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

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(Preliminary draft – June 2025. Comments are welcome.)

Abstract

While interconnections between banks are crucial for financial stability, they can also shape industry performance by fostering coordinated behavior, such as herding, benchmarking, or peer-like interactions dynamics. This paper examines the less-explored link between interconnectedness, measured through the interbank lending market, and banking efficiency. Using detailed confidential administrative records of Chilean banks' interbank loans and balance sheets (2008–2020), we construct time-varying interbank lending networks. We employ a novel two-step GMM stochastic frontier approach that incorporates network dependence to estimate bank-level cost efficiency. Our findings indicate that interconnectedness is a statistically significant factor influencing cost efficiency. Specifically, we estimate a negative average network dependence parameter, suggesting that network connections are associated with improved cost efficiency (i.e., reduced inefficiency) in the Chilean case. Decomposing total inefficiency, we find that network effects account for a median reduction of approximately 35 percentage points in cost inefficiency relative to idiosyncratic inefficiency. This result adds a layer to the need for policymakers to monitor banking networks, not only for their role in financial contagion but also for their potential influence on industry performance.

JEL codes: G21, D24, C23, L14, G01.

Keywords: Banking Interconnections, Interbank Market, Banking, Network Effects, Stochastic Frontier Analysis, Chile.

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*Notes: 1. This version is incomplete and represents a very preliminary draft, prepared specifically to meet the conference submission deadline. Please do not cite or circulate this draft. A more comprehensive and refined version of the paper will be provided well in advance of the event. For any inquiries, please contact Luis. 2. The regulatory authority of Chile, *Comisión para el Mercado Financiero* (CMF), kindly provided data through the Call for Research Projects 2023/2024. The views, findings, and conclusions expressed herein are solely those of the authors and do not necessarily represent those of the CMF. All errors and omissions are the responsibility of the authors. 3. The financial support from the Agencia Nacional de Investigación y Desarrollo (ANID) through project Fondecyt Iniciación en Investigación 11250893 is gratefully acknowledged by Luis Chanci. 4. Contact information. Luis: Universidad Santo Tomás, Chile, *luischanci@santotomas.cl*; Subal: Binghamton University, USA, *kkar@binghamton.edu*; Paulo: CMF, Chile, *pbobadilla@cmfchile.cl*.

1 Introduction

The network of relationships linking financial institutions, particularly evident in interbank lending markets, forms a critical infrastructure in modern economies (Allen and Gale, 2000; Freixas et al., 2000). These interactions facilitate the efficient allocation of financial resources, effective management of liquidity fluctuations, and risk diversification across participating institutions. While essential for smooth functioning, this inherent interconnectedness is most widely studied for its potential role in propagating shocks and generating systemic risk, a focus greatly intensified by events such as the 2007–2009 global financial crisis (Jackson and Pernoud, 2021; Glasserman and Young, 2016; Acemoglu et al., 2015). Consequently, much of the academic and policy attention concerning financial networks centers on stability and contagion.

However, the influence of these networks likely extends beyond crisis dynamics to shape bank behavior and operational performance during periods of relative calm. While the literature on financial risk and contagion through networks is vast, considerably less empirical attention has been paid to how interconnectedness affects other key outcomes, such as bank efficiency and productivity. Several channels suggest such links are plausible. Network ties might facilitate coordinated behaviors, such as herding or peer effects, potentially leading banks to reduce information costs by mimicking others. Banks could also learn from the operational successes or failures of their direct connections, leading to performance benchmarking (positive or negative) that impacts efficiency. Furthermore, the network structure could influence market power, the speed of information diffusion, or the pace of technological adoption, thereby affecting overall industry performance. Exploring these dimensions is important for a better understanding of the persistent role interconnectedness play in the banking sector.

Despite plausible theoretical foundations, empirical evidence quantifying the impact of interbank relationships on banking industry performance remains scarce. Methodological and practical challenges contribute to this gap. Detailed data tracing specific transactions and linkages between individual financial institutions, crucially linked to their balance sheets, are often confidential and inaccessible. This forces researchers to rely on aggregated data, simulations, or network proxies (like geographical distance) that may not capture the true underlying structure of financial interdependence. Moreover, adequately modeling performance metrics like efficiency while simultaneously accounting for complex network structures requires novel econometric tools that are still work in progress.

This paper aims to bridge this empirical gap by directly investigating the relationship between interconnectedness and bank performance, leveraging unique administrative data from the Chilean financial system. Specifically, we ask: How does interconnectedness among banks, as defined by interbank lending network structures, influence their operational cost efficiency?

To investigate this question, we employ a novel empirical strategy combining unique administrative data with recent advances in the econometric modeling of efficiency analysis. Our data is directly facilitated by the Chilean regulatory authority of the financial market (the *Comisión para el Mercado Financiero* - CMF) and is based on detailed daily transaction records from the interbank lending market (Form C-18, according to local accounting codes) linked to comprehensive monthly bank balance sheet information (Form MB-2) for virtually all banks operating in Chile during 2008–2020 (**NOTE: This**

version of the paper is based on a sub-sample 2016-2017 and extending to the full sample is still ongoing work). This rich data allows us to construct time-varying network adjacency matrices based on actual lending relationships, overcoming significant data limitations encountered in previous literature.

Methodologically, we employ a two-step Generalized Method of Moments (GMM) estimation approach, inspired by recent advances in stochastic frontier analysis (SFA) models incorporating spatial dependencies (e.g., Hou et al., 2023; Chanci et al., 2024). While previous empirical studies often approximate interconnectedness using geographical distance, we utilize actual lending transactions. This approach provides a more precise measure of interbank relationships, particularly in the specific banking context of our study. Our strategy thus enables the estimation of bank-level cost efficiency using a flexible translog specification, explicitly accounting for interbank network structures and controlling for unobserved heterogeneity. Additionally, this method avoids the computational complexities associated with traditional Maximum Likelihood estimation, particularly when dealing with time-varying network effects in SFA frameworks.

Our empirical analysis suggests that the overall Chilean banking system exhibits relatively high levels of cost efficiency during the studied period. Crucially, we find that interconnectedness is a statistically significant factor influencing these efficiency levels. Preliminary results yield an average network dependence parameter estimate ($\hat{\rho}$) of approximately -0.5 within the cost inefficiency model. This negative estimate indicates that, on average, network connections in the Chilean interbank market are associated with lower inefficiency (enhanced cost efficiency). Further decomposing total inefficiency, to assess the relative importance of this network effect, we find that it accounts for a reduction of approximately 35 percentage points in cost inefficiency for the median bank-period observation, relative to the bank's idiosyncratic inefficiency. These findings align with potential mechanisms involving competitive pressures or benchmarking opportunities within the network. These results also highlight that fostering a well-functioning, efficient banking system through understanding network dynamics is not merely a secondary policy objective but a key component supporting overall economic performance and stability.

This study contributes to the literature in several respects. Firstly, it provides direct empirical evidence linking actual interbank networks to operational performance, expanding the discussion beyond traditional systemic risk and contagion analyses. Methodologically, it exemplifies the application of advanced SF techniques incorporating network dependencies utilizing granular administrative data. From a policy perspective, our results emphasize the importance of monitoring banking network structures not only for their implications regarding financial stability and shock propagation but also for their tangible influence on the fundamental cost efficiency and operational health of the banking sector. Thus, fostering a well-functioning, efficient banking system is critical for overall economic performance, and understanding the role network dynamics play in achieving this efficiency merits ongoing attention from researchers and policymakers alike.

The remainder of this paper is organized as follows: Section 2 reviews the relevant literature. Section 3 details the econometric methodology. Section 4 describes the data and variable construction. Section 5 presents the empirical results, including the efficiency estimates and decomposition analysis. Section 6 discusses the findings and concludes with policy implications.

2 Related Literature

Our paper relates to and contributes to several distinct strands of literature. First, our research engages broadly with the extensive body of work examining the crucial role and multifaceted implications of financial interconnectedness (Acemoglu et al., 2012; Glasserman and Young, 2016; Elliott et al., 2014; Allen and Gale, 2000; Freixas et al., 2000). A central theme in this literature is the inherent trade-off within financial networks. On the one hand, interconnections facilitate vital banking functions such as efficient liquidity management, payment settlements, and risk diversification across institutions. On the other hand, a densely interconnected financial system may increase susceptibility to systemic risk and cascading failures, potentially exacerbated by institutions being 'too-connected-to-fail.' While acknowledging the significance of network structures highlighted by this literature, our study extends the analysis beyond systemic risk to empirically explore a less-studied yet critical economic outcome—banking performance, specifically cost inefficiency—during periods of economic stability.

Second, our paper contributes to the literature on peer effects and herding in finance. Drawing insights from this literature (e.g., Manski, 1993), it is often conjectured that banks may gain efficiency by reducing information costs through imitation or learning from their peers. For instance, the foundations of herd behavior, where decisions are influenced by the actions of other banks rather than solely by private information, are theoretically reviewed by Scharfstein and Stein (1990) and Bikhchandani et al. (1998). These authors emphasize informational cascades where banks follow peers to benefit from perceived superior information or expertise (see also, Banerjee, 1992). Empirically, Margaretic et al. (2021), a work closely related to ours, provide relevant evidence of peer effects from the Chilean interbank market, documenting how decisions by some lenders to reduce exposure to a stressed bank were mimicked by others.

We aim to contribute to this literature by extending the implications of peer effects beyond behavioral contagion to quantifiable changes in bank operational performance. That is, unlike Margaretic et al. (2021), who focus primarily on modeling the structural dependencies in lending behaviors using balance-sheet-defined peer characteristics, our work centers on how these interconnections affect a specific performance outcome—cost efficiency—estimated through a stochastic frontier approach. Thus, we take a different route by proposing how to include interconnectedness directly into an econometric model of efficiency analysis and by empirically providing estimates of the magnitude of banking interconnections' role.

Third, our paper also aligns with prior research linking networks and banking performance (e.g., Silva et al., 2018, 2016; Elliott et al., 2014). This literature identifies potential channels through which interconnectedness can enhance operational efficiency, such as improved liquidity management, operational specialization, outsourcing via network partnerships, or accelerated diffusion of information and technological advancements. Nonetheless, empirical evidence remains limited. For instance, Silva et al. (2016) represents one of the few studies directly examining the influence of interbank network structures on bank productivity. They investigate how core-periphery financial network structures affect bank cost, profit, and risk-taking efficiency, initially estimating bank efficiencies through stochastic frontier analysis and subsequently regressing these efficiencies on network topology measures. Their findings suggest that core-periphery structures are positively associated with cost efficiency but negatively associated with risk-taking efficiency. While insightful, our study differs fundamentally in its econometric modeling approach. Rather than using aggregated network statistics as explanatory variables in a stochastic frontier model, we draw on models of social interactions and incorporate network dependencies directly into the composite error term of the stochastic cost frontier (via the adjacency matrix, W_t). This approach enables a contemporaneous modeling of how a bank's (in)efficiency is directly influenced by that of its network peers through interbank lending, offering a more precise and structurally grounded assessment of network effects on efficiency.

Fourth, our paper offers contributions related to data and econometric methodology. Given the challenges posed by confidentiality in accessing detailed banking transaction data, interconnectedness has historically been approximated using proxies such as correlations in portfolios, common asset holdings, or geographical proximity, which may not always adequately capture actual financial linkages. In contrast, our use of granular interbank loan transaction data provides a precise measure of both the strength and directionality of financial relationships, directly addressing limitations previously highlighted in the literature (see, for instance, the discussions in Das et al., 2022; Brunetti et al., 2019).

Finally, considering that the Stochastic Frontier Analysis (SFA) framework is a standard approach in efficiency measurement due to its flexibility and robust theoretical foundation (e.g., Kumbhakar et al., 2015), our study innovatively extends recent advancements in SFA that incorporate interconnections. We build upon methodologies presented in Hou et al. (2023), Kutlu et al. (2020), Glass et al. (2016), and Tran and Tsionas (2023). In particular, we adapt the two-step GMM estimation strategy proposed by Hou et al. (2023) for semiparametric spatial stochastic frontier models and its application in Chanci et al. (2024) to a panel data model with fixed effects. While these works typically focus on frameworks based on production functions with a single output and proxy interactions with geographically based spatial weights, our methodological innovation extends their approach to a multi-output banking cost function context, incorporating time-fixed effects and using an alternative measure of interconnectedness based on actual financial transactions. This methodological refinement allows for more accurate modeling and assessment of network dependencies within the context of banking cost efficiency.

3 Empirical Strategy

We adopt a widely used approach in the banking performance literature by estimating a stochastic cost frontier model (e.g., Mamonov et al., 2024; Hughes et al., 2019; Tabak et al., 2012; Kumbhakar and Lovell, 2000). However, we extend the traditional econometric specification of the inefficiency term by explicitly incorporating interactions among banking units. In doing so, we leverage the richness and temporal variation present in our dataset, enhancing our identification strategy. This section outlines the empirical framework and estimation approach that we propose.

3.1 Econometric Specification

The cost function We begin by defining the translog stochastic cost frontier model, drawing from the extensive literature on bank efficiency analysis. In this setting, cost efficiency is defined as a bank's ability to minimize costs given its output volume ($\boldsymbol{y}$), the factor input prices it faces ($\boldsymbol{p}$), and a set of quasi-fixed inputs ($\boldsymbol{z}$). The translog stochastic cost function for bank i, where $i = 1, \ldots, N$, in time period t, where $t = 1, \ldots, T$, is specified as follows:

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

where $Cost_{it}$ represents the variable cost of bank i; α_t is a time-fixed effect to control for macroeconomic shocks and inherent time heterogeneity, including potential shifts in the cost frontier; $TL(\cdot)$ denotes the translog cost frontier; $\boldsymbol{y}$ is a vector of outputs (e.g., loans and other income-generating activities); $\boldsymbol{p}$ is a vector of input prices; and the vector $\boldsymbol{z}$ represents quasi-fixed inputs, including equity, which, owing to its limited time variation, effectively functions as a bank-specific fixed effect, thus mitigating unobserved heterogeneity across banks. The vector $\boldsymbol{\beta}$ represents the parameters to be estimated. Furthermore, to ensure comparability across banks, and in line with standard assumptions in empirical cost function estimation, both cost and input price variables are normalized by one input price (p_{1it}).

Interconnectedness and efficiency In the stochastic frontier literature, the error term ε_{it} in equation (1) is decomposed into two components (Kumbhakar and Lovell, 2000; Kumbhakar et al., 2015): a standard noise term v_{it} and a non-negative inefficiency term u_{it}. We build on this framework and follow a standard model of social interactions to incorporate network effects among banks. Specifically, we model the composite error term $\varepsilon_{it} = v_{it} + u_{it}$ as a function of a weighted combination of the composite errors of other banks, using an $N \times N$ adjacency matrix W_t. Formally, we specify:

$$\begin{aligned} \varepsilon_t &= \rho W_t \varepsilon_t + \dot{\varepsilon}_t, \\ \dot{\varepsilon}_{it} &= \dot{v}_{it} + \dot{u}_{it}, \end{aligned} \tag{2}$$

where the $N \times 1$ vector ε_t depends on $W_t \varepsilon_t$, a weighted combination of the inefficiency components of other banks to which bank i is financially connected. The matrix W_t captures the degree of interconnectedness, where the elements w_{ij} represent the weight assigned to the influence of bank j's outcomes (i.e., inefficiency) on those of bank i. These weights are predetermined and non-stochastic, with the standard restriction $w_{ij} = 0$ for $i = j$.

Since u_{it} in the stochastic frontier literature is inefficiency (Kumbhakar and Lovell, 2000; Kumbhakar et al., 2015), and, since we use the stochastic frontier as a tool for modeling banking performance, we rely on the standard assumptions in the stochastic frontier literature. These are: $\dot{v}_{it}$ and $\dot{u}_{it}$ are both i.i.d., and that $\dot{u}_{it} \sim \mathcal{N}^{+}(0, \sigma_{\dot{u}}^2)$ and $\dot{v}_{it} \sim \mathcal{N}(0, \sigma_{\dot{v}}^2)$. The notation $\mathcal{N}^{+}$ means positive values of the normal distribution, also known as a half-normal distribution.

Our overall model's foundational structure draws from established econometric frameworks. Specifically, it mirrors frameworks common in spatial econometrics (Elhorst, 2014; LeSage and Pace, 2009; Pace and Barry, 1997), where terms such as $W_t \varepsilon_t$ —often expressed component-wise as $\sum_j w_{tij} \varepsilon_{jt}$— represent the endogenous spatial lag of a variable like ε. Similarly, recent stochastic frontier models, for example by Hou et al. (2023), have incorporated comparable dependence structures. Our model therefore aligns with these econometric traditions. Furthermore, it connects with the broader literature on peer effects, which often utilizes adjacency matrices based on various definitions of proximity, extending beyond simple geographic distance to capture more nuanced interactions.

While our econometric specification shares similarities with these established approaches, and our estimation strategy (detailed below) builds upon recent work by Hou et al. (2023) and Chanci et al. (2024), a key distinction and contribution of our study lies in the construction of the weighting matrix. Rather than relying on geographical proximity or other indirect proxies common in the literature, we leverage detailed administrative data on interbank loan transactions to define W_t. This approach allows for a more direct and economically meaningful measure of interconnectedness, capturing actual financial linkages and their varying strengths.

A further significant novelty of our approach is the utilization of a time-varying adjacency matrix, made possible by the rich temporal dimension of our data. Many empirical studies employing network structures assume a static, often constrained by data limitations or a focus on identifying long-term, stable interactions (see, e.g., Margaretic et al., 2021, for a discussion on using a single connection matrix). In contrast, we exploit the granularity of our interbank transaction data to allow W_t to evolve monthly. This dynamic specification is crucial for capturing the changing nature of interbank connections, thereby yielding a more realistic depiction of network effects and potentially enhancing the model's identification. By integrating both the precise definition of network links and their time-varying nature, our approach offers a comprehensive view of how interbank relationships influence cost efficiency in the banking sector.

3.2 Estimation strategy

Given that a model can be consistently estimated when it is identified, we proceed directly to estimation, rather than addressing identification and consistency issues individually. In particular, for the estimation we follow Hou et al. (2023) and Chanci et al. (2024) and employ a two-step Generalized Method of Moments (GMM) estimation technique for stochastic frontier models involving interactions across units. This GMM framework presents notable advantages over Maximum Likelihood (ML) estimation in this context. Firstly, unlike the Maximum Like ML method, this approach avoids making full distributional assumptions. Secondly, it circumvents significant numerical optimization complexities associated with ML, such as the requirement for high-dimensional numerical integration within the log-likelihood function or the computational burden arising from a time-variant spatial weighting matrix.[1]

The two-step approach we implement can be summarized as follows: First, we leverage the panel data structure to transform the model and employ a cross-sectional demeaning (or 'between') estimator, thereby avoiding strong initial distributional assumptions. Second, we compute pseudo-residuals from the first-stage estimation. These pseudo-residuals are then used to recover estimates of (in)efficiency, incorporating the adjacency matrix. This step is conducted using GMM, where the moment conditions are based on distributional assumptions for the noise and inefficiency terms. In what follows, we discuss these steps in detail.

3.2.1 First step - Transformation

The model in Equation (1) does not satisfy the standard assumption of classical regression models that the expected value of the error term is zero. Specifically, when u_{it} follows the structure defined in Equation (2), the composite error $\varepsilon_{it} = v_{it} + u_{it}$ has a non-zero expectation: $\mathbb{E}[\varepsilon_{it}] = \mathbb{E}[v_{it} + u_{it}] = \mathbb{E}[u_{it}]$, which represents the mean inefficiency level.

Nonetheless, although the error mean is non-zero, it is possible to rewrite the model by absorbing this term into a time-specific intercept. The model from Equation (1) then becomes:

$$\ln \text{Cost}_{it} = \alpha_t^* + TL(\boldsymbol{y}_{it}, \boldsymbol{p}_{it}, \boldsymbol{z}_{it}; \boldsymbol{\beta}^*) + \varepsilon_{it}^*, \tag{3}$$

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 $\varepsilon_{it}^* = v_{it} + u_{it} - \mathbb{E}[u_{it}]$. Therefore, by construction, $\mathbb{E}[\varepsilon_{it}^*] = 0$, and the resulting model belongs to the family of panel data models (i.e., a panel cost function featuring time-specific effects, where time-invariant individual heterogeneity is primarily accounted for by including quasi-fixed inputs, rather than via separate individual-specific intercepts).

Considering that the fixed effects are nuisance parameters in our case, and given that the time dimension, T, in our dataset is large, we rely on a within-time transformation rather than using time dummy variables for the time fixed effects. Hence, we first employ a transformation approach to eliminate the time effects in equation (3). Let $Q = (I_N - (1/N)\iota_N \iota_N')$ be the $N \times N$ matrix used to compute the demeaned variables in the within-time transformation, as established in the panel data literature (e.g., Baltagi, 2021), where ι_N is an $N \times 1$ vector of ones. In this way, one can remove the time effects α_t^* using Q. Specifically, let us denote a vector variable with a tilde as the result of pre-multiplying the vector by Q. For instance, $\widetilde{\boldsymbol{z}}_t$ is an $N \times 1$ vector, resulting from $Q\boldsymbol{z}_t$, where $\boldsymbol{z}_t = (z_{1t}, ..., z_{Nt})'$.[2] Applying this transformation to Equation (3) eliminates the time-specific effect α_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

[1] If W_t enters the likelihood function via the error structure (e.g., through terms involving $(I - \rho W_t)^{-1}$ that must be computed for each time period t), it substantially complicates the ML optimization compared to the moment-based GMM approach used here.

[2] This is also equivalent to $\widetilde{z}_{it} = (z_{it} - z_{\cdot t})$, where $z_{\cdot t} = N^{-1} \sum_i z_{it}$.

remains linear in $\boldsymbol{\beta}^*$:

$$\widetilde{\ln \text{Cost}}_t = \sum_k \beta_k^* \widetilde{X}_{kt} + \widetilde{\varepsilon}_t^* \tag{4}$$

where the regressors $\widetilde{X}_{kt}$ are the transformed versions (QX_{kt}) of each vector X_{kt} representing a term required by the translog specification (e.g., vectors of element-wise logs like $\ln y_{it}$, squares like $(\ln y_{it})^2$, or cross-products like $\ln y_{it} \ln p_{it}$), constructed from the original data vectors $(\boldsymbol{y}_t, \boldsymbol{p}_t, \boldsymbol{z}_t)$. As the transformed error $\widetilde{\varepsilon}_t^* = Q\varepsilon_t^*$ retains the zero-mean property (since $\mathbb{E}[\varepsilon_t^*] = \mathbf{0}$), Equation (4) satisfies the requirements for consistent estimation of $\boldsymbol{\beta}^*$ via Ordinary Least Squares (OLS). Therefore, applying OLS yields the first-stage estimates $\hat{\boldsymbol{\beta}}^*$ of $\boldsymbol{\beta}^*$ without using distributional assumptions on v_{it} and u_{it}, avoiding computational challenges associated with the ML method.

3.2.2 Second step: GMM estimation

The second stage of our estimation procedure utilizes the parameter estimates $\hat{\boldsymbol{\beta}}^*$ obtained from the first step. Recalling Equation (1):

$$\ln \text{Cost}_{it} - TL(\boldsymbol{y}_{it}, \boldsymbol{p}_{it}, \boldsymbol{z}_{it}; \boldsymbol{\beta}^*) = \beta_0 + \alpha_t + v_{it} + u_{it}$$

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

$$e_{it} = \ln \text{Cost}_{it} - TL(\boldsymbol{y}_{it}, \boldsymbol{p}_{it}, \boldsymbol{z}_{it}; \hat{\boldsymbol{\beta}}^*) \tag{5}$$

These pseudo-residuals approximate the composite error term plus the intercept and time effects, $e_{it} \approx \beta_0+\alpha_t+v_{it}+u_{it}$. As established earlier, we can decompose the right-side of this expression into a time-specific mean component $\alpha_t^* = (\beta_0+\alpha_t+\mathbb{E}[u_{it}])$ and a zero-mean error component $\varepsilon_{it}^* = (v_{it}+u_{it}-\mathbb{E}[u_{it}])$. Thus, $e_{it} \approx \alpha_t^* + \varepsilon_{it}^*$. Since by construction $\mathbb{E}[\varepsilon_{it}^*] = 0$, the time-specific mean component α_t^* can be consistently estimated by the cross-sectional average of the pseudo-residuals for each period t.

These pseudo-residuals approximate the composite error term plus the intercept and time effects, $e_{it} \approx \beta_0 + \alpha_t + v_{it} + u_{it}$. As established earlier, we can decompose the right-side of this expression into a time-specific mean component $\alpha_t^* = (\beta_0 + \alpha_t + \mathbb{E}[u_{it}])$ and a zero-mean error component $\varepsilon_{it}^* = (v_{it} + u_{it} - \mathbb{E}[u_{it}])$. Thus, $e_{it} \approx \alpha_t^* + \varepsilon_{it}^*$. Since by construction $\mathbb{E}[\varepsilon_{it}^*] = 0$, the time-specific mean component α_t^* can be consistently estimated by the cross-sectional average of the pseudo-residuals for each period t: $\hat{\alpha}_t^* = N^{-1} \sum_i e_{it}$. In what follows, we use this estimate $\hat{\alpha}_t^*$ to obtain residuals suitable for estimating the (in)efficiency structure. In particular, we define the adjusted residuals $\bar{e}_{it}$ by removing this estimated time-specific mean: $\bar{e}_{it} = e_{it} - \hat{\alpha}_t^*$. Thus, substituting the approximations yields the central equation for the second stage:

$$\bar{e}_{it} = v_{it} + u_{it} - \mathbb{E}[u_{it}] \tag{6}$$

Equation (6) represents a Stochastic Frontier (SF) model structure based on these adjusted residuals $\bar{e}_{it}$. Here, v_{it} is the two-sided random noise and $(u_{it} - \mathbb{E}[u_{it}])$ is the (mean-shifted) one-sided inefficiency term. Therefore, the second-stage GMM procedure can use distributional assumptions on the underlying components ν_{it} and u_{it} (particularly their network-independent counterparts $\dot{\nu}_{it}, \dot{u}_{it}$) to formulate moment conditions for estimating the spatial parameter ρ, the variance parameters $\sigma_{\dot{\nu}}^2$ and $\sigma_{\dot{u}}^2$, and the mean inefficiency $\mathbb{E}[u_{it}]$.

As mentioned, given that our model specification in Equation (2) incorporates dependency in banking performance via the time-variant weights matrix W_t, the ML estimation for the becomes complex. Thus, we closely follow the estimation approach proposed by Hou et al. (2023) (henceforth, HZK). They propose GMM estimation for a semiparametric stochastic frontier model incorporating spatial dependence. Although their model features functional coefficients while our specification uses constant parameters (including fixed effects), the dependence structure applied to the second-stage error components is analogous, allowing the adaptation of their GMM procedure.

In short, the GMM estimation identifies the structurally dependence parameter ρ and the variance parameters $(\sigma_{\dot{\nu}}^2, \sigma_{\dot{u}}^2)$ associated with the underlying structurally independent noise ($\dot{\nu}_{it}$) and inefficiency ($\dot{u}_{it}$) components. This relies on exploiting moment conditions derived from the distributional assumptions on $\dot{\nu}_{it}$ and $\dot{u}_{it}$. In particular, let $S(\rho, W_t) = (I_N - \rho W_t)^{-1}$. Thus, under the assumption that $\dot{u}_{it}$ has a half-normal distribution independent of $\dot{\nu}_{it}$, the second-moment condition based on the variance-covariance structure of $\boldsymbol{\varepsilon}_t = \boldsymbol{\nu}_t + \boldsymbol{u}_t = (I_N - \rho W_t)^{-1}(\dot{\boldsymbol{\nu}}_t + \dot{\boldsymbol{u}}_t) = S(\rho, W_t)(\dot{\boldsymbol{\nu}}_t + \dot{\boldsymbol{u}}_t)$ is:

$$\mathbb{V}(\boldsymbol{\varepsilon}_t) = \mathbb{V}(S(\rho, W_t)(\dot{\boldsymbol{\nu}}_t + \dot{\boldsymbol{u}}_t)) = \left[\sigma_{\dot{\nu}}^2 + \left(1 - \frac{2}{\pi}\right)\sigma_{\dot{u}}^2\right] S(\rho, W_t)(S(\rho, W_t))^\top \tag{7}$$

The sample counterpart for the $N \times N$ theoretical variance-covariance matrix $\mathbb{V}(\boldsymbol{\varepsilon}_t)$ is constructed for each time period t using the adjusted residuals $\bar{\boldsymbol{e}}_t = (\bar{e}_{1t}, \ldots, \bar{e}_{Nt})^\top$ from Equation (6). Thus, as $\mathbb{E}[\bar{e}_{it}] = 0$, the time-specific sample variance-covariance matrix is calculated as $\hat{V}_t = \bar{\boldsymbol{e}}_t \bar{\boldsymbol{e}}_t^\top$. According to HZK, leveraging the principle of minimum distance estimation, the unknown parameter vector $\boldsymbol{\theta} = (\rho, \sigma_{\dot{\nu}}^2, \sigma_{\dot{u}}^2)$ can be estimated by minimizing the distance between these sample covariance matrices $\hat{V}_t$ and their theoretical counterparts $\mathbb{V}(\boldsymbol{\varepsilon}_t; \boldsymbol{\theta})$ over time. Specifically, the parameters are chosen to minimize the GMM objective function:

$$\min_{\boldsymbol{\theta}} Q(\boldsymbol{\theta}) = \min_{\boldsymbol{\theta}} \sum_{t=1}^{T} \left\| \hat{V}_t - \mathbb{V}(\boldsymbol{\varepsilon}_t; \boldsymbol{\theta}) \right\|_F^2 \tag{8}$$

where $\|\cdot\|_F$ denotes the Frobenius norm, and $\mathbb{V}(\boldsymbol{\varepsilon}_t; \boldsymbol{\theta})$ is the theoretical variance-covariance matrix defined in Equation (7).

Furthermore, considering that practical optimization of $Q(\boldsymbol{\theta})$ may encounter challenges such as multiple local minima or irregular objective function surfaces, we adopt a improved deviation from HZK regarding the numerical computation of $\boldsymbol{\theta}$. Specifically, we enhance numerical stability and efficiency by noting that the estimation must respect the constraint $|\rho| < 1$, associated with the invertibility of the $S(\rho, W_t)$ term. We thus implement a grid search strategy, widely used in the spatial econometrics literature (see, e.g., Elhorst, 2014, 2010; Pace and Barry, 1997). This involves a grid search over the permissible range $\rho \in (-1, 1)$. For each candidate value ρ_j from the grid, the GMM objective function $Q(\rho_j, \sigma_{\dot{\nu}}^2, \sigma_{\dot{u}}^2)$

is minimized with respect to $\sigma_{\dot{\nu}}^2$ and $\sigma_{\dot{u}}^2$ to obtain conditional estimates $\hat{\sigma}_{\dot{\nu}}^2(\rho_j)$ and $\hat{\sigma}_{\dot{u}}^2(\rho_j)$. The optimal estimate $\hat{\rho}$ is then selected as the value ρ_j that yields the minimum value of the GMM objective function in Equation (8) across all tested grid points, along with its corresponding conditional estimates $\hat{\sigma}_{\dot{\nu}}^2(\hat{\rho})$ and $\hat{\sigma}_{\dot{u}}^2(\hat{\rho})$.[3]

3.2.3 Post-Estimation Calculations

Once the GMM estimation yields consistent estimates of the parameters $\hat{\rho}$, $\hat{\sigma}_{\dot{\nu}}^2$, and $\hat{\sigma}_{\dot{u}}^2$, further quantities of interest can be derived.

First, we estimate the mean inefficiency component $\mathbb{E}[u_{it}]$. This calculation utilizes the estimate $\hat{\sigma}_{\dot{u}}^2$ and the distributional assumption made for the underlying network-independent inefficiency component $\dot{u}_{it}$. Given that $\dot{u}_{it}$ follows a half-normal distribution (implying $\mathbb{E}[\dot{\boldsymbol{u}}_t] = \sqrt{2/\pi}\hat{\sigma}_{\dot{u}}\iota_N$), the estimate incorporating the network multiplier is given by $\hat{\mathbb{E}}[u_{it}]$:

$$\hat{\mathbb{E}}[u_{it}] = \tau_i \mathbb{E}[\boldsymbol{u}_t]\Big|_{(\rho=\hat{\rho}\,,\ \sigma_{\dot{u}}=\hat{\sigma}_{\dot{u}})} = \sqrt{\frac{2}{\pi}}\hat{\sigma}_{\dot{u}}\tau_i S(\hat{\rho}, W_t)\iota_N$$

where ι_N is an $N \times 1$ vector of ones, and τ_i is a $1 \times N$ row vector selecting the i-th element. Since in our application the weights matrix W_t is row-normalized for each t, the mean (in)efficiency is a constant term.

Second, we recover estimates of the combined constant and time fixed effects, which will be later used in the computation of the standard errors. Recalling the estimated time-specific component $\hat{\alpha}_t^* = \bar{e}_t$, which consistently estimates $\alpha_t^* = \beta_0 + \alpha_t + \mu$, one can compute: $\widehat{(\beta_0 + \alpha_t)} = \hat{\alpha}_t^* - \hat{\mathbb{E}}[u_{it}]$.[4]

Third, following HZK's adaptation of Jondrow et al. (1982) (JLMS), we predict the bank-specific inefficiency component. This term is defined by the conditional expectation of the underlying network-independent $\dot{u}_{it}$ given the underlying network-independent composite error $\dot{\varepsilon}_{it}$:

$$\dot{\mu}_{it} = \mathbb{E}[\dot{u}_{it}|\dot{\varepsilon}_{it}] = \mu_{it}^* + \sigma_* \frac{\phi(-\mu_{it}^*/\sigma_*)}{1 - \Phi(-\mu_{it}^*/\sigma_*)} \tag{9}$$

where $\mu_{it}^* = \dot{\varepsilon}_{it}\sigma_{\dot{u}}^2/(\sigma_{\dot{u}}^2 + \sigma_{\dot{\nu}}^2)$ and $\sigma_* = \sqrt{\sigma_{\dot{u}}^2\sigma_{\dot{\nu}}^2/(\sigma_{\dot{u}}^2 + \sigma_{\dot{\nu}}^2)}$, using the estimated variance parameters.

The unobserved $\dot{\varepsilon}_{it}$ required for Equation (9) is obtained via the relationship $\dot{\boldsymbol{\varepsilon}}_t = (I_N - \rho W_t)\boldsymbol{\varepsilon}_t$. Thus, we approximate the unobserved vector $\boldsymbol{\varepsilon}_t = \boldsymbol{\nu}_t + \boldsymbol{u}_t$ by combining the adjusted residuals with the estimated mean inefficiency according to Equation (6), $\hat{\boldsymbol{\varepsilon}}_t \approx \bar{\boldsymbol{e}}_t + \hat{\mathbb{E}}[\boldsymbol{u}_t]$. Subsequently, we compute the estimate $\hat{\dot{\boldsymbol{\varepsilon}}}_t$. The i-th element of this vector, $\hat{\dot{\varepsilon}}_{it}$, is then plugged into Equation (9) to obtain the conditional estimate $\hat{\dot{\mu}}_{it} = \widehat{\mathbb{E}[\dot{u}_{it}|\dot{\varepsilon}_{it}]}$. The final prediction of the actual inefficiency term is constructed from these estimates using the specific network transformation, $\text{Inefficiency}_t = \hat{\boldsymbol{\mu}}_t = S(\hat{\rho}, W_t) * \hat{\dot{\boldsymbol{\mu}}}_t$, as detailed in

[3] To efficiently locate the minimum, we first employ a coarser grid for ρ (e.g., using 0.1 increments) to find an initial optimum, followed by a finer grid search (e.g., using 0.001 increments) in the neighborhood of that initial value. This vectorized grid search approach, potentially combined with parallel computing techniques, speeds up the estimation within the GMM framework.

[4] Separating the overall constant β_0 from the individual time effects α_t would require an additional normalization constraint (e.g., $\sum_t \alpha_t = 0$), which is not pursued here.

HZK.

Finally, we conduct a decomposition of (in)efficiency estimates that offers valuable insights into the relative importance of internal factors versus interconnectedness in determining observed banking performance. Specifically, considering that total bank inefficiency is related to underlying network-independent components via $S(\hat{\rho}, W_t)\hat{\boldsymbol{\mu}}_t$, we can decompose the estimated total cost inefficiency into effects originating from the bank's own underlying inefficiency component and effects spilling over from other banks through the network (e.g., peer effects). Let the total inefficiency for bank i at time t be $\sum_{j=1}^{N} s_{ij}\hat{\mu}_{jt}$, where s_{ij} is an element of $S(\hat{\rho}, W_t)$. This sum can thus be separated into two terms as follows:

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

Thus, the Direct Effect isolates the impact of a bank's own underlying inefficiency, scaled by the feedback effect s_{ii} from the diagonal of the multiplier matrix S. The Indirect Effect, on the other hand, captures the net influence of all other banks' underlying inefficiencies propagated through the network via the off-diagonal elements (s_{ij}) of S.

3.2.4 Computation of Standard Errors via Wild Bootstrap

Given the multi-step nature of our GMM estimation procedure for the stochastic cost frontier with interconnectedness, deriving analytical standard errors is complex. Therefore, we employ a wild bootstrap approach to assess the sampling variability of the estimated parameters ($\hat{\rho}$, $\hat{\sigma}_{\dot{v}}$, and $\hat{\sigma}_{\dot{u}}$. This method is well-suited for models with complex error structures and potential heteroskedasticity, and its applicability to spatial models has been already discussed (see, e.g., HZK for simulation results in a related GMM framework, and Gonçalves and Perron, 2020, for wild bootstrap with cross-sectional dependence).

Our wild bootstrap procedure is adapted to the specific structure of our model, where the composite error ε_{it} is transformed into an underlying, network-independent structural error $\dot{\varepsilon}_{it}$ via the relation $\dot{\varepsilon}_t = (I_N - \hat{\rho}W_t)\varepsilon_t$. The core idea is to resample these estimated network-independent residuals $\hat{\dot{\varepsilon}}_{it}$. In particular, for each bootstrap replication $b = 1, \ldots, B$, the procedure is as follows:

1. **Generate bootstrap multipliers:** We generate a vector of bootstrap multipliers $\boldsymbol{\xi}^{(b)}$ of dimension $NT \times 1$ (where N is the number of banks in period t, and NT is the total number of observations). These multipliers are drawn independently from the Mammen (1993) two-point distribution:

$$\xi_{it}^{(b)} = \begin{cases} -(\sqrt{5}-1)/2 & \text{with probability } p = (\sqrt{5}+1)/(2\sqrt{5}) \\ (\sqrt{5}+1)/2 & \text{with probability } 1-p \end{cases}$$

   The estimated underlying structural residuals $\hat{\dot{\varepsilon}}_{it}$ are then perturbed to create bootstrapped structural residuals: $\dot{\varepsilon}_{it}^{(b)} = \hat{\dot{\varepsilon}}_{it} \cdot \xi_{it}^{(b)}$.

2. **Construct bootstrapped dependent variable:** Using the parameters from the initial estimation

($\widehat{\beta_0+\alpha_t}$, $\hat{\boldsymbol{\beta}}^*$, and $\hat{\rho}$), we construct the bootstrapped log-cost variable, $\ln Cost_{it}^{(b)}$:

$$\ln \boldsymbol{Cost}_t^{(b)} = (\widehat{\beta_0+\alpha_t})\boldsymbol{\iota}_{N_t} + TL(\boldsymbol{y}_t, \boldsymbol{p}_t, \boldsymbol{z}_t; \hat{\boldsymbol{\beta}}^*) + (I_N - \hat{\rho}W_t)^{-1}\, \hat{\boldsymbol{\varepsilon}}_t^{(b)}$$

3. **Re-estimate parameters:** The full two-step estimation procedure, as outlined in Section 3, is applied to the dataset with $\ln Cost_{it}^{(b)}$ as the dependent variable.

This entire process is repeated B times and the standard error for each parameter $\theta \in \{\rho, \sigma_{\dot{v}}, \sigma_{\dot{u}}\}$ is then calculated as the empirical standard deviation of its B bootstrapped estimates.

4 Data

Our research utilizes a granular dataset combining detailed records from the Chilean interbank lending market with bank-specific balance sheet characteristics. Access to this confidential administrative data, provided by the Chilean Financial Market Commission (CMF), enables a precise analysis of banking interconnectedness and its impact on performance. As previously noted, our dataset addresses common limitations identified in the literature, where researchers often lack direct measures of micro-level linkages and instead rely on aggregated data or proxy approximations.[5]

Although Chile is a relatively smaller economy compared to global financial hubs such as the United States or Europe, its banking system provides an ideal context for investigating the role of interconnectedness in bank performance for several reasons. First, despite comprising a limited number of institutions—our sample includes 20 banks, virtually representing the entire sector—the Chilean banking system is mature, relatively concentrated, and plays a substantial role proportional to the overall economy (Margaretic et al., 2021). Such characteristic enhances the visibility and measurability of network dynamics and their effects on individual institutions. Second, and crucially for our empirical strategy, Chile offers exceptional access to detailed administrative datasets. These comprehensive datasets enable the accurate construction of real interbank lending networks using daily transaction records and detailed monthly balance sheets over an extended period (e.g., 2008–2020 in our full dataset). Thus, the high-frequency monthly data introduces a rich temporal dimension (T), resulting in a substantial and informative panel dataset. This dataset allows for robust analysis of dynamic network effects and efficiency, offering insights often unavailable from larger systems with less comprehensive data.

Information on interbank exposures is obtained from regulatory reports submitted by all active banks in Chile to the CMF. Specifically, we use Form C-18, titled Daily Balances of Obligations with Other Domestic Banks (*Saldos Diarios de Obligaciones con Otros Bancos del País*, in Spanish), which details all daily bilateral exposures between institutions. These reports are comprehensive, categorizing obligations

[5]Due to confidentiality concerns, initial model development and preliminary analyses were conducted using anonymized data that preserves essential statistical properties while safeguarding bank identities. Final computational analyses using the complete, non-anonymized dataset were executed exclusively by authorized CMF personnel to ensure data security and confidentiality. External researchers, therefore, did not have direct access to sensitive identifying information.

across a range of financial instruments, including current accounts, other sight obligations, repurchase agreements, term deposits, and financial derivative contracts. Furthermore, the data differentiates exposures by residual maturity using three specific categories: sight obligations, obligations with maturity up to one year, and obligations with maturity over one year. The data also classifies each obligation by its currency of payment, distinguishing between non-indexed Chilean pesos, indexed domestic currency, and foreign currency.

For the main round of results presented in this paper, we construct the weights matrix (W_t) using a comprehensive measure of total interbank obligations. The weight of the connection between any two banks is defined as the sum of all reported financial instruments (including term deposits, repurchase agreements, and derivatives) across all available maturity categories (sight, up to one year, and over one year). Consistent with the C-18 reporting structure, our network is directed, with edges running from the borrower (the reporting institution) to the lender (the creditor institution). After aggregating the data to a monthly frequency, we apply a row-normalization to the resulting time-varying adjacency matrices. This is a standard and effective way to measure the relative importance of each lender to a specific borrower, as the normalized weight represents a lender's share of a given borrower's total obligations.

While this comprehensive matrix based on total obligations forms the basis of our core results, we leverage the granularity and depth of our administrative data to explore alternative specifications of W_t in a subsequent section. These alternative settings—which consider different combinations of financial instruments and maturities, alternative normalization methods, and the reverse lender-to-borrower direction—serve as both robustness checks and a method for analyzing potential transmission channels. The ability to construct and test these varied network specifications using direct, dynamic, and detailed transaction data provides a uniquely rich framework for analyzing the multifaceted role of interconnectedness.

Complementing the interbank exposure data, we employ comprehensive bank-specific financial information from monthly balance sheets submitted to the CMF (Form MB-2). These reports provide detailed information on each bank's financial position, operational activities, and risk profiles.

The final dataset is constructed as a monthly panel that combines bilateral interbank exposure data—used to define the network structures (W_t)—with detailed bank-specific balance sheet variables for the full set of the 20 most important banks operating in Chile. This rich, panel-structured dataset allows for robust empirical analysis of banking performance through advanced econometric techniques designed for panel and network data, while effectively controlling for bank heterogeneity and time-specific effects.

Note: Although our full dataset spans from 2008 to 2020, covering virtually the entire Chilean interbank market, this preliminary analysis (working paper) utilizes data for the period from January 2016 to December 2017. To ensure comparability over time, all nominal variables have been deflated using the Chilean Consumer Price Index (CPI), with 2018 as the base year.

4.1 Variable Definitions for the Cost Function Estimation

Following the standard intermediation approach in the banking literature (e.g., Sealey Jr and Lindley, 1977; Malikov et al., 2015), we define bank outputs, inputs, and input prices based on the balance sheet information derived from the CMF data.

Table 1: Variable Definitions and Statistics

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 (x) and Prices (p)	
x_1	Labor
x_2	Physical capital (Fixed assets)
x_3	Deposits and other borrowed funds
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

Notes: The table reports the definitions and construction of the variables employed in the stochastic frontier cost function estimation.

We specify four output categories representing key earning assets: commercial loans, real estate loans, consumer loans, and securities and other investments. All outputs are measured in real Chilean Pesos of 2018.

Variable inputs include labor, measured by total personnel expenses and number of employees; physical capital, represented by the book value of fixed and leased assets; and borrowed funds (including deposits). Input prices are computed by dividing the respective expenses by the input quantities.

We include equity capital as a quasi-fixed input to control for bank heterogeneity and scale. Total variable operating cost is constructed as the sum of interest expenses, commissions, personnel expenses, and selected administrative expenses, excluding depreciation to avoid double counting with the capital input price.

5 Results

5.1 The Cost Function and Network Dependence

As previously discussed, while the first-stage allows us to obtain the central parameters in the empirical cost function, $\boldsymbol{\beta}$, the second-stage GMM estimation enables the quantification of the average degree of interdependence in bank cost performance deviations, through the parameter ρ, and the key standard deviations in the Cost Function. Given the large numbers of terms in the vector, and as it is common in the literature, for the estimated trans-log cost function we mainly report key associated results, such as the standard deviations that allow the differentiation of the two components in the composited residual and the computation of the estimates of cost efficiency.

Our estimation, reported in Table 2, yields $\hat{\rho} = -0.542$, which is statistically significant. The negative estimate indicates a negative correlation in inefficiency deviations among interconnected banks. In other words, a bank linked to peers exhibiting higher-than-average inefficiency tends to show lower adjusted inefficiency itself. This pattern suggests that banks connected to less efficient neighbors, on average, operate more efficiently relative to their own expected cost levels. Such a finding is consistent with the notion that banks may face competitive pressures or engage in negative benchmarking—improving their efficiency by observing and avoiding the mistakes made by underperforming peers. These dynamics point to meaningful network effects, potentially driven by strategic responses to peer underperformance or by negative learning mechanisms, wherein banks adapt their strategies after witnessing adverse outcomes among their counterparts.

In the following subsections we present relevant post-estimation results, including bank-level inefficiency scores and a decomposition of the relative contributions of direct and network effects to overall performance. We conclude by exploring potential mechanisms underlying the observed negative network dependence.

Table 2: Results for the central parameters

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

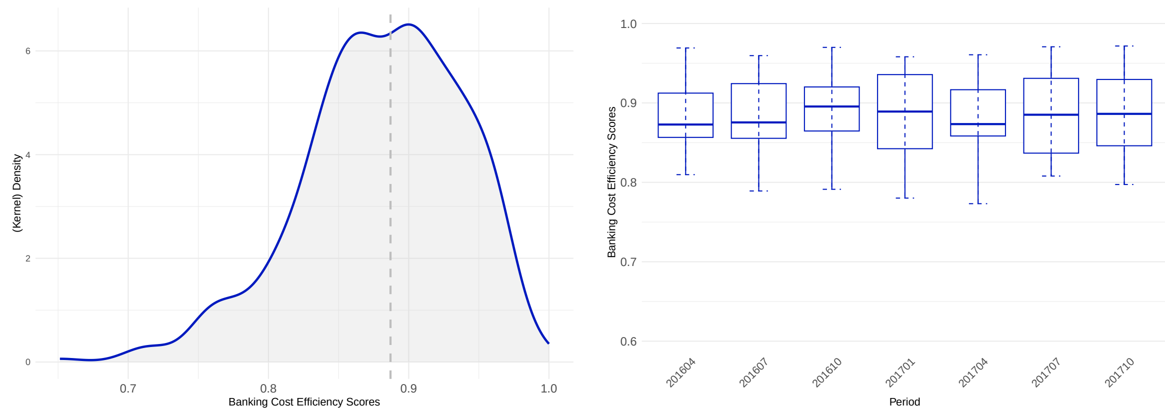
Notes: 1. The table reports the central results for the parameters in equations (1) and (2). The 'Controls in the Translog Cost Function' row indicates the inclusion of all first-order, second-order (squared), and interaction terms for outputs, input prices, and quasi-fixed inputs as specified in the translog cost function $TL(\boldsymbol{y}_{it}, \boldsymbol{p}_{it}, \boldsymbol{z}_{it}; \boldsymbol{\beta}^*)$ in equation (1). 2. Data: Chilean banking system (2016m1–2017m12). 3. Standard errors (in parentheses) computed via wild bootstrap. 4. *** significant at 1%; ** 5%; * 10%.

5.2 Baseline Banking Performance: Cost Efficiency Levels

We first briefly present the baseline estimates of banking cost efficiency derived from our stochastic cost frontier model. This initial overview serves to characterize the general performance landscape of the Chilean banking industry and to verify that our estimates, despite the econometric novelties introduced, align broadly with findings from previous research on this sector.

Figure 1 illustrates the empirical distribution and temporal evolution of the technical efficiency scores, calculated as $TE_{it} = \exp(-\hat{\mu}_{it})$, where $\hat{\mu}_{it}$ is the estimated cost inefficiency presented in subsection 3.2.3. Panel (a) of the figure shows the kernel density estimate of these scores, and Panel (b) presents a time series of monthly boxplots illustrating their distribution. The results suggest that the Chilean banking system generally operates at high levels of cost efficiency. The scores are predominantly concentrated towards the upper end of the scale, with a central tendency suggesting typical efficiency levels around 90% (i.e., a TE score of approximately 0.9). While exhibiting some cross-sectional heterogeneity, these efficiency levels are relatively stable over the observed period. These initial findings are consistent with other empirical assessments of the Chilean banking industry (e.g., Cobas et al., 2024), which supports our model's baseline characterization of bank performance as a necessary preliminary step before analyzing network effects.

Figure 1: Technical Efficiency Scores



(a) Distribution (b) Temporal Evolution

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 negative estimated cost inefficiency term, i.e., $\mathrm{TE}_{it} = \exp(-\hat{\mu}_{it})$.

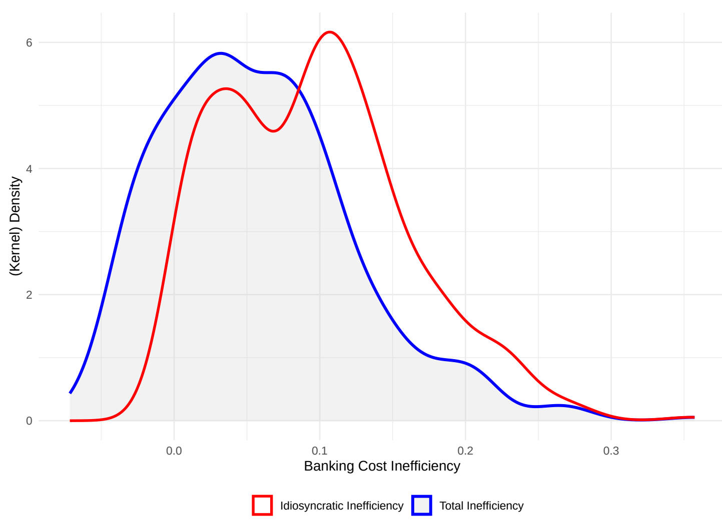
5.3 Interconnectedness and Banking Performance

The statistically significant network dependence parameter ($\hat{\rho}$) presented in Table 2 provides initial empirical evidence for the role of interbank interconnectedness in shaping banking performance within our dataset, an overall result that aligns with previous findings on peer effects (Margaretic et al., 2021). A key novelty of our econometric approach, however, is its ability to leverage this estimated parameter and the weights matrix (W_t) to quantify the importance of such interconnectedness. This is achieved by decomposing the total estimated cost inefficiency into a Direct Effect component (representing Idiosyncratic Inefficiency, $s_{ii}\hat{\mu}_{it}$) and an Indirect (Network) Effect component ($\sum_{j\neq i} s_{ij}\hat{\mu}_{jt}$), as detailed in Subsection 3.2.3.

We find that the Indirect (Network) Effect component is, on average, negative. This finding is directly associated with our negative estimate for the network dependence parameter ($\hat{\rho} = -0.542$), given that the underlying, network-independent inefficiency estimates ($\hat{\mu}_{it}$ from Equation 9) and the elements of the weights matrix (W_t) are non-negative. Specifically, a negative $\hat{\rho}$ introduces negative dependencies within the network multiplier matrix $S(\hat{\rho}, W_t)$. Consequently, for a bank connected to peers with higher underlying inefficiency, the network effect tends to yield a net reduction in that bank's total cost inefficiency, relative to its own Direct Effect component.

Figure 2 visually presents this efficiency-enhancing role of network interactions in the Chilean interbank market. The figure presents kernel density estimates comparing the distributions of the Idiosyncratic Inefficiency component (Direct Effect, red line) and the final Total Inefficiency estimate (blue line) across all bank-period observations. A clear leftward shift is observed for the distribution of Total Inefficiency relative to that of the Idiosyncratic Inefficiency. This displacement means that the predominantly negative Indirect (Network) Effects lead to Total Inefficiency levels that are, on average, lower than what would be implied by banks' idiosyncratic components alone. Thus, the interconnections within the interbank lending market, as captured by our model, appear to play a significant role in improving overall cost efficiency in the sector.

Figure 2: Kernel Density of the Direct and Total Effects



Notes: The figure contains two kernel density plots. These depict estimates of the Direct or Idiosyncratic component of cost inefficiency (red line) and the Total component (blue line), with data pooled across all banks and months in the sample period.

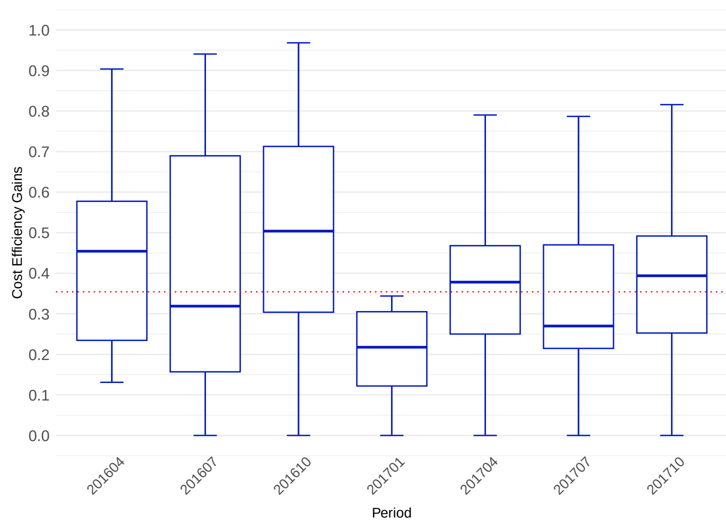
To further quantify the economic significance of the network effects—suggested by the leftward shift in the inefficiency distributions shown in Figure 2—we introduce an intuitive metric termed "Efficiency Gain." This measure captures the percentage reduction in a bank's cost inefficiency attributable to network interactions, relative to its Direct (Idiosyncratic) Effect. Formally, it is computed as $(1 - \text{Total Inefficiency}_{it}/\text{Direct Effect}_{it}) \times 100\%$.[6]

Figure 3 illustrates the temporal evolution of these efficiency gains through monthly boxplots for

[6]This formulation stems from the decomposition Total Inefficiency = Direct Effect + Indirect Effect. Thus, the gain is $1 - \frac{\text{Direct Effect+Indirect Effect}}{\text{Direct Effect}}$. Since our estimated Indirect Effect is predominantly negative (indicating an efficiency improvement), this formula quantifies the positive percentage gain. For instance, if Direct Effect = 0.10 and Total Inefficiency = 0.07, the gain is $(0.10 - 0.07)/0.10 = 0.30$ or 30%. A small number of observations yielding extreme gain values (e.g., those initially above the 95th percentile), often resulting from division by Direct Effect values close to zero.

the 2016m01–2017m12 period, while Table 3 provides their overall descriptive statistics. The results highlight the benefits of networks, as measured by interbank loans, in the Chilean industry. The median bank-period observation experiences an efficiency gain of approximately 20%, indicating a substantial reduction in operational costs attributable to network effects beyond its own idiosyncratic baseline. The considerable range of gains also shows significant heterogeneity in how different banks leverage, or are affected by, network interactions. Thus, our findings reinforce that interconnectedness not only influences the shape of the inefficiency distribution but also translates into economically meaningful improvements in cost efficiency for a significant portion of the Chilean banking sector.

Figure 3: Temporal Evolution of Network-Driven Efficiency Gains (%)



Notes: The figure presents a time series of monthly boxplots illustrating the distribution of Efficiency Gains for selected months over 2016m01–2017m12. 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.

Table 3: Descriptive Statistics for Network-Driven Efficiency Gains

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
Value	0.000	0.171	0.354	0.384	0.548	0.990

Note: The table reports descriptive statistics for the Efficiency Gain metric over the period 2016m01–2017m12, calculated as $(1 - \text{Total Inefficiency}_{it}/\text{Direct Effect}_{it})$. Total Inefficiency and Direct Effect components are derived from the stochastic cost frontier estimation.

5.4 Exploring Alternative Network Specifications as Robustness Checks and Channel Analysis

Our central finding of a negative network dependence parameter ($\hat{\rho} \approx -0.5$), suggesting that interconnectedness is associated with improved cost efficiency (lower inefficiency), aligns with several plausible economic mechanisms. Banks may experience heightened competitive pressures from their interconnected peers, incentivizing cost optimization. Alternatively, they might engage in learning or benchmarking behaviors, specifically 'negative benchmarking,' where banks actively observe and avoid operational inefficiencies exhibited by connected institutions.

A rigorous empirical disentanglement of these specific channels is complex and may be beyond the scope of this paper. Nevertheless, we leverage the richness of our administrative data (Form C-18) to explore how our findings hold up under alternative definitions of the network adjacency matrix (W_t). By systematically varying the underlying financial instruments and maturity categories that define the network, we can conduct comprehensive robustness checks of our main finding. Additionally, observing how the results change across these specifications allows us to conjecture about the potential mechanisms at play. For example, if network effects are stronger for certain types of obligations, it may suggest which kinds of interbank relationships are the primary conduits for these efficiency-enhancing spillovers.

5.4.1 Robustness to Network Definition by Maturity

We first exploit the maturity information in the C-18 data to construct three distinct versions of the adjacency matrix W_t, each based on the total value of obligations within a specific maturity category. Table 4 presents the estimation results for networks defined by: (1) 'Overnight/at sight' obligations, (2) obligations with maturity 'Up to one year', and (3) obligations with 'More than one year' maturity. The final column reports our baseline model, which uses all obligations combined.

We find no statistically significant network effect when interconnectedness is defined solely by at-sight obligations. This suggests that these very short-term exposures, likely reflecting daily operational liquidity management, may not be the primary channel for the strategic interactions that influence overall cost efficiency. Conversely, networks based on obligations with longer maturities exhibit strong, statistically significant, and negative dependence parameters. For obligations up to one year ($\hat{\rho} = -0.455^{***}$) and those exceeding one year ($\hat{\rho} = -0.295^{***}$), interconnectedness is robustly associated with improved cost efficiency. The effect is largest in magnitude for the intermediate 'Up to one year' category. This may indicate that relationships with this maturity—which likely reflect core operational financing and risk management decisions beyond immediate liquidity needs—are particularly important conduits for competitive pressures or active benchmarking among banks.

Table 4: Model Results for Networks Defined by Obligation Maturity

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				
$\sigma_{\dot{v}}$	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: 1. The table reports the central results for the parameters in equations (1) and (2). The 'Controls in the Translog Cost Function' row indicates the inclusion of all first-order, second-order (squared), and interaction terms for outputs, input prices, and quasi-fixed inputs as specified in the translog cost function $TL(\boldsymbol{y}_{it}, \boldsymbol{p}_{it}, \boldsymbol{z}_{it}; \boldsymbol{\beta}^*)$ in equation (1). 2. Data: Chilean banking system (2016m1–2017m12). 3. Standard errors (in parentheses) computed via wild bootstrap. 4. *** significant at 1%; ** 5%; * 10%.

5.4.2 Robustness to Network Definition by Financial Instrument

We now explore the sensitivity of our findings by examining variations in the construction of the interbank network adjacency matrix (W_t) based on different combinations of financial instruments reported in Form C-18. Specifically, we construct alternative versions of W_t as follows: first, we define a network based exclusively on financial derivative contracts (*Derivatives Only*); second, we define an unsecured exposure network by subtracting collateral values from total obligations, thus isolating pure credit risk exposures (*Unsecured Exposures*); and third, we construct a traditional funding network using only term deposits (*Term Deposits Only*). Finally, we include our baseline network constructed from total obligations, which encompasses all instruments (*All Obligations (Baseline)*), for comparison.

Overall, the results presented in Table 5 strongly support the robustness of our central finding. The consistently significant and negative network dependence parameter across all specifications indicates that the efficiency-enhancing effect is not driven by a single type of instrument. However, the results from these different specifications allow us to conjecture about the potential channels at play. For instance, the significant effect in the *Derivatives Only* network suggests that interactions related to risk management and hedging activities may serve as a channel for learning or benchmarking best practices. Similarly, the strong effect observed for *Unsecured Exposures* may highlight the role of heightened market discipline; the absence of collateral could intensify incentives for banks to actively monitor counterparts and to operate more efficiently to signal their creditworthiness. Finally, the finding for the *Term Deposits* network confirms that these efficiency-enhancing pressures are also present within the most traditional interbank funding markets, likely reflecting competitive forces. Collectively, these results suggest that the positive impact of interconnectedness on efficiency is a multifaceted phenomenon, driven by a combination of risk management benchmarking, heightened market discipline, and traditional competitive pressures.

Table 5: Model Results for Networks Defined by Financial 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				
$\sigma_{\dot{v}}$	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: 1. The table reports the central results for the parameters in equations (1) and (2). The 'Controls in the Translog Cost Function' row indicates the inclusion of all first-order, second-order (squared), and interaction terms for outputs, input prices, and quasi-fixed inputs as specified in the translog cost function $TL(\boldsymbol{y}_{it}, \boldsymbol{p}_{it}, \boldsymbol{z}_{it}; \boldsymbol{\beta}^*)$ in equation (1). 2. Data: Chilean banking system (2016m1–2017m12). 3. Standard errors (in parentheses) computed via wild bootstrap. 4. *** significant at 1%; ** 5%; * 10%.

5.4.3 Other Specifications and Mechanisms (Ongoing Research)

(Further work is in progress to explore additional specifications, including changing the network directionality from borrower-to-lender to lender-to-borrower and employing alternative normalization methods. We are also developing formal tests to explore the roles of market competition and other network characteristics—such as centrality or concentration indices—in mediating the observed efficiency effects.)

6 (Preliminary) Conclusions

This paper research the influence of bank interconnectedness, as measured through the interbank lending market, on operational cost efficiency within the Chilean banking sector. Motivated by the extensive literature focusing primarily on the systemic risk and financial contagion aspects of financial networks, especially during crises, our study aimed to contribute to the less explored domain of how these network structures shape banking performance and efficiency during periods of relative economic stability.

Utilizing unique, transaction-level administrative data from the Chilean Financial Market Commission (CMF) for the period 2008–2020, we constructed time-varying network adjacency matrices (W_t) representing actual interbank lending relationships. To analyze these rich data, we employed a novel two-step Generalized Method of Moments (GMM) estimation strategy within a stochastic frontier analysis (SFA) framework. This approach integrated network dependencies via a spatial/network autoregressive parameter (ρ) in a flexible translog cost function, enabling the estimation of bank-specific cost inefficiencies while controlling for unobserved heterogeneity and network influences.

Our empirical analysis reveals robust evidence that interconnectedness is a statistically significant determinant of bank cost efficiency in Chile. We estimate an average network dependence parameter ($\hat{\rho}$) of approximately -0.5 , suggesting that, on average, network connections in the Chilean interbank market are associated with improved cost efficiency (i.e., lower cost inefficiency). Density estimates show a leftward shift in the distribution of total cost inefficiency relative to its idiosyncratic (Direct Effect) component. Quantifying this impact, our decomposition analysis reveals that network effects contribute to a significant "Efficiency Gain"; for the median bank-period observation, these network interactions account for a reduction in cost inefficiency of approximately 35 percentage points, relative to the bank's idiosyncratic baseline. These findings suggest that interbank networks may facilitate mechanisms such as competitive pressures or enhanced benchmarking opportunities, leading to tangible improvements in operational efficiency.

This study makes several contributions. Primarily, it extends empirical evidence beyond the traditional focus on systemic risks by providing quantitative insights into how interbank relationships concretely influence bank operational performance under normal economic conditions. Methodologically, our work demonstrates the application of advanced econometric techniques that effectively incorporate network dependencies with time-varying structures into stochastic frontier models using granular administrative data, specifically within a multi-output cost function context for banking. From a policy perspective, the findings highlight that interbank network structures are not only conduits of potential systemic risk but also critical elements influencing the efficiency and operational strength of the banking sector. Consequently, understanding and monitoring these network dynamics is essential for policymakers aiming to support robust, efficient, and stable financial systems that underpin broader economic health.

Given these preliminary results, avenues for future research include a deeper investigation into the specific channels through which interconnectedness translates into efficiency gains.

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