

Ownership Networks, Financing and Firm Growth

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Motivation: Explaining Firm Growth/Firm Size Dynamics

Firm Growth and a simultaneous size and age dependence:

- Gibrat's Law (1931).
- Jovanovic (1982): learning and selection explain age effects.
- The literature finds negative relationships between size, age, and growth (Evans, 1987; Dunne et al., 1989).
- Hopenhayn (1992): persistent idiosyncratic productivity determines size.
- Haltiwanger et al. (2013): age, more than size, explains average growth.

Key limitation: These models do include possible financial considerations in firm growth

Motivation: Financial, Size, and Age Effects

Cooley and Quadrini (2001), and Cabral and Mata (2003) introduce financial variables:

- Simultaneous size and age dependence explained with productivity and financial heterogeneity

Huynh and Petrunia (2010) examine the empirical relationship between firm growth with firm size, firm age, and firm leverage:

- Firm size and age relationships remain
- Positive firm growth-leverage relationship

What about other financial variables? **Network ownership structure?**

Return to the question: "What about other financial variables?"

- Ownership Equity Networks
- Broader equity network $\Rightarrow$ broader access to financial resources
- Allen et al. (2022) ownership networks in China (SOEs a big part of the Chinese economy)

Caveat: Network benefits beyond financing

Network structures create implicit links among participants:

- Production—supply chain
- Technology sharing and Knowledge spillovers
- Social

Main Contributions

1. We extend the firm dynamics literature by including ownership networks as a structural determinant of growth:
 - Unlike Huynh et al. (2010) and Petrunia (2007), we consider financing sources beyond leverage.
 - We connect our proposal to recent studies such as Allen et al. (2022) for China.
 - Consider both within industry ownership networks and overall ownership network
2. We provide evidence for a context with minimal state presence:
 - Unlike China, Ecuador's manufacturing sector is predominantly private.
3. We use quantile regression with dynamic fixed effects:
 - Captures heterogeneity across the entire conditional growth distribution.
 - Addresses the bias from lagged variables in dynamic panels.
4. We combine accounting and capital data to reconstruct real networks:
 - We use public information on capital movements from Ecuador's Superintendence of Companies.

Data

Data Source: Ecuadorian Manufacturing Firms

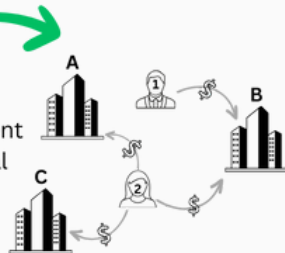
- Source: Ecuadorian Company Superintendence
- Time frame: 2009-2019

Firms

- Firm ID
- Established year
- Firm type
- Location
- ISIC code
- **Financial statements**

Owners

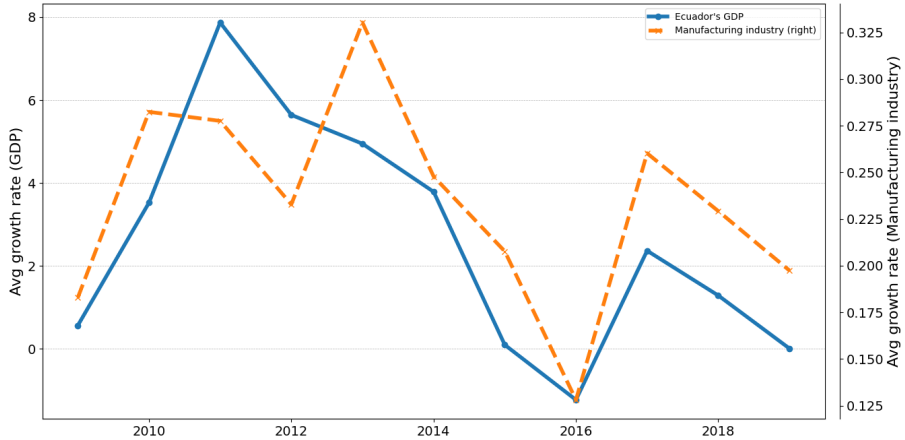
- National ID
- Full name
- Type of investment
- Amount of capital



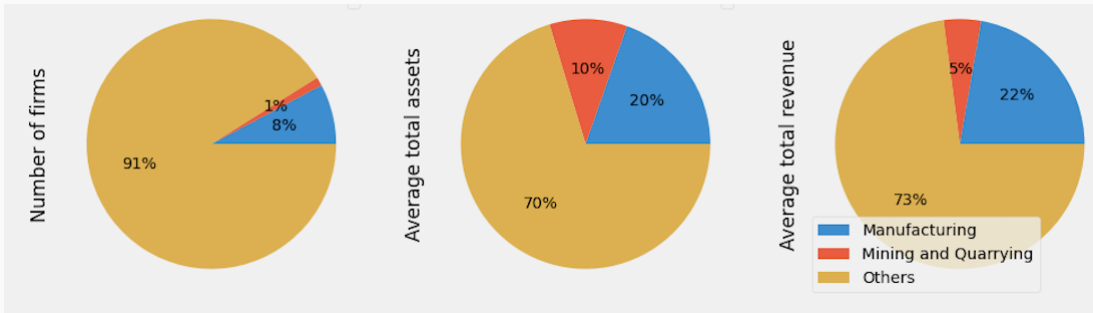
An ownership structure in which multiple firms share an owner or a group of owners

→ **Common-ownership network: Network of firms that share common owner(s)**

Trends in Average Growth Rates: GDP vs. Manufacturing Industry



Contribution of Manufacturing, Mining and Quarrying, and Other Industries



Older Firms Are Larger, Use Less Debt, and Grow More Slowly

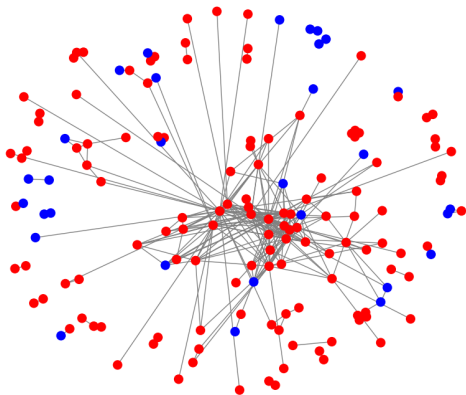


On Average, Highly Leveraged Firms Grow Faster

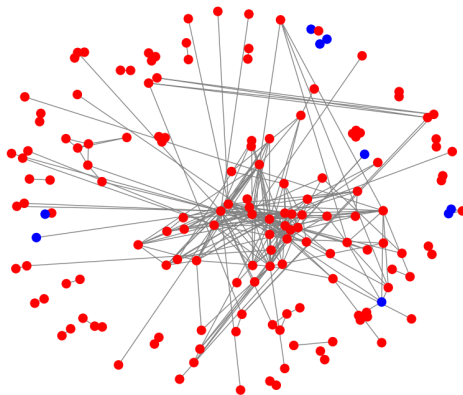


Firm Ownership Network

Network Graph for 2010

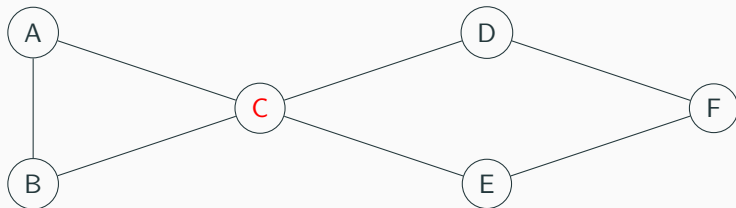


Network Graph for 2019



• Young (< 13 years) • Old (≥ 13 years)

Example of Degree and Cluster Coefficient



Degree of node C: 4

Clustering coefficient of C:

- Neighbors: A, B, D, E
- There are 6 possible links among its neighbors: AD, AE, BD, BE, DE, and AB (which already exists)
- The **clustering coefficient** for C is the ratio of existing to potential connections: $\frac{1}{6}$.

Descriptive statistics, $N = 29,004$

	Mean	SD	q25	Median	q75
Revenue (USD '000)	16154.93	57584.60	557.32	2208.72	9229.57
Sales Growth (%)	1.79	59.67	-10.79	3.51	17.59
Firm Age (years)	17.26	15.26	5.8	13.5	26.2
Leverage Ratio (%)	62.2	23.59	41.90	62.3	80.1
Public Indicator	0.06	0.25	0.00	0.00	0.00
Initial Assets (USD '000)	6425.36	26869.71	127.87	687.04	2833.38
In-degree	1.80	5.43	0.00	1.00	1.00
Total-degree	6.19	22.40	1.00	2.00	4.00
Clustering Coefficient	0.20	0.32	0.00	0.00	0.33

Empirical Strategy

Baseline Specification

- We follow the model of Huynh and Petrunia (2010) with some modifications:

$$\begin{aligned}\Delta \log(\text{Size}_{it}) = & \eta_i + \alpha \log(\text{Size}_{i,t-1}) + \delta_1 \log(\text{Age}_{it}) + \delta_2 \text{leverage}_{i,t-1} + \\ & \phi_1 [\log(\text{Age}_{it}) - c_a]^2 + \phi_2 [\log(\text{Age}_{it}) - c_a] \times [\text{leverage}_{i,t-1} - c_l] + \\ & \lambda_1 \log(\text{Assets}_{i0}) + \lambda_2 \log(\text{in-degree}_{it}) + \lambda_3 \log(\text{total-degree}_{it}) + \\ & \lambda_4 \text{Cluster}_{it} + \varepsilon_{it}\end{aligned}$$

- $\Delta \log(\text{Size})$: log change in sales.
- η_i : unobserved firm fixed effect.
- c_a, c_l : centering constants for selected variables.
- Degree and Cluster: network characteristics.
- Fixed effects are controlled at the subgraph level (695 in our sample).

Why Model Quantiles in Dynamic Panels?

In economics, many variables—such as growth or investment—exhibit:

- unobserved heterogeneity
- temporal dependenceand
- Asymmetric responses

Solutions: Dynamic Panel Data Quantile Regression

- The Dynamic panel model controls for unobserved firm-level heterogeneity, persistence, divergent paths, and cumulative effects.
- Quantile regression captures heterogeneous effects across the firm growth distribution, avoid restrictive assumptions of normality and homoskedasticity, and analyzes **divergent trajectories** across firms or individuals.

Problem: classical methods suffer from **bias in the presence of fixed effects**, especially when T is small.

Our empirical strategy is based on estimating the following fixed-effects quantile specification:

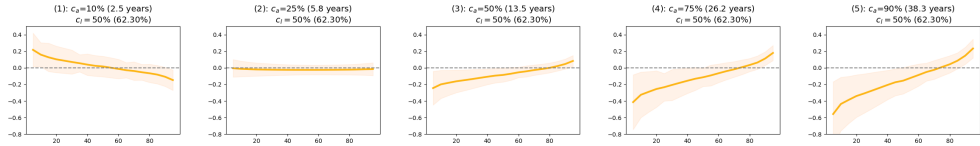
$$\begin{aligned} Q_{\Delta \log(\text{size}_{it})}(\tau \mid \cdot) = & \eta_i + \alpha(\tau) \log(\text{size}_{i,t-1}) + \delta_1(\tau) \log(\text{age}_{it}) + \delta_2(\tau) [\log(\text{age}_{it}) - c_a]^2 + \\ & \delta_3(\tau) \text{leverage}_{i,t-1} + \delta_4(\tau) \log(\text{assets}_{i0}) + \\ & \delta_5(\tau) [\log(\text{age}_{it}) - c_a] \times [\text{leverage}_{i,t-1} - c_l] + \\ & \lambda_1(\tau) \log(\text{in-degree}) + \lambda_2(\tau) \log(\text{total-degree}) + \lambda_3(\tau) \text{cluster} + \varepsilon_{it} \end{aligned}$$

- We combine the structural robustness of Galvão (2011) to address endogeneity with the computational efficiency of Machado–Santos Silva (2019) for robust quantile estimation.
 - **MMQREG** command
- This integration enables identification of heterogeneous causal effects in dynamic panel settings with time dependence, unobserved heterogeneity, and endogeneity.

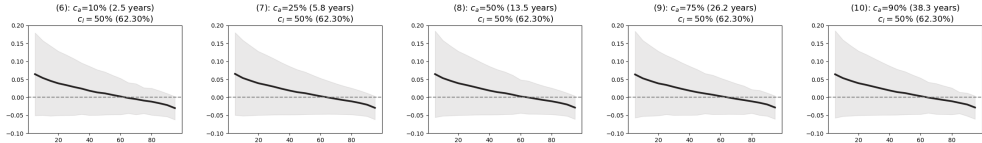
Results

Results: Age Effects

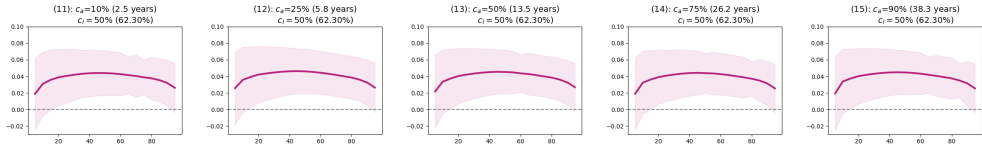
Quantile estimations for the coefficient of $\log(\text{age})$: σ_1



Quantile estimations for the coefficient of $\log(\text{in} - \text{degree})$: λ_1

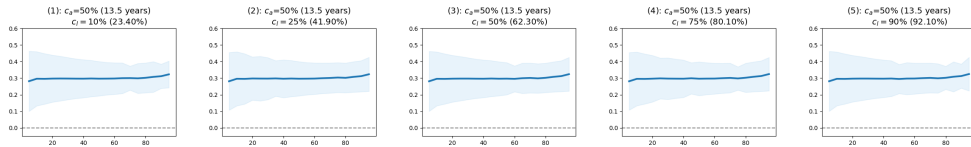


Quantile estimations for the coefficient of $\log(\text{totaldegree})$: λ_2

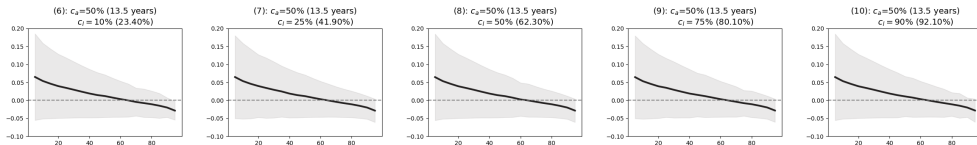


Results: Leverage Effects

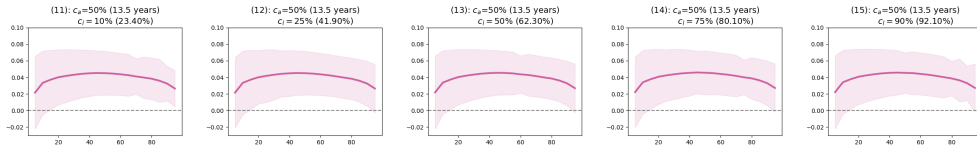
Quantile estimations for the coefficient of leverage: σ_3



Quantile estimations for the coefficient of $\log(\text{in} - \text{degree})$: λ_1



Quantile estimations for the coefficient of $\log(\text{totaldegree})$: λ_2



Main Findings: Ownership Networks and Firm Growth

- **Heterogeneous Age Effects:**

- No significant relationship between age and growth for young firms (bottom quartile of age distribution).
- For older firms (upper quartile of age distribution), increasing age widens the firm growth distribution, with a notably negative impact on growth at the lower end.

- **Firm Growth and Leverage:**

- Positive relationship between firm growth and leverage persists with ownership network variables included.
- The relationship becomes slightly more positive in the upper part of the firm growth distribution.

- **Network Effects:**

- Significant positive relationship between the number of ownership connections and firm growth.
- No significant relationship between network clustering and firm growth.

- **Extension of Firm Dynamics Literature:**

- Incorporates ownership networks into the study of firm finance-growth relationship.
- Contrasts with existing studies that focus on leverage only.

- **Quantile Regression Methodology:**

- Provides a broader empirical perspective by examining heterogeneous impacts across the entire firm growth distribution.
- Controls for firm fixed effects and addresses lagged dependent variable issues.

- **Developing Economies Context:**

- Highlights the relevance of ownership networks in Ecuadorian manufacturing firms, contrasting with findings from economies with substantial state-owned enterprises.

Thank you!

Estimation Procedure Steps

- For a given quantile τ , define the objective function:

$$R_{\tau}(\eta_i, \alpha, \xi, \gamma) = \sum_{i=1}^N \sum_{t=1}^T v \rho_{\tau} \left(\Delta \log(\text{size}_{it}) - \alpha(\tau) \log(\text{size}_{i,t-1}) - \eta_i \right. \\ \left. - X'_{it} \beta(\tau) - \gamma(\tau) \log(\text{size}_{i,t-2}) \right)$$

Where $X'_{it} \beta(\tau)$ includes the other regressors, $\log(\text{size}_{i,t-2})$ is the instrumental variable, $\rho(\tau) = u(\tau - I(u < 0))$ is the check loss function (Koenker and Bassett, 1987), and v denotes weights that control the influence of quantile τ on η_i estimates.

- Define a grid of values $\{\alpha_j, j = 1, 2, \dots, J; |\alpha| < 1\}$.

Estimation Procedure Steps (cont.)

- For the chosen τ , run the quantile panel regression of $(\Delta \log(\text{size}_{it}) - \alpha(\tau) \log(\text{size}_{i,t-1}))$ on $(X_{it}, \log(\text{size}_{i,t-2}))$ for each value α_j (Machado and Santos Silva, 2019):

$$\left(\hat{\eta}_i(\alpha_j, \tau), \hat{\beta}(\alpha_j, \tau), \hat{\gamma}(\alpha_j, \tau) \right) = \min_{\eta_i, \beta, \gamma} R_{\tau}(\eta_i, \alpha_j, \beta, \gamma)$$

- Choose $\hat{\alpha}$ as the value that minimizes $\|\hat{\gamma}(\alpha_j, \tau)\|$, i.e., the coefficient on the instrument tends to zero (Chernozhukov and Hansen; 2006, 2008).
- The selection of $\hat{\beta}$ for a given quantile τ yields the corresponding estimates of $\hat{\beta}(\alpha_j, \tau)$.

This five-step procedure is repeated for each value of τ .

How to Detect if the Instrument is Weak? OPTIONAL

Context: Quantile regression for dynamic panel data (Galvão, 2011)

- **Instrument:** second lag of the log of size:

$\log(\text{size}_{i,t-2})$ (following Chernozhukov and Hansen, 2006, 2008)

- **Evaluation procedure:**

- Define a grid of possible α values: $\{\alpha_j\}$
- Estimate the quantile model for each α_j , obtaining $\hat{\gamma}(\alpha_j)$
- Select $\hat{\alpha}$ such that $\|\hat{\gamma}(\alpha_j)\|$ is **minimized**

- **Practical criterion:**

- If $\hat{\gamma}(\alpha_j)$ is close to zero only for one α_j , the instrument is **strong**.
- If it is close to zero for many, the instrument may be **weak**.

- **Note:** no F-statistic is used, as in traditional IV.

Weak instruments? Robust Check

