Interconnectedness and Banking Performance: Insights from the Interbank Lending Market in Chile

Luis Chancí
Universidad Santo Tomás, Chile

Subal C. Kumbhakar
Binghamton University, USA

Paulo Bobadilla
CMF, Chile

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Motivation

- Interbank networks are essential for liquidity management, payment settlements, and risk diversification.

  Their critical role gained prominence after the 2007–2009 GFC (‘too-connected-to-fail’).

- Extensive literature has primarily focused on financial contagion and systemic risk, especially during crises.

  E.g., networks as shock propagation channels (Jackson & Pernoud, 2021; Acemoglu et al., 2015). But how about their role in other crucial outcomes, such as operational performance, during stable times?

- Networks potentially shape bank behavior through peer effects, herding, and benchmarking.

  E.g., the theory by Scharfstein & Stein, (1990) or empirical evidence in Margaretic et al. (2021)

In this paper

We investigate:

How does interconnectedness, as defined by interbank lending network structures, influence the operational cost efficiency of banks?

- We model interconnectedness using a **network autoregressive model** on the error term of a cost function.
  This captures how one bank's cost inefficiency relates to the performance of its network peers.
- We measure banking performance using **Stochastic Frontier Analysis (SFA)**.
  This allows us to estimate bank-specific cost technical efficiency scores.
- We use a rich administrative dataset from Chile and a novel **two-step GMM-SFA approach**, controlling for fixed effects and network dependence.

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- We use a rich administrative dataset from Chile and a novel **two-step GMM-SFA approach**, controlling for fixed effects and network dependence.

Why should we care? (our contributions)

- Banking networks may influence both stability and performance.
  We provide novel empirical evidence on how interbank networks affect operational **performance**, moving beyond the focus on systemic risk.

- Policy Implications.
  Our findings suggest that network structures are not just about risk, but also about the fundamental **operational health and efficiency** of the banking sector.

- Methodological Application.
  We apply an innovative GMM-SFA framework to a **multi-output banking cost function** with a **time-varying network structure** based on actual transaction data, not proxies.

What do we find? (Preliminary results based on a 2016-2017 sample)

Two main takeaways:

1. Interconnectedness is associated with an **improvement** in banks' cost efficiency in the Chilean case.
   - The estimated network dependence parameter is negative and significant.
   - For the median bank, network interactions reduce cost inefficiency by approximately **35%** relative to its own idiosyncratic component.

   This result is consistent with competitive pressures and benchmarking mechanisms.

2. Understanding network dynamics is crucial for policies aiming for an efficient and stable banking system.

Related literature

Main strands of literature:

- We build on an extensive literature highlighting **the importance of network connectedness in the banking sector**. (e.g., Acemoglu et al. 2015; Elliot et al. 2014; Glasserman & Young 2016). We shift the focus from risk to operational performance.

- Our work adds to the scarce literature on **peer effects and herding in banking** (e.g., Scharfstein and Stein, 1990; Margaretic et al., 2021; Gangopadhyay and Nilakantan, 2021). We quantify outcomes beyond behavioral contagion.

- Our approach contribute to **recent GMM-SFA methods incorporating network or spatial dependence** (e.g., Kutlu et. al. 2020; Tran and Tsionas 2023; Hou et al. 2023; Chanci et al. 2024; Silva et al. 2018). We extend this framework to a multi-output cost function with time-fixed effects.

Econometric Specification

- Canonical Translog Stochastic Cost Function (e.g., Mamonov et al., 2024):

$$\ln(\text{Cost}_{it}) = \alpha_t + \textit{Translog}(\text{outputs}_{it}, \text{input prices}_{it}, \text{quasifixed inputs}_{it}; \beta) + \varepsilon_{it}$$

where the composite error term is $\varepsilon_{it} = v_{it} + u_{it}$, with $u_{it} \geq 0$ representing **cost inefficiency**.

- We then introduce network dependence directly into the error structure (Hou et al. 2023):

$$\varepsilon_t = \rho \boldsymbol{W_t} \varepsilon_t + \dot{\varepsilon}_t \qquad \text{where} \qquad \dot{\varepsilon}_t = \dot{\boldsymbol{v}}_t + \dot{\boldsymbol{u}}_t$$

ρ is the key parameter capturing average network dependence; $\boldsymbol{W_t}$ is the adjacency matrix of interbank linkages; $\dot{\boldsymbol{u}}_t$ is the underlying network-independent inefficiency (half-normal); and $\dot{\boldsymbol{v}}_{it}$ is idiosyncratic noise (normal).

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Estimation Strategy

While ML estimation is possible, it is computationally challenging with our model structure:

- The likelihood function becomes complex with network dependencies ($I - \rho W_t$).
- High-dimensionality from the time-varying weights (W_t) and fixed effects, adding significant burden.

We employ an alternative **two-step GMM estimation strategy** (inspired by Hou et al. 2023, Chanci et al. 2024):

1. **First Step:** Estimate Translog parameters (β) via within-time transformation (OLS, minimal assumptions).

2. **Second Step:** Use the residuals from Step 1 to construct moment conditions from the variance-covariance structure of the errors. These moments are used to estimate the network and variance parameters ($\rho, \sigma_v^2, \sigma_u^2$) via GMM.

(more details)

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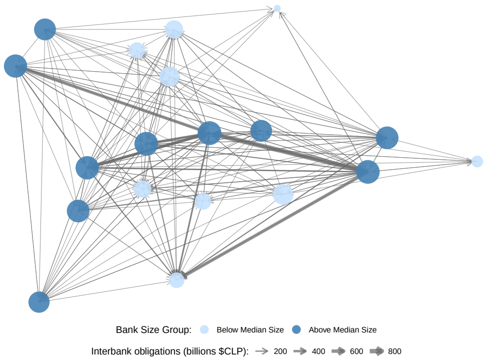
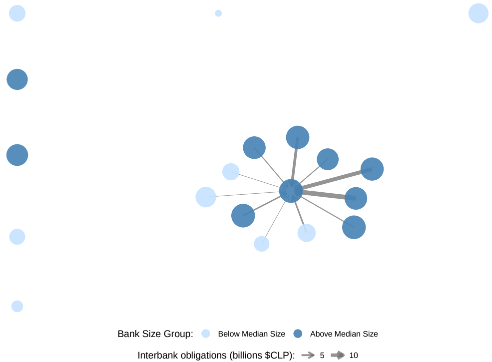
Data

We use a unique, confidential administrative dataset from the Chilean **CMF** (2008-2020).

1. **Network of Interbank Obligations (Form C-18).**
   We construct the time-varying, row-normalized weights matrix $\boldsymbol{W_t}$ using detailed daily bilateral obligations, exploring variations across financial instruments and maturities, as illustrated in the following network plots.



(a) Total Obligations



(b) Short-term Derivatives Only

Data (cont.)

2. **Bank Balance Sheets (Form MB-2).**

We use monthly data, from Form MB-2 (assets, liabilities, costs, etc. for each bank) to define the variables for the stochastic cost function (e.g., Mamonov et al. 2024; Malikov et al. 2015).

Variable	**Description**
Outputs (y)	
y_1	Commercial loans
y_2	Real estate loans (Mortgages)
y_3	Consumer loans
y_4	Securities and other investments
Inputs Prices (p)	
p_1	Labor price
p_2	Physical capital price
p_3	Price of funds
Quasi-fixed Input (z)	
z_1	Equity capital
Cost Variable (C)	Total variable operating cost

Core Result: Interbank connections are associated with improved cost efficiency

	Baseline Model
	Based on Total Obligations
Panel A. Interconnectedness parameter	
$\boldsymbol{\rho}$	**-0.542** ***
	(0.112)
Panel B. Cost frontier main parameters	
$\sigma_{\dot{\nu}}$	0.102 ***
	(0.011)
$\sigma_{\dot{u}}$	0.013 ***
	(0.005)
Controls in the Translog Cost Function	Yes
Time fixed effects	Yes
Observations	418

Notes: 1. The table reports the central results using total obligations. 2. The ‘Controls in the Translog Cost Function‘ row includes full second-order and interaction terms. 3. Data: Chilean banking system, 2016m1–2017m12. 3. Standard errors (in parentheses) computed via wild bootstrap. 4. *** significant at 1%; ** 5%; * 10%.

Post-Estimation Calculations

We next use the estimates to provide quantitative insights into how interbank relationships influence bank operational performance (inefficiency).

- First: We compute efficiency estimates.
  As benchmark, we explore whether, despite the econometric modification, basic results are comparable with previous findings (e.g., Cobas et al. 2024).

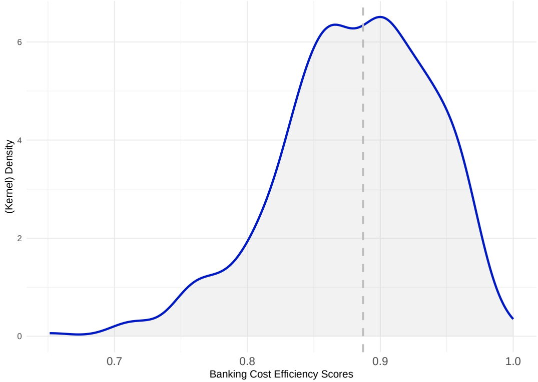
- Second: We assess the importance of those network effects.
  Our approach allows us to decompose total cost inefficiency for each bank into two terms:

$$\text{Total Inefficiency}_{it} = \text{Direct (Idiosyncratic) Effect}_{it} + \text{Indirect (Network) Effect}_{it}$$

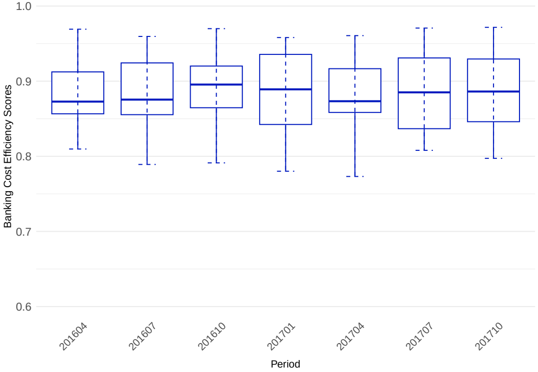
(more details)

First, Technical Efficiency: T.E. Scores are about 90%

Results for technical efficiency are comparable to those previously reported by other researchers



(a) Kernel of the banking efficiency scores

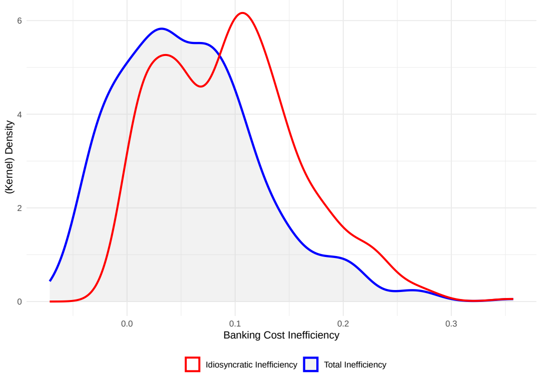


(b) Temporal Evolution of Efficiency Scores

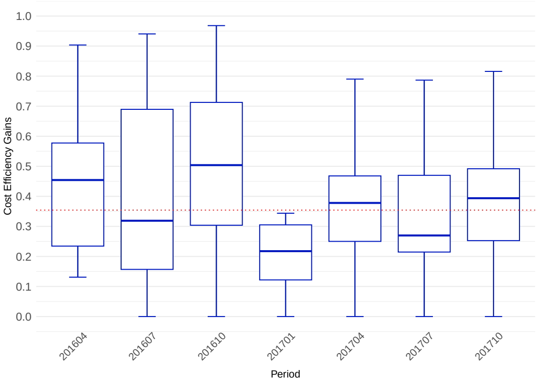
Notes: The figure has two panels and presents the Distribution and Temporal Evolution of Bank Technical Efficiency Scores (2016m01–2017m12). Panel (a) displays the kernel density estimate of technical efficiency scores pooled across all banks and months in the sample period. Panel (b) presents a time series of monthly boxplots, illustrating the distribution of these scores for selected months. Technical efficiency scores (TE_{it}) are calculated as the exponential of the

Second, Quantifying the Network's Impact:"Efficiency Gains"

$\text{Total Inefficiency}_{it} = \text{Direct (Idiosyncratic) Effect}_{it} + \text{Indirect (Network) Effect}_{it}$



(a) Kernels: Idiosyncratic vs. Network Cost Ineff.



(b) Evolution of Network-Driven Efficiency Gains

Notes: The figure has two panels. Panel (a) displays two kernel density plots. The Direct or Idiosyncratic component of cost inefficiency (red line) and the Total component (blue line). Panel (b) presents a time series of monthly boxplots, illustrating the distribution of Efficiency Gains for selected months. Efficiency Gains are calculated as $(1 - \text{Total Inefficiency}_{it}/\text{Direct Effect}_{it})$. The horizontal dashed red line indicates the overall mean value of these gains across the sample period.

Robustness Checks and Potential Channels

1. Robustness via alternative definitions of network matrices:
   - Maturities (overnight, short-term, long-term)
     Strongest effects observed for longer-term obligations.
   - Financial instruments (derivatives, unsecured loans, term deposits)
     Clear efficiency impacts found with derivatives and unsecured exposures.

2. Potential channels (ongoing research):
   - Current results align with banks facing **competitive pressures** or engaging in **negative benchmarking**—improving efficiency by learning from peers' mistakes.
   - Additionally, we explore alternative network specifications (directionality from borrower-to-lender versus lender-to-borrower and alternative normalization methods).

Robustness Checks 1: Network Definition by Maturity

Strong effects for longer-term relationships (Suggests immediate liquidity management is not the primary channel)

Obligations	**Overnight/ at sight**	**Up to one year**	**More than one year**	**All Obligations (Baseline)**
Panel A. Interconnectedness parameter				
$\boldsymbol{\rho}$	**0.009**	**-0.455*****	**-0.295*****	**-0.542*****
	(0.064)	(0.115)	(0.068)	(0.112)
Panel B. Cost frontier main parameters				
$\sigma_{\dot{\nu}}$	0.110***	0.101***	0.107***	0.102***
	(0.004)	(0.005)	(0.008)	(0.011)
$\sigma_{\dot{u}}$	0.016***	0.022***	0.019***	0.013***
	(0.005)	(0.005)	(0.004)	(0.005)
Controls in the Translog Cost Function	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Observations	418	418	418	418

Notes: The 'Controls in the Translog Cost Function' row indicates the inclusion of all first-order, second-order, and interaction terms for outputs, input prices, and quasi-fixed inputs as specified in the translog cost function $TL(\boldsymbol{y}_{it}, \boldsymbol{p}_{it}, \boldsymbol{z}_{it}; \boldsymbol{\beta}^*)$. Standard errors (in parentheses) computed via wild bootstrap. *** significant at 1%; ** 5%; * 10%.

Robustness Checks 2: Network Definition by Instrument Type

	Derivatives Only	Unsecured Exposures	Term Deposits	All Obligations (Baseline)
Panel A. Interconnectedness parameter				
ρ	**-0.360*****	**-0.540*****	**-0.372*****	**-0.542*****
	(0.064)	(0.111)	(0.117)	(0.112)
Panel B. Cost frontier main parameters				
$\sigma_{\dot{\nu}}$	0.107***	0.102***	0.106***	0.102***
	(0.013)	(0.012)	(0.005)	(0.011)
$\sigma_{\dot{u}}$	0.017***	0.013***	0.019***	0.013***
	(0.004)	(0.004)	(0.004)	(0.005)
Controls in the Translog Cost Function	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Observations	418	418	418	418

Notes: The 'Controls in the Translog Cost Function' row indicates the inclusion of all first-order, second-order, and interaction terms for outputs, input prices, and quasi-fixed inputs as specified in the translog cost function $TL(\boldsymbol{y}_{it}, \boldsymbol{p}_{it}, \boldsymbol{z}_{it}; \boldsymbol{\beta}^*)$. Data: Chilean banking system (2016m1–2017m12). Standard errors (in parentheses) computed via wild bootstrap. *** significant at 1%; ** 5%; * 10%.

Summary

- We study the link between interbank interconnectedness and bank cost efficiency, moving beyond the traditional focus on systemic risk.
- We use a rich administrative dataset from Chile and a novel GMM-SFA approach to model network dependencies.
- We find a significant, negative network dependence. This indicates that interconnectedness, on average, is associated with **improved cost efficiency**.
- For the median bank, network effects account for a substantial reduction in cost inefficiency (approx. 35% gain).
- Results suggest that monitoring bank networks is crucial not just for financial stability, but also for understanding the drivers of the sector's fundamental operational performance.

Thanks!

Appendix: Estimation Strategy (more info)

Step 1: within-time estimation

Since $\mathbb{E}[\varepsilon_{it}] = \mathbb{E}[\nu_{it} + u_{it}] = \mathbb{E}[u_{it}] \neq 0$, transform the model:

$$\ln \text{Cost}_{it} = \alpha_t^* + TL(\boldsymbol{y}_{it}, \boldsymbol{p}_{it}, \boldsymbol{z}_{it}; \boldsymbol{\beta}^*) + \varepsilon_{it}^*, \tag{1}$$

where the parameter vector $\boldsymbol{\beta}^*$ now excludes the original intercept β_0; the new time-specific intercept is $\alpha_t^* = \beta_0 + \alpha_t + \mathbb{E}[u_{it}]$; and the transformed error term is $\varepsilon_{it}^* = \nu_{it} + u_{it} - \mathbb{E}[u_{it}]$. Therefore, by construction, $\mathbb{E}[\varepsilon_{it}^*] = 0$, and the resulting model belongs to the family of panel data models.

Let $Q = (I_N - (1/N)\iota_N \iota_N')$. And denote a vector variable with a tilde as the result of pre-multiplying the vector by Q (e.g., $\widetilde{\boldsymbol{z}}_t$ is an $N \times 1$ vector, resulting from $Q\boldsymbol{z}_t$). Thus, since the translog function $TL(\cdot)$ is linear in the parameters $\boldsymbol{\beta}^*$, and the Q transformation is a linear operator, the resulting model remains linear in $\boldsymbol{\beta}^*$:

$$\widetilde{\ln \text{Cost}}_t = \sum_k \beta_k^* \widetilde{X}_{kt} + \widetilde{\varepsilon}_t^* \tag{2}$$

where $\widetilde{X}_{kt}$ are the transformed versions (QX_{kt}) of each vector X_{kt} representing a term required by the translog specification. Since $\mathbb{E}[\varepsilon_t^*] = \boldsymbol{0}$, estimation of $\boldsymbol{\beta}^*$ is conducted via OLS.

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Appendix: Estimation Strategy (more info)

Step 2: GMM-SFA

Construct the pseudo-residuals, denoted by e_{it}, using the first-step estimates $\hat{\boldsymbol{\beta}}^*$:

$$e_{it} = \ln \text{Cost}_{it} - TL(\boldsymbol{y}_{it}, \boldsymbol{p}_{it}, \boldsymbol{z}_{it}; \hat{\boldsymbol{\beta}}^*) \quad \Rightarrow \quad e_{it} \approx \beta_0 + \alpha_t + \nu_{it} + u_{it}$$

Since by construction $\mathbb{E}[\varepsilon^*_{it}] = 0$, the time-specific mean component $\alpha^*_t = (\beta_0 + \alpha_t + \mathbb{E}[u_{it}])$ is estimated by the cross-sectional average of the pseudo-residuals for each period t. Thus, by computing $\bar{e}_{it} = e_{it} - \hat{\alpha}^*_t$ we obtain the central equation for the second stage:

$$\bar{e}_{it} = \nu_{it} + u_{it} - \mathbb{E}[u_{it}] \qquad \text{(which is a SF model)} \tag{3}$$

Since $\boldsymbol{\varepsilon}_t = \boldsymbol{\nu}_t + \boldsymbol{u}_t = (I_N - \rho W_t)^{-1}(\dot{\boldsymbol{\nu}}_t + \dot{\boldsymbol{u}}_t) = S(\rho, W_t)(\dot{\boldsymbol{\nu}}_t + \dot{\boldsymbol{u}}_t)$, we use the second-order moments:

$$\mathbb{V}(\boldsymbol{\varepsilon}_t) = \mathbb{V}(S(\rho, W_t)(\dot{\boldsymbol{\nu}}_t + \dot{\boldsymbol{u}}_t)) = \left[\sigma^2_{\dot{\nu}} + \left(1 - \frac{2}{\pi}\right)\sigma^2_{\dot{u}}\right] S(\rho, W_t)(S(\rho, W_t))^\top \tag{4}$$

Specifically, the parameters are chosen to minimize the GMM objective function:

$$\min_{\boldsymbol{\theta}} Q(\boldsymbol{\theta}) = \min_{\boldsymbol{\theta}} \sum_{t=1}^{T} \left\| \hat{V}_t - \mathbb{V}(\boldsymbol{\varepsilon}_t; \boldsymbol{\theta}) \right\|_F^2 \tag{5}$$

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Appendix: Decomposition of Cost Inefficiency Estimates

The total estimated cost inefficiency can be decomposed to isolate the influence of network effects.

- Since $\boldsymbol{u}_t = \rho W_t \boldsymbol{u}_t + \dot{\boldsymbol{u}}_t$, the total inefficiency ($\boldsymbol{u}_t$) is a function of the underlying, network-independent inefficiency ($\dot{\boldsymbol{u}}_t$) and the network multiplier, S:

$$\hat{\boldsymbol{u}}_t = S(\hat{\rho}, W_t)\hat{\dot{\boldsymbol{u}}}_t$$

  where $\hat{\dot{\boldsymbol{u}}}_t$ is a vector of bank-specific estimates recovered using the JLMS method (i.e., $\hat{\dot{u}}_{it} = \mathbb{E}[\dot{u}_{it}|\hat{\dot{\varepsilon}}_{it}]$).

- The network multiplier matrix, S, captures how an initial inefficiency shock at one bank propagates through the network:

$$S(\hat{\rho}, W_t) = (I_N - \hat{\rho} W_t)^{-1}$$

- Expanding the first equation for a single bank i allows us to separate its total inefficiency into two components:

$$\text{Total Inefficiency}_{it} = \underbrace{s_{ii}\hat{\dot{u}}_{it}}_{\text{Direct Effect}} + \underbrace{\sum_{j \neq i} s_{ij}\hat{\dot{u}}_{jt}}_{\text{Indirect (Network) Effect}}$$

  The **Direct Effect** reflects the bank's own idiosyncratic inefficiency, while the **Indirect Effect** captures the net influence of all peers.

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Appendix: Standard Errors via Wild Bootstrap

Given the multi-step GMM procedure, analytical standard errors are complex. We employ a wild bootstrap approach.

1. Create bootstrapped structural residuals, $\dot{\varepsilon}_{it}^{(b)}$, by multiplying the original estimates with random multipliers, $\xi_{it}^{(b)}$, drawn from the Mammen (1993) two-point distribution.

$$\dot{\varepsilon}_{it}^{(b)} = \hat{\dot{\varepsilon}}_{it} \cdot \xi_{it}^{(b)}$$

2. Generate a bootstrapped log-cost variable, $\ln \text{Cost}_{it}^{(b)}$, using the original parameter estimates ($\hat{\rho}$, $\hat{\boldsymbol{\beta}}^*$, etc.) and the new residuals.

$$\ln \boldsymbol{Cost}_t^{(b)} = (\widehat{\beta_0 + \alpha_t})\boldsymbol{\iota}_N + \text{TL}(\ldots; \hat{\boldsymbol{\beta}}^*) + (I_N - \hat{\rho} W_t)^{-1} \hat{\dot{\boldsymbol{\varepsilon}}}_t^{(b)}$$

3. Apply the two-step GMM estimation procedure to the new dataset using $\ln \text{Cost}_{it}^{(b)}$ as the dependent variable to obtain a new set of parameters ($\hat{\rho}^{(b)}$, $\hat{\sigma}_{\dot{v}}^{(b)}$, $\hat{\sigma}_{\dot{u}}^{(b)}$).

4. This process is repeated B times. The standard error for each parameter is the empirical standard deviation of its B bootstrapped estimates.