  2. not subject to frictions
- ▶ Capital is
  1. predetermined by previous period investment

$$K_{jt+1} = I_{jt} + (1 - \delta)K_{jt}$$

2. Investment is subject to **adjustment costs**

## Model – Capital adjustment costs

- Fixed costs governed by  $FC_K$

$$FC_K 1 \left\{ \left| \frac{I_{jt}}{K_{jt}} \right| > 0.01 \right\} \quad \text{with } FC_K \geq 0,$$

- Convex adjustment costs governed by  $\gamma$

$$\frac{\gamma}{2} \left( \frac{I_{jt}}{K_{jt}} \right)^2 K_{jt} \quad \text{with } \gamma \geq 0,$$

- Transaction costs governed by  $p_K$

—price-gap between the buying and selling price for capital—

$$I_{jt} 1 \{ I_{jt} \geq 0 \} + p_K I_{jt} 1 \{ I_{jt} < 0 \} \quad \text{with } p_K \in [0, 1)$$

# Model – Estimation

- ▶ Parameters not governing adjustment costs are set externally [▶ More](#)
- ▶ Estimate the adjustment costs using SMM and targeting
  1. SD of the investment rate – 0.631
  2. Serial correlation of investment rates – 0.150
  3. Spike rate of positive investment – 0.159
- ▶ Compare the results under the two productivity processes
  1. Nature of adjustment costs
  2. Firm investment dynamics

# Nature of adjustment costs

		Targeting NL		Targeting AR(1)	
	Data	NL	AR(1)	NL	AR(1)
Parameters					
$FC_k$		0.085	0.085	0.134	0.134
$\gamma$		0.123	0.123	0.057	0.057
$p_k$		0.798	0.798	0.733	0.733
Loss function		1.142	899.673	2001.341	434.087
Targeted moments					
SD investment rate	0.631	0.626	0.533	1.001	0.682
Serial correlation of investment rates	0.150	0.150	0.430	-0.099	0.351
Spike rate: positive investment	0.159	0.150	0.202	0.127	0.159

- ▶ Model under NL process captures better targeted moments  
—loss function more than 2-orders of magnitude smaller—
- ▶ Larger role of convex cost vs fixed cost under the NL process  
—canonical process needs to reduce serial correlation of investment—

# Non-targeted firm investment moments

		Targeting NL		Targeting AR(1)	
		NL	AR(1)	NL	AR(1)
Parameters					
$\gamma$		0.123	0.123	0.057	0.057
$FC_k$		0.085	0.085	0.134	0.134
$p_k$		0.798	0.798	0.733	0.733
Non-targeted moments					
Spike rate: negative investment	0.204	0.088	0.068	0.087	0.045
Frac of obs with neg investment	0.645	0.742	0.774	0.770	0.828
Inaction rate: investment	0.057	0.026	0.002	0.009	0.001
Average investment rate	0.073	0.099	0.088	0.168	0.114
Correlation profit shocks and investment	0.100	0.364	0.418	0.314	0.418
Percentiles of investment distribution					
$P_{10}$	-0.301	-0.187	-0.119	-0.184	-0.117
$P_{25}$	-0.179	-0.118	-0.113	-0.118	-0.112
$P_{50}$	-0.065	-0.103	-0.107	-0.105	-0.108
$P_{75}$	0.061	0.006	-0.100	-0.022	-0.102
$P_{90}$	0.490	0.704	0.839	0.538	0.933

- Closer-to-data investment dynamics along all non-targeted moments

# Conclusion

- ▶ Productivity data features non-linearity and non-normality
  - ▶ Estimated NL process captures accurately these features
  - ▶ Canonical AR(1) fails by construction
- ▶ Important implications for understanding the investment behavior
  - ▶ NL process captures
    1. the marginal propensities to invest
    2. the investment distribution
  - ▶ Canonical process does not do as well
  - ▶ NL implies different structure of adjustment costs
    - ▶ lower fixed costs and higher convex adjustment costs
  - ▶ and more accurate investment dynamics than canonical AR(1)
- ▶ Implications for the aggregate economy (next iteration of the paper)

Thank you!



# Modification of ACF I

1. *First stage.* Regress  $y_{jht}$  on  $\tilde{\Phi}_t(k_{jht}, l_{jht}, m_{jht})$ , which is the non-parametric function  $\Phi_t(k_{jht}, l_{jht}, m_{jht})$  interacted with time dummies, following Hahn et al. (2020), via OLS:

$$y_{jht} = \tilde{\Phi}_t(k_{jht}, l_{jht}, m_{jht}) + \varepsilon_{jht}.$$

2. *Modified second stage.*

- *Obtaining residuals*  $\chi_t(\beta_{l,h}, \beta_{k,h})$ . Obtain an estimate of  $\beta_{0,h} + \omega_{jht}$  from a given guess of  $\beta_{l,h}$  and  $\beta_{k,h}$  via the following equation

$$\beta_{0,h} + \widehat{\omega_{jt}}(\beta_{l,h}, \beta_{k,h}) = \tilde{\Phi}_t(k_{jt}, l_{jt}, m_{jt}) - \beta_{l,h}l_{jt} - \beta_{k,h}k_{jt}.$$

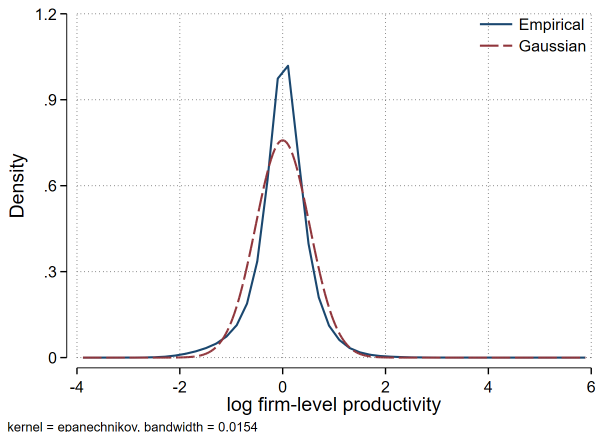
and regress  $\widehat{\beta_{0,h} + \omega_{jht}}(\beta_{l,h}, \beta_{k,h})$  on a third-order polynomial of  $\widehat{\beta_{0,h} + \omega_{jht-1}}(\beta_{l,h}, \beta_{k,h})$ . Get residual  $\chi_t(\beta_{l,h}, \beta_{k,h})$ .

## Modification of ACF II

- *CUGMM*. Estimate  $\beta_{l,h}$  and  $\beta_{k,h}$  with the following over-identified moment conditions via CUGMM:

$$\mathbb{E} \left( \chi_t(\beta_{0,h}, \beta_{l,h}, \beta_{k,h}) \otimes \begin{pmatrix} 1 \\ k_{jt} \\ l_{jt-1} \\ l_{jt-2} \\ k_{jt-1} \end{pmatrix} \right) = 0. \quad (1)$$

# Firm-level productivity estimates [▶ Back](#)



- ▶ Large heterogeneity on firm-level productivity
- ▶ Subtle deviation of firm productivity distribution from log-normality

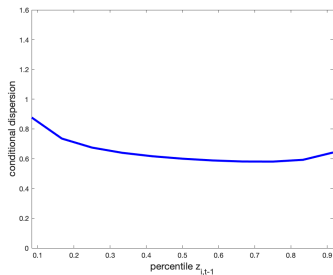
# Features of productivity data

[▶ Back](#)

## Dispersion and kurtosis

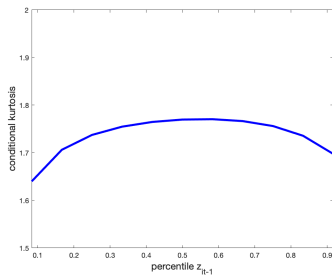
### Dispersion

$$\Delta = P90 - P10$$



### Kurtosis

$$\kappa = \frac{P92 - P8}{P83 - P17}$$



# Model specification [▶ Back](#)

## Nonlinear productivity dynamics

Following ABB, we specify the quantile functions for the persistent and transitory components as linear combinations of bivariate (Hermite) polynomial basis functions  $f_k$ , for  $k = 0, 1, \dots$ :

$$Q_{\eta}(\tau | \eta_{it-1}, age_{it}) = \sum_{k=1}^K a_k^{\eta}(\tau) f_k(\eta_{it-1}, age_{it})$$

$$Q_{\varepsilon}(\tau, age_{it}) = \sum_{k=1}^K a_k^{\varepsilon}(\tau) f_k(age_{it})$$

$$Q_{\eta_{i1}}(\tau) = \sum_{k=1}^K a_k^{\eta_1}(\tau) f_k(age_{i1})$$

where  $age_{it}$  is the age of the firm at time  $t$ .

# Canonical productivity process [▶ Back](#)

## Estimation results

**Table:** Parameters of the linear AR(1) process

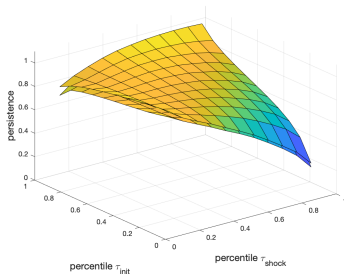
Parameter	Estimate (Std. Err.)
Autoregressive coeff. of persistent component	0.924 (0.086)
Std. dev. of innovation to persistent component	0.231 (0.065)
Std. dev. of the transitory component	0.223 (0.091)
Std. dev. of the initial condition	0.608 (0.121)

Note: We report the parameter estimates of the linear AR(1) process for productivity. Standard errors are computed via the asymptotic variance calculation. Data from the Spanish Central de Balances, from 1999 to 2017.

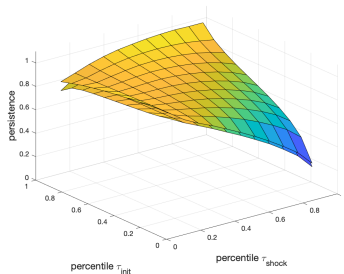
# Productivity dynamics

Standard errors – persistence

Data



Nonlinear model

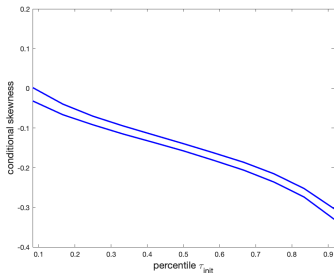


*Note: These graphs are 95% confidence bands estimated from a nonparametric bootstrap with 500 bootstrap replications.*

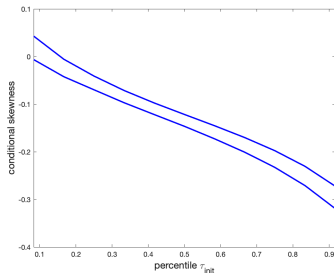
# Productivity dynamics [▶ Back](#)

## Standard errors – skewness

Data



Nonlinear model



*Note: These graphs are 95% confidence bands estimated from a nonparametric bootstrap with 500 bootstrap replications.*



# Model specification

## Empirical investment policy functions

- ▶ We specify the conditional distribution of investment rates given capital and the components of productivity as the following quantile model for a given quantile  $\tau_I$ :

$$i_{jt} = \sum_{k=0}^K a'_k(\tau_I) f_k(k_{jt}, \eta_{jt}, \varepsilon_{jt}, age_{jt}) + \mathbf{X}'_{jt} \beta(\tau_I) \quad (2)$$

where  $f_k(\cdot)$  is a dictionary of functions.

- ▶ In practice, we use tensor products of lower-order Hermite polynomials with order (2,2,1,1).
- ▶ Controls  $\mathbf{X}_{jt}$ : time dummies at the sector level (allowed to be quantile specific)

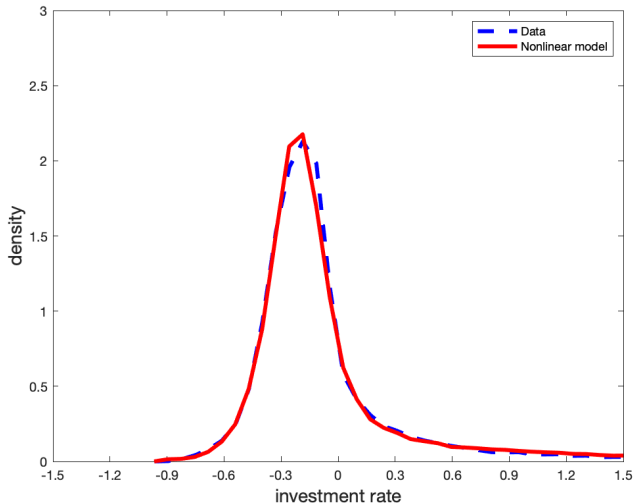
Starting with an initial guess of the investment function  $\hat{\mu}^{(0)}$ , iterate from  $s = 1, 2, \dots$  until convergence of the  $\hat{\mu}^{(s)}$  process:

1. *Stochastic E step*: For each firm, draw observations of the persistent component  $\eta_j^{(m)} = (\eta_{j1}^{(m)}, \dots, \eta_{jT}^{(m)})$  from the posterior distribution  $f(\eta_{jt} | k_{jt}, i_{jt+1}, \varepsilon_{jt}; \hat{\mu}^s, \hat{\theta})$ . [In practice, MCMC.]
2. *M-step*: Compute:

$$\min_{a_0^l(\tau_l), \dots, a_K^l(\tau_l)} \sum_{j=1}^N \sum_{t=1}^T \sum_{m=1}^M \rho_{\tau_l} \left( i_{jt+1} - \sum_{k=0}^K a_k^l(\tau_l) f_k(k_{jt}, l_{jt}, \eta_{jt}^{(m)}, \varepsilon_{jt}^{(m)}, \text{age}_{jt+1}) - \mathbf{x}_{jt}' \beta(\tau_l) \right)$$

for  $l = 1, \dots, L$ , where  $\rho_{\tau_l}(\cdot)$  is the usual check function of quantile regression.

# Investment distribution [▶ Back](#)



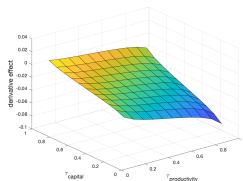
- ▶ EIPF under NL productivity process fit the investment distribution

# Marginal propensities to invest

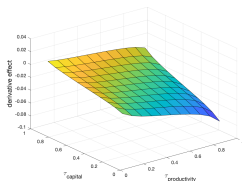
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## Capital

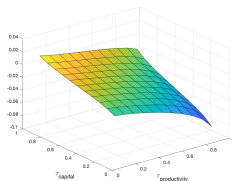
Data



Non-linear



Canonical

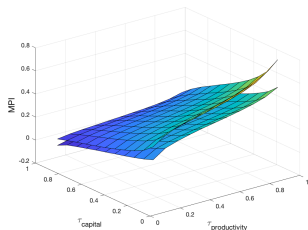


- ▶ MPI is increasing with productivity and capital (MPI ranges from -0.08 to 0.00)
- ▶ MPI under NL productivity dynamics (-0.07 to 0.00) vs. canonical productivity dynamics (-0.09 to 0.02)

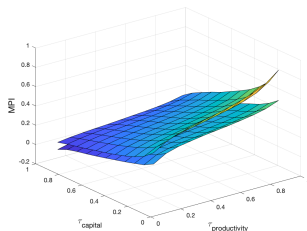
# Empirical investment functions

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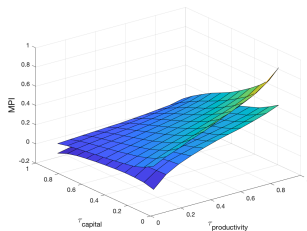
## Standard errors



Data



NL



Canonical

*Note: 95% confidence bands from a nonparametric bootstrap with 500 replications.*

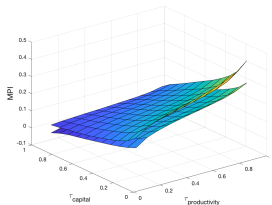
# Empirical investment functions

[▶ Back](#)

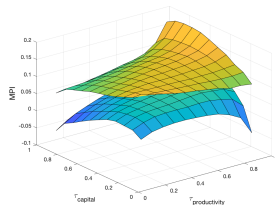
Standard errors

Non-linear

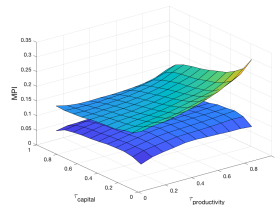
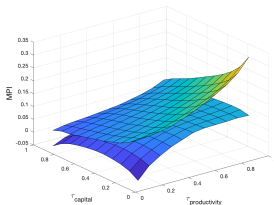
Persistent



Transitory



Canonical



*Note: 95% confidence bands from a nonparametric bootstrap with 500 replications.*

## More on estimation process [▶ Back](#)

Table: External parameters

Parameter		Value	Target/Source
Annual discount factor	$\beta$	0.95	Cooper & Haltiwanger (2006)
Annual depreciation	$\delta$	0.11	CBI (own calculations)
Capital share	$\alpha_k$	0.3*0.85	Span-of-control parameter 0.85
Labor share	$\alpha_l$	0.7*0.85	Labor share 70%

- ▶ Given these parameters, use minimization algorithm to minimize the sum of the square differences between data and model moments.
- ▶ Set hicks-neutral productivity term in each economy such that average firm size is constant across all of them.