Market power and TFP growth in Chile

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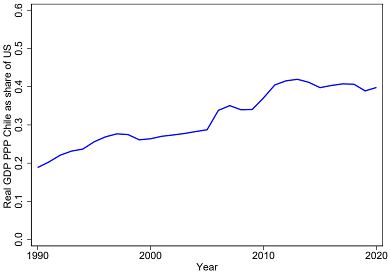
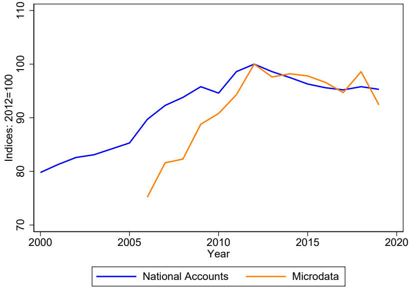
Motivation

Real GDP per capita in PPP:
Chile as a share of the US



Traditional TFP measures



Main Research question: Why TFP Growth in Chile has stagnated for the last decade?

Preview

What this paper do:

(a) Estimates firm-level market power for 2005-2020 using rich administrative micro-data from tax records.
  - Using data on prices and quantities at the firm level.

(b) Performs a growth accounting computation in presence of firm-level market power.

(c) Describes firm-level distortions spread out through production networks driving macroeconomic inefficiencies.

Key takeaway : Markups affected Chilean aggregated allocative efficiency by distorting factor allocations. The latter might account for a portion of Chile's TFP growth stagnation for the last decade.

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1. Methods
   - Market power measure
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Markup: Production Approach, DLW, 2012 (1)

- Cost minimization of firm i given its technology (Q_{it}), capital stock (K_{it}) and variable inputs (V_{it})

- Lagrangian:

$$\mathcal{L}(V_{it}, K_{it}, \lambda_{it}) = \sum_{V} P_{it}^{V} V_{it} + r_{it} K_{it} + \lambda_{it}(\bar{Q}_{it} - Q_{it}(V_{it}, K_{it}))$$

- FOC with respect to variable input V:

$$\frac{\partial \mathcal{L}}{\partial V_{it}} = P_{it}^{V} - \lambda_{it} \frac{\partial Q(.)}{\partial V_{it}} = 0$$

- Rearranging and multiplying by $\frac{V_{it}}{Q_{it}}$:

$$\frac{\partial Q(.)}{\partial V_{it}} \frac{V_{it}}{Q_{it}} = \frac{1}{\lambda_{it}} \frac{P_{it}^{V} V_{it}}{Q_{it}}$$

Markup: Production Approach, DLW, 2012 (2)

Markup: price to marginal cost ratio ($\mu = \frac{P}{MC}$ with $MC = \lambda$)

$$\frac{P_{it}}{\lambda_{it}} = \underbrace{\frac{\partial Q(.)}{\partial V_{it}} \frac{V_{it}}{Q_{it}}}_{\theta_{it}^{V}} \underbrace{\frac{P_{it} Q_{it}}{P_{it}^{V} V_{it}}}_{1/s_{it}^{V}}$$

$$\mu_{it} = \frac{\theta_{it}^{V}}{s_{it}^{V}}$$

Markup relies on two objects:

- Variable input share (s_{it}^{V}): Usually observed in the data
- Output elasticity of variable input (θ_{it}^{V}): Need to estimate it, this is the key challenge!

Aggregation: Setup (BF, 2020) Cost function

Firm i produces according to the following cost function:

$$\frac{1}{A_i}\mathbf{C}_i\left[p_1, \ldots, p_N, w_1, \ldots, w_F\right] y_i$$

- A_i: Hicks-neutral productivity.
- y_i: Firm i total output.
- The price includes a markup measure: $p_i = \mu_i \frac{C_i}{A_i}$
- μ_i: Firm i markup.

Aggregation: Setup (BF, 2020) Input-output objects (1)

Revenue-based input-output matrix. ij^{th} element is the expenditure of firm i on inputs from firm j as a share of firm i total revenue:

$$\Omega_{ij} \equiv \frac{p_j x_{ij}}{p_i y_i} \tag{1}$$

Cost-based input-output matrix. Captures the change in the marginal cost function of firm i (C_i) when the price of firm j changes. Using Sheppard's Lemma is possible to express it as the expenditure of firm i on inputs from firm j as a share of firm i total costs:

$$\tilde{\Omega}_{ij} \equiv \frac{\partial \log \mathbf{C}_i}{\partial \log p_j} = \frac{p_j x_{ij}}{\sum_{k=1}^{M} p_k x_{ik}} \tag{2}$$

Both are related by **markup harmonic mean matrix**.

$$\tilde{\Omega} = \text{diag}(\mu)\Omega \tag{3}$$

diag(μ) is a Diagonal matrix with ii^{th} element: $\frac{\#\text{firms}}{\sum_t (\mu_{it})^{-1}}$

Aggregation: Setup (BF, 2020) Input-output objects (2)

Leontief inverse matrix capture both the direct and indirect firm exposures through the production networks:

$$\tilde{\Psi} \equiv (I - \tilde{\Omega})^{-1} = I + \tilde{\Omega} + \tilde{\Omega}^2 + \dots \tag{4}$$

Defining **sales shares**

$$b_{it} = \frac{p_{it} c_{it}}{\sum_{j=1}^{N} p_{jt} c_{jt}} \tag{5}$$

To form the **cost-based Domar Weight**; suppliers' relevance in final goods demand, both directly and through production networks.

$$\tilde{\Lambda}' \equiv b' \tilde{\Psi} \tag{6}$$

Aggregation: Setup (BF, 2020) Growth accounting (1)

A shock to supply factor f is described by the cost-based share of that factor minus the sum over all other factors g changes due to the shock to f:

$$\frac{d \log Y}{d \log L_f} = \tilde{\Lambda}_f - \sum_g \tilde{\Lambda}_g \frac{d \log \Lambda_g}{d \log L_f} \tag{7}$$

$\Longrightarrow$ the traditional Solow residual is inconsistent when aggregating shocks considering changes to indirectly affected factors

Aggregation: Setup (BF, 2020) Growth accounting (2)

TFP decomposition:

$$\underbrace{\Delta \log Y_t - \tilde{\Lambda}'_{t-1}(\Delta \log L_t + \Delta \log K_t)}_{\Delta \text{ Distorted Solow Residual}}$$
$$\approx \underbrace{\tilde{\Lambda}'_{t-1}\Delta \log A_t}_{\Delta \text{ Technology}} - \underbrace{\tilde{\Lambda}'_{t-1}\Delta \log \mu_t - \tilde{\Lambda}'_{t-1}(\Delta \log Sh^K_t + \Delta \log Sh^L_t)}_{\Delta \text{ Allocative Efficiency}}$$

This distortion-adjusted Solow residual weighs factor changes by the cost-based Domar weight ($\tilde{\Lambda}$) rather than by its share in aggregate income.

Key object: $\tilde{\Lambda}$: Cost-based Domar weight represents suppliers' relevance directly and through the production network in final goods demand.

Data Sources

1. Sales, materials, investment: F29 (2005-2019)
2. Wage bill, employment: DJ1887 (2005-2019)
3. Initial capital stock: F22 (2005-2019)
   - Capital stock using perpetual inventory methods combining capital stock with investment.
4. I-O matrices: Buying and selling books (forms 3327-3328) (2005-2014)
   - Firm-year level output and input flows.
5. Output and input prices: F2F electronic receipts (2015-2019)
   - Firm-year level output and input prices weighted by F2F transaction flows.

Data Cleaning

- Final sample does not include firms with a missing variable of sales, capital, wage bill, or materials.
- Winzorized labor, capital and materials shares over sales at 1% of both tails of the distribution.
- Firms with negative value added (sales minus materials), less than two workers, or capital less than 10.000 CLP (USD 15) are excluded.

Around 120,000 firms a year in the final sample.

Using prices to recover quantities sold.

Challenge: Different units for the same product; units are not reported.

$\implies$ Build a firm-level weighted price index:

$$\ln(Q_{it}) \approx \ln(\underbrace{P_{it}Q_{it}}_{\text{data}}) - \ln(\underbrace{I_{it}}_{\text{data}})$$

Where:

- $I_{it} = \sum_{j}^{J} \alpha_{ijt} P_{ijt}$
- α_{ijt}: share of product j in firm i total revenue.

Homologous procedure for intermediate inputs.

Markup: Estimation decisions

Benchmark estimation:

- Second order translog production function using three factors (K, L, M).
- Estimation performed separately by six industries.
- Control for output and input prices using F2F electronic receipts.
- Materials is the variable input assumed.
- βs are time-invariant while materials-output elasticities are time-varying due to yearly factors usage interactions.

Markup: Estimation Production function functional form

$$
\begin{aligned}
q_{it} = {} & \omega_{it} + \beta_l \ l_{it} + \beta_k \ k_{it} + \beta_m \ m_{it} + \beta_{lk} \ l_{it} \ k_{it} + \beta_{lm} \ l_{it} \ m_{it} \\
& + \beta_{mk} \ m_{it} \ k_{it} + \beta_{ll} \ l_{it}^2 + \beta_{kk} \ k_{it}^2 + \beta_{mm} \ m_{it}^2 + \beta_{lkm} \ l_{it} \ k_{it} \ m_{it} + \epsilon_{it}
\end{aligned}
$$

Intermediate inputs are assumed to be the variable input in production, and thus the markup estimation is performed using materials output elasticity and its share.

$$
\theta_{it}^M = \frac{\partial q_{it}}{\partial m_{it}} = \beta_m + \beta_{lm} \ l_{it} + \beta_{mk} \ k_{it} + 2\beta_{mm} \ m_{it} + \beta_{lkm} \ l_{it} \ k_{it}
$$

$$
\mu_{it} = \frac{\theta_{it}^M}{s_{it}^M}
$$

Markup: Estimation Problems (1)

Methodology: Ackerberg, Caves, & Frazer (Econometrica, 2015).
Details

The main challenge is correctly estimating the variable input-output elasticity θ_{it}^{M}. As Dorazselski & Jaumandreu (2021) noted, the critical assumption used in OP, LP, and ACF is that the choice of materials is a function of only capital, labor, and productivity (scalar unobservable assumption). Ignoring any possible demand-driven shock given the timing of firms' production decisions.

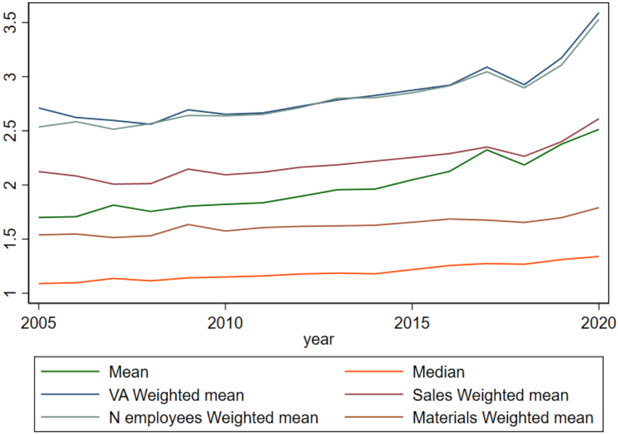
This is a troublesome assumption in non-perfect competitive setups as the demand for production inputs might also depend on other firms' productivities.

Markup: Estimation Problems (2)

The data used in this work allows controlling for transaction levels prices (goods sold and inputs bought by any firm), preventing prices from being inside the residual when estimating materials markups (rather than labor markups).

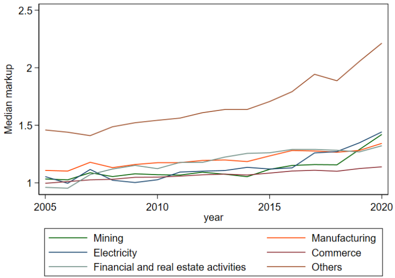
The latter does not solve the scalar unobservable assumption violation but alleviates any bias coming from the prices of goods sold and inputs bought by firms.

Markup: Time evolution

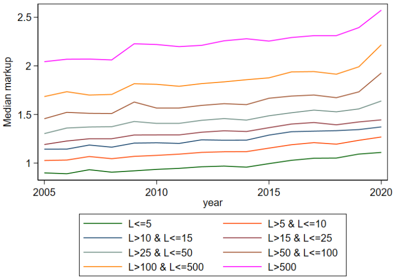


Markup: Heteronegeity in industry/firm size

Industry

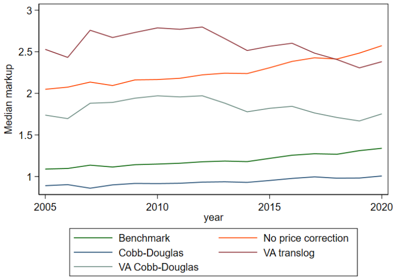


Size

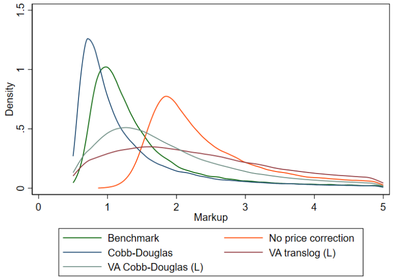


Markup: different estimation strategies

Time series

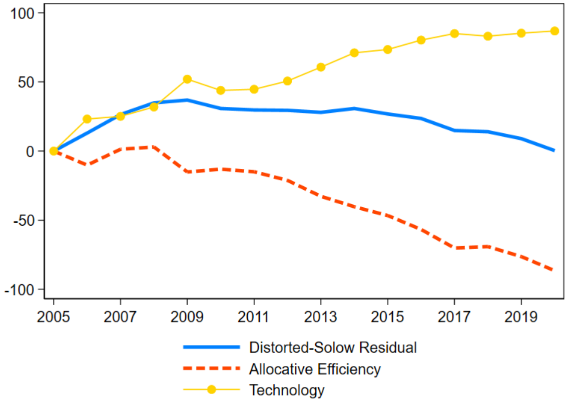


Distribution



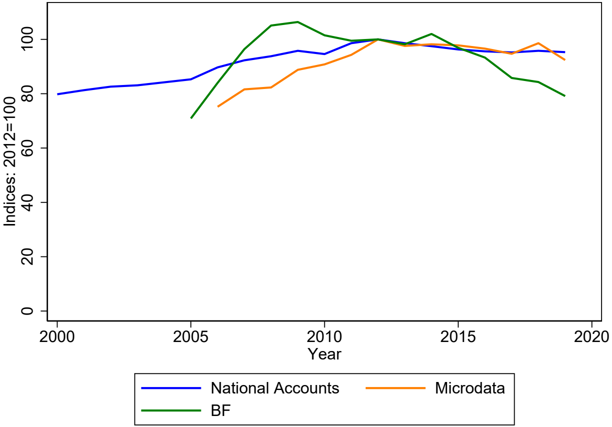
Aggregation: Distorted Solow residual decomposition

Percentage growth relative to 2005 levels CD markups



$$\underbrace{\Delta \log Y_t - \tilde{\Lambda}'_{t-1}(\Delta \log L_t + \Delta \log K_t)}_{\Delta \text{ Distorted Solow Residual}} \approx \underbrace{\tilde{\Lambda}'_{t-1}\Delta \log A_t}_{\Delta \text{ Technology}} - \underbrace{\tilde{\Lambda}'_{t-1}\Delta \log \mu_t - \tilde{\Lambda}'_{t-1}(\Delta \log Sh^K_t + \Delta \log Sh^L_t)}_{\Delta \text{ Allocative Efficiency}}$$

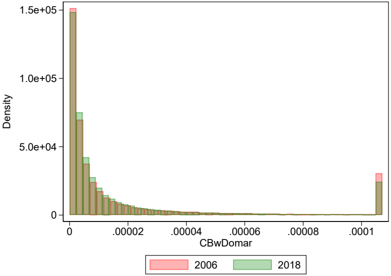
Aggregation: Comparing TPFs



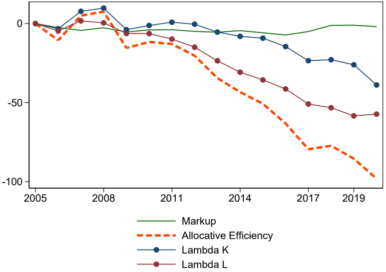
Aggregation: Decomposing the allocative efficiency (1)

$$\underbrace{\Delta \log Y_t - \tilde{\Lambda}'_{t-1}(\Delta \log L_t + \Delta \log K_t)}_{\Delta \text{ Distorted Solow Residual}} \approx \underbrace{\tilde{\Lambda}'_{t-1}\Delta \log A_t}_{\Delta \text{ Technology}} - \underbrace{\tilde{\Lambda}'_{t-1}\Delta \log \mu_t - \tilde{\Lambda}'_{t-1}(\Delta \log Sh_t^K + \Delta \log Sh_t^L)}_{\Delta \text{ Allocative Efficiency}}$$

Cost-based Domar W.



Markups and factor shares

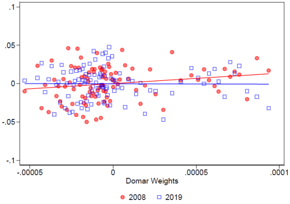


$\Longrightarrow$ Flat markups, decreasing Labor and Capital shares.

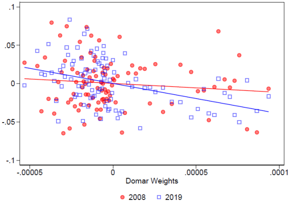
Aggregation: Decomposing the allocative efficiency (2)

By industry

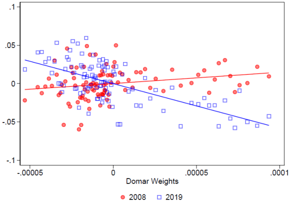
Δ log allocative efficiency components and $\tilde{\Lambda}$ 2008 vs 2019



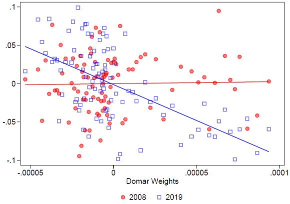
(a) Markups



(b) Capital Share



(c) Labor Share

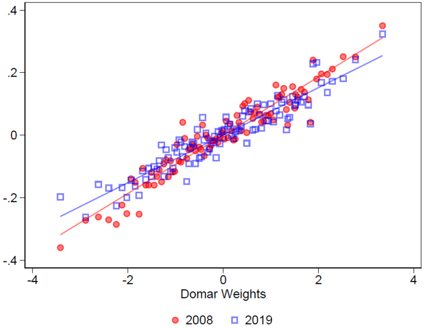


(d) Labor + Capital Shares

What is driving the result? Central firms (1)

Why is markup evolution flat, but aggregate Labor and Capital Share decreases over time?

Log Markup and Log $\tilde{\Lambda}$

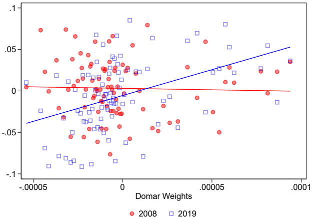


Central firms (high $\tilde{\Lambda}$) have relatively high markups over the period.

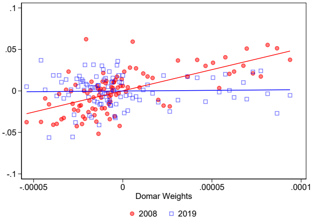
$\Longrightarrow$ Have relatively high MRPK and MRP.

$\Longrightarrow$ Hire fewer factors with respect to a competitive setup.

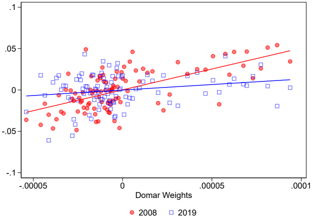
What is driving the result? Central firms (2)



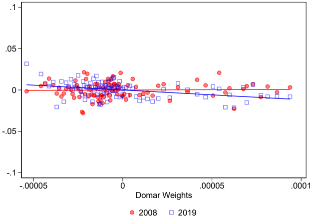
a) Increasing Value Added



b) Decreasing wagebil



c) Decreasing Labor



d) Flat Wages

What is driving the result? Rationalization

- Central firms (high cost-based Domar Weight) have flat and relatively high markups over the period.
- These firms increase their value-added, decrease their wage bill and labor usage, and have not changed the average wages paid.

$\Longrightarrow$ Central firms are charging higher Markdwowns ($MRPL/W_L$)

Wrapping up

- Technological improvements are not generating a boost in aggregate TFP growth due to inefficient factor allocations.
- Key to understanding distorted factor allocations is to precisely estimate markups by considering sales and materials prices.

Still, I need to estimate firm levels Mardonws (work in progress) to describe the specific channel through which firm-level markups spread out through production networks generating aggregate productivity losses.

Thanks

Thanks!

Appendix

Markup: Estimation (1)

Assumptions following Ackerberg, Caves & Frazier (ACF, 2015):

- A general production function with x_{it} being all production function inputs and interactions and ω_{it} the hicks-neutral firm productivity:

$$q_{it} = f(x_{it}; \beta) + \omega_{it} + \epsilon_{it}$$

- First order Markov process for productivity with innovation to productivity:

$$\omega_{it} = \omega_{it-1} + \varphi_{it}$$

- Moment conditions relying on instruments Z_{it}:

$$\mathbb{E}[Z_{it}\ \varphi_{it}(\beta)] = 0$$

Go back

Markup: Estimation (2)

(a) Estimate the production function to get rid of measurement error: $q_{it} = q^*_{it} + \epsilon_{it}$

(b)
- First recover productivity as: $\omega_{it}(\beta) = q^*_{it} - x'_{it}\beta$
- Then recover innovations to productivity (φ_{it}) by solving: $\varphi_{it}(\beta) = \omega_{it}(\beta) - \mathbb{E}[\omega_{it}(\beta)|\omega_{it-1}(\beta)]$
- Use the productivity innovations to form moments and, by GMM, estimate the production function parameters (β)
- Use β to form the desired output elasticity of variable input

I will not dig deeper into Dorazselski's critique: Choice of materials is a function of only capital, labor, and productivity (scalar unobservable assumption) does not necessarily hold.

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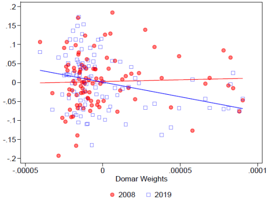
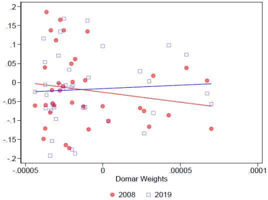
Aggregation: Decomposing the allocative efficiency (3)

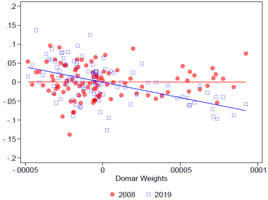
Δ log Labor share and $\tilde{\Lambda}$



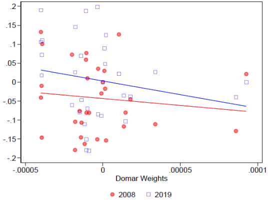
(a) Agriculture



(b) Mining



(c) Manufacturing



(d) Utilities

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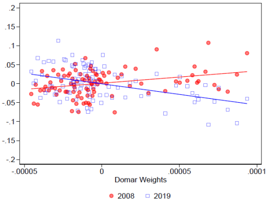
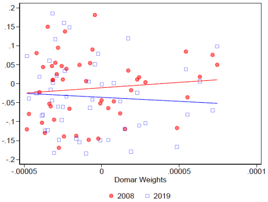
Aggregation: Decomposing the allocative efficiency (4)

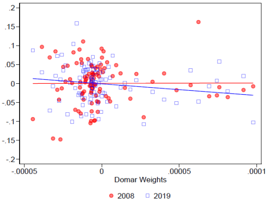
Δ log Labor share and $\tilde{\Lambda}$



(e) Commerce



(f) Financial & Real Estate



(g) Others

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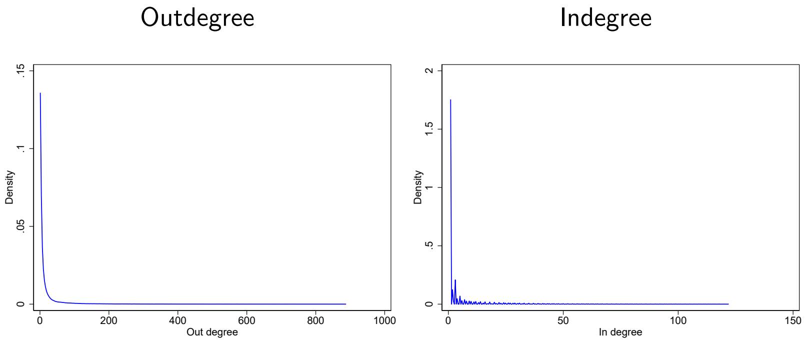
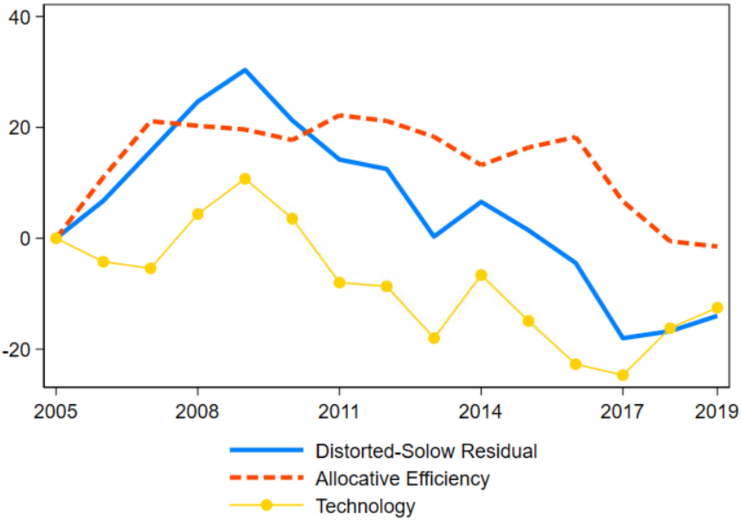
Production Newtork: Descriptive stats

- Outdegree (N clients): Mean: 64.5; Median: 5; Standard deviation: 1,216
- Indegree (N providers): Mean: 9.6; Median: 1; Standard deviation: 36

Figure: Densities



Distorted TFP using CD markup estimation



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