SECTION 4

APPLICATIONS OF FINANCIAL NETWORKS

CHAPTER 10

FINANCIAL CONTAGION IN CROSS-HOLDINGS NETWORKS: THE CASE OF ECUADOR

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ABSTRACT

Financial contagion refers to the propagation of shocks that can generate widespread failures. The authors apply a financial contagion model proposed by Elliott, Golub, and Jackson (2014) to a cross-shareholding network of firms in Ecuador. The authors use a novel dataset to study the potential channels for contagion. Although diversification is not high, results reveal enough conditions for a contagion event to occur. However, the low level of integration attenuates the effects of shocks. The authors run simulations affecting a particular firm at the time, and find that two firms coming from the finance and trade industry cause the highest contagion. In addition, when an entire industry receives a shock, trade and manufacturing industries contagion more companies than the rest. Finally, the model can assist policymakers to monitor the market and evaluate the fragility of the network in different scenarios.

Keywords: Financial contagion; cross-holding; network; cascade effects; dependency matrix, diversification, and integration

JEL classifications: F36; F65; G32; G33

1. INTRODUCTION

Firms are connected, and these networks materialize as informal relations, mergers, acquisitions, R&D alliances, and competition for resources (Ozman, 2009).

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Hence, interconnections can create potential channels for contagion and amplification of shocks (Jackson, Rogers, & Zenou, 2017).

As firms have strategic incentives to be interconnected, Turnbull, Ford, and Cunningham (1996) argue that organizations interact with each other to develop business relationships and take advantage of their resources. According to Barney (2001), firms can benefit from the competitive advantage that emerges from these relationships. Similarly, a company can configure alliance network activities through interconnections that provide strategic opportunities and affect the firm's behavior and value (Lavie, 2006).

In a cross-shareholding situation, a firm owns a fraction of the shares issued by other companies (Fedenia, Hodder, & Triantis, 1994). Firms share ownership of project returns and some positive externalities. For instance, a cross-shareholding of equity may bring stability to the relationship of two firms since this association can mitigate the effects of uncertainty (Sinha, 1998). Furthermore, cross-shareholding relationships can present possible risks. When a firm acquires a large percentage of equity share, the organization should consider the possible side effects of its business decisions. Liu, Lin, and Qin (2018) argue that this behavior diminishes aggressive competition. In addition, Lee (2005) states that cross-shareholders who are also suppliers could have conflicting interests that may cloud their investment decisions. Hence, the risk of financial contagion emerges from these interconnections. This outcome refers to the propagation of shocks, induced by a firm, which can generate widespread failures.

A cross-shareholding network assesses the impact of a company's bankruptcy on the market value of its cross-holders. Thus, policymakers can calculate the minimum level of intervention to avoid a cascade of failures, monitor the market, and anticipate future losses.

In this chapter, we apply the model proposed by Elliott et al. (2014) to a network of firms in Ecuador where the nodes are firms, and the links are the cross-shareholding among firms. We use the dataset provided by Superintendence of Companies, Securities and Insurance of Ecuador (SUPERCIAS)[1] of 2016, the latest year available. To the best of our knowledge, this is the first application of Elliott et al.'s (2014) model to this type of network.

Results suggest that in spite of the low level of diversification, the contagion still spreads out. Furthermore, the network exhibits low integration which implies a high exposure of firms' assets to some negative shocks. We find the presence of giant connected component, although most of the links are weak. This could explain why we cannot observe high effects for the shock in most of the cases. We evaluate the sensitivity of results at different thresholds of default, and we find that the finance and trade industries cause the highest contagion.

The chapter is organized as follows. Section 2 gives a brief overview of the most relevant literature on financial contagion. Then, we illustrate the model in Section 3. We detail the data, sample selection, parameters, and main variables in Section 4. Finally, we present results and conclusions in Sections 5 and 6, respectively.

2. LITERATURE REVIEW

Literature has highlighted two problems regarding financial networks. The first consists of modeling financial networks and capturing a good understanding of real-world markets. Existing literature has described a variety of interconnections such as direct loss spillovers through defaults, mark-to-market losses, contagion through correlation, and common exposures (Glasserman & Young, 2016). For instance, Allen & Babus (2009) claim that both assets and liabilities could serve as network links. In the same line, Gai Prasanna and Kapadia Sujit (2010) model a financial system in which agents connect by financial claims, that is, interbank markets and payment systems. Moreover, Acemoglu, Ozdaglar, and Tahbaz-Salehi (2015) focus on liabilities when forming financial networks, using standard debt contracts.

Even though most empirical studies have focused on the structure of interbank networks, it is relevant to study the interconnections that emerge from the mutual ownership of firms and the structure that these cross-shareholding networks present. In the literature, the topology and structure of interbank networks are analyzed using network statistics such as degree distribution, centrality measures, and clustering analysis. For instance, power-law distributions appear in the Austrian interbank lending network, Brazilian interbank network, Mexican banking system, and the Japanese and US payment systems (Boss & Elsinger, 2004; Cont, Moussa, & Santos, 2013; Inaoka, Ninomiya, Taniguchi, Shimizu, & Takayasu, 2004; Martinez-Jaramillo, Alexandrova-Kabadjova, Bravo-Benitez, & Solórzano-Margain, 2014; Soramäki, Bech, Arnold, Glass, & Beyeler, 2007).

The second problem is about how resilient the structure of networks is to measure contagion in the systemic risk. According to Cabrales, Gale, and Gottardi (2016), it is essential to study financial networks and contagion to discover the extent of defaults in the system and the incidence of link formation. Even though the selected assumptions can lead to different conclusions about the interconnection, a standard methodology explains the mechanisms of how shocks spread through the network (Glasserman & Young, 2016).

The model developed by Elliott et al. is based on Eisenberg and Noe (2001), and the studies on cross-shareholdings from Brioschi, Buzzacchi, and Colombo (1989) and Fedenia et al. (1994). Eisenberg and Noe (2001) consider a system of firms with obligations to each other via debt claims and liability of equity. They develop a financial contagion algorithm that adjusts dynamically through a fictitious sequential default. In this algorithm, systemic risk is measured on how many waves of defaults are required to induce a firm to fail. Based on Eisenberg and Noe, Elsinger (2009) develops a model in which banks are connected through financial obligations and cross-holdings. He extends the work of Eisenberg and Noe by taking cross-holdings and a detailed seniority structure of debt explicitly into account.

Financial networks and contagion models have been widely studied, and researchers have proposed many theoretical models. We use cross-shareholdings as the basis of network interconnections, and we illustrate how the structure of the network has implications on the welfare and the resilience of the network.

3. THE FINANCIAL CONTAGION MODEL

The model of financial contagion networks proposed by Elliott et al. (2014) defines how the firm's market value is affected by its primitive assets and how the cross-shareholding network is structured. When a negative shock hits a firm, its market value can fall and generates a cost because the firm may allocate cash flow to alleviate the losses.

The initial shock could affect the company's ability to meet its obligations with other companies, and due to interdependencies, the other firms may also fail to meet their obligations as well, and so on. This succession of failures can occur either all at once or in different periods. However, as Elliott et al. (2014) suggest, it is useful to think about that succession as waves (or cascades) of failures.

The extent of waves depends on the firms' network structure. From a firm's perspective, the more assets held by other firms, the higher the exposure of the firm. This effect is known as integration, and it measures how much of a firm is held by others (Elliott et al., 2014). A firm can be less or more integrated, but the overall propagation will depend on how the firm's assets are spread out across the network. If a firm becomes more diversified, the probability of being infected decreases once an initial shock occurs. It means that the firm is less sensitive to the cascade of failures. However, the extent of cascades could be magnified if firms form links with other firms that belong to the same industry (homophily).

Next, we define the book and the market value of a firm, emphasizing the network perspective. Then, we give a detailed explanation of the financial contagion model and how network characteristics affect the extent of the cascades.

3.1. The Book and Market Values of a Firm

We consider a firm i, whose book value V_i is defined as the total value of its share. Those shares are held by either other firms, outside shareholders, or both. Mathematically, the book value is

$$V_i = \sum_{k}^{K} D_{ik} p_k + \sum_{j}^{N} D_{ij} V_j \tag{1}$$

The first term on the right-hand side is the value of firm i's assets. We assume that there are K types of assets, such that D_{ik} is the share value of primitive asset $k \in K$ held by firm $i \in N$. Let p_k be the market price of the asset k. The second term on the right is the value of firm i's claims on other firms. We define $C_{ij} \geq 0$, the fraction of firm j's shares held by firm i, for any $i, j \in N$. In Elliott et al. (2014), C_{ij} represents a direct link of ownership or *ownership paths*: firm i owns a positive share of j, otherwise when $C_{ij} = 0$, firms i and j are not directly related.

As cited by Elliot, Brioschi et al. (1989) argue that the market value of a firm i is the value of shares held by its outside investor. Let $\sum_j C_{ji} V_i$ be the part of firm i's value owned by other firms in cross-shareholdings. Thus, we define $\hat{C}_{ii} = 1 - \sum_j C_{ji}$ as the part of asset value held in firm i, or the share values under firm i's control. Mathematically, the market value is expressed as

$$\begin{aligned} v_i &= \hat{C}_{ii} V_i \\ &= V_i - \sum_j C_{ji} V_i \\ &= \sum_k D_{ik} p_k + \sum_j C_{ij} V_j - \sum_j C_{ji} V_i \end{aligned} \tag{2}$$

3.2. The Effect of Cascades of Failures

Elliott et al. (2014) develop a model to analyze the financial contagion using a network of financial interdependencies. As explained by them, the connection among firms is captured by the dependency matrix, where each element in that matrix represents the cross-shareholding between two companies. Given a negative shock that affects a firm, they studied how this disturbance propagates through the network and generates a cascade of failures.

Consider a firm *i* whose value is given by v_i (see equation (2)), and let $\underline{v}_i = \theta v_i$ be a failure threshold, where $\theta \in (0, 1)$. We assume that if the value v_i falls below that threshold, the firm ceases operations and liquidates its assets. Once $v_i < \underline{v}_i$, the firm incurs failure costs $\beta\underline{v}_i$, where $\beta \in [0, 1]$, this cost affects the market value such that,

$$v_i = \sum_k D_{ik} p_k + \sum_j C_{ij} V_j - \sum_j C_{ji} V_i - \beta \underline{v}_i I_{v_i \le \underline{v}_i} \tag{3}$$

where *I* is an indicator function taking value 1 if $v_i < \underline{v}_i$ and 0 otherwise. β can be thought as liquidation cost.

Given a negative shock, we assume that the initial market value v_i^0 for firm *i* is reduced by α%. The first term on the right-hand side of equation (3) is affected. Once the initial shock occurs, the new asset value v_i^1 can be estimated. The *first wave of failure* occurs when a certain number of firms besides *i* satisfy the condition $v_j < \underline{v}_j$ for all $j \neq i$. These firms incur in a failure cost $\beta\underline{v}_i$. The cascades continue to occur until the initial shock infects no more firms.

3.3. Diversification, Integration, and Homophily

Specific characteristics of the network can increase or decrease the potential spread of financial contagion. We focus on three characteristics: diversification, integration, and homophily.

Diversification measures the number of cross-holders in firm *i*, which is calculated as the out-degree of nodes. If diversification increases, the firm *i* will not depend on a particular cross-shareholder. Therefore, it is more challenging to start a contagion. In addition, when the shock is sufficiently big, the contagion propagation is more suitable.

$$d_i = \sum_j C_{ij} \tag{4}$$

Integration of firm *i* is the percentage of its share capital that does not belong to outside investors. If integration decreases (increases), firms will be less (more) exposed to other firms. Hence, the probability and extent of contagions also decrease (increases). The opposite action is that the firm becomes more (less) dependent on its assets. We measure integration as

$$t_i = 1 - \hat{C}_{ii} \tag{5}$$

Homophily measures the tendency of a firm to form links with comparable firms. According to Elliott et al. (2014), if homophily increases, the connections among firms that belong to the same industry increase. Hence, the possible contagion to the full network will be lower. Newman (2003) claims that if firms prefer to connect with others like them, the network shows assortative mixing or matching. The opposite is called disassortative mixing. We use the assortative matching coefficient to measure homophily.

$$r = \frac{\sum_i e_{ii} - \sum_i a_i b_i}{1 - \sum_i a_i b_i} \tag{6}$$

Equation (6) calculates the assortative coefficient using the mixing matrix **e**, where the element e_{ij} is the fraction of edges in a network that connects a node of type i to one of type j, a_i and b_i are the fraction of each type of end of an edge that is attached to vertices of type i. Hence, the assortative mixing coefficient estimates the joint probability that vertices of type i is connected to vertices of type j.[2]

In the next section, we explain the data, which contains detailed information about shareholders and firms.

4. DATA DESCRIPTION

To illustrate the model of financial contagion proposed by Elliott et al. (2014), we use firm-level data provided by SUPERCIAS, the regulatory agency that monitors and controls the organization and operation of companies. SUPERCIAS collects information about the financial statements and other indicators of the firms. Since, Elliott et al.'s (2014) model is static, we collect information of 2016, the latest year available. According to SUPERCIAS records, there were more than 49,000 firms in 2016. However, only 504 firms had cross-holdings of shares among them. Our analysis is based on that sample, which is not representative.

Table 1 presents summary statistics at the industry level. The trade and general services industries are the most representative in our sample, with 100 and 132 companies, respectively, and manufacturing and trade industries reported the highest level of assets. This table also shows that the financial activities industry owns more than USD 133 million in other industries assets, but it owns USD 6 million within the same industry. Although the sample only represents 1.02% of the total firms, the proportion of assets is around 12% of the total. At the industry level, these proportions go from 10% to 18%, except for the agriculture industry, which represents 3%.

4.1. Cross-holding Matrix and Values of Organizations[3]

We define **C** as an $N \times N$ matrix, whose elements C_{ij} represents the fraction of firm j owned by firm i. SUPERCIAS provides information about the amount

Table 1. Descriptive Statistics of Assets and Cross-holdings at Industry Level.

Industry	Total Firms	Assets		Cross-holdings		% Assets
		Mean	Std	In	Out	
Agriculture	27	8,748	16,992	978	3,082	3
Construction	25	25,482	67,830	76,412	164	13
Financial activities	79	8,260	13,952	6,285	133,601	18
General services	132	15,514	83,693	1,409	31,455	10
Manufacturing	57	49,424	101,056	1	3,826	15
Real estate	55	10,584	18,270	330	6,661	10
Trade	100	32,427	147,097	31,236	36,839	14
Transportation	29	23,996	97,661	9,351	136	18
Total	504	21,804	68,318	126,002	215,764	12

Notes: Assets and cross-holdings are in thousands of dollars.
% Assets measures the proportion of assets of the sample concerning the total assets in the industry.

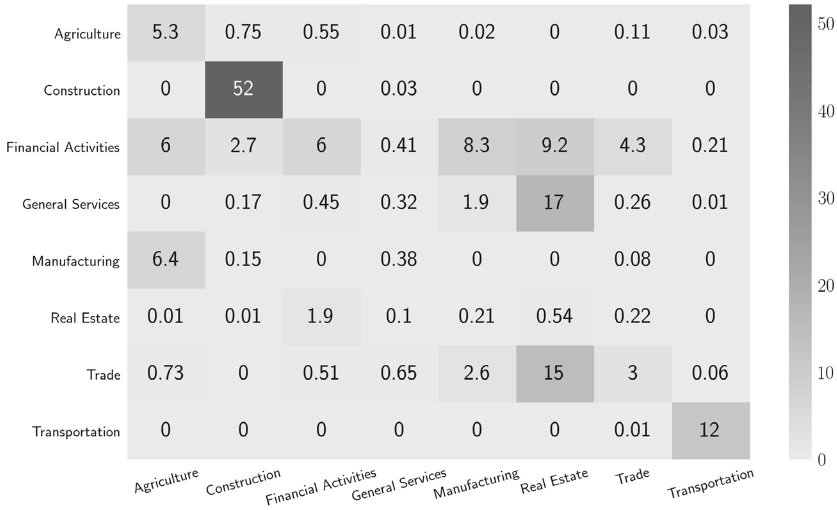

Fig. 1. Cross-holding Industry Matrix.

of shares held by firms and outside investors. To construct **C**, we consider the amount held only by other firms. To account for the amount of shares held by outside investors, we calculate the share $\hat{C}_{ii}$. Namely, $\hat{C}_{ii} = 1 - \sum_j C_{ij}$.

Fig. 1 shows matrix **C** at the industry level. Using the International Standard Industrial Classification codes, we classify firms into eight sectors. Based on this result, the finance industry has a significant proportion of shares of general services, trade, and manufacturing. Due to the nature of financial activities, its cross-shareholdings are likely to have more connections with different industries. This table suggests that the general services industry is the most *homophilic* since most of its links connect firms inside the same industry. The wide range of businesses included in general services could explain this situation.

To define the market value of each firm, equation (2) requires to define both the matrix **D**, and the vector **p**, where p_k is the market price of asset k. Unfortunately, we cannot identify these elements with the current data available. However, SUPERCIAS reports the $n \times 1$ vector **Dp**, where each entry contains the values of firm i's primitive assets.

4.2. Dependency Matrix

The dependency matrix **A** reflects the flow of assets among firms. Using previous results, we calculate it as $\mathbf{A} = \hat{\mathbf{C}}(\mathbf{I} - \mathbf{C})^{-1}$. Fig. 2 shows the dependency matrix at industry level. As we expected, the flow of assets is more interconnected. However, it seems that the dependency inside the same industry is higher concerning the connections to other industries.

Fig. 2 is revealing in several ways. First, the flow of assets inside the manufacturing industry has a significant difference from the cross-shareholding connection. Second, construction, manufacturing, and trade industries have more dependency on assets inside the same industry than cross-shareholders. Thus, the dependency matrix not only increases the connections among firms, but it can also increase more the connections inside the same industry than outside.

4.3. Simulation Parameters

The methodology explained in previous section requires to define the values for some parameters. Following Davydenko, Strebulaev, and Zhao (2012), we set the failure costs $\theta\% = \{20, 25, 30\}$. We define the grid for threshold $\beta = \{0.85, 0.90, 0.95\}$. Finally, the simulation is executed using three drop market values $\alpha\% = \{50, 75, 100\}$.

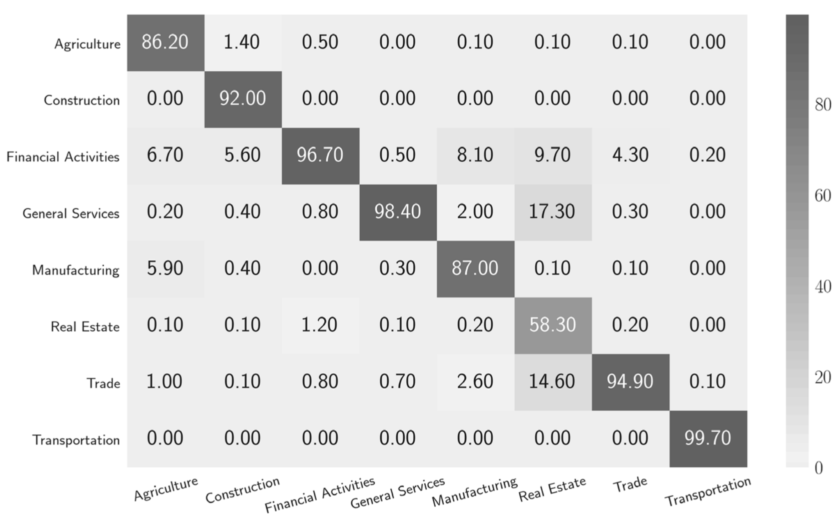

Fig. 2. Dependency Industry Matrix.

5. RESULTS

To assess how the network structure of cross-shareholdings impact on the propagation of cascades, we start with a single firm's failure. Then, we measure the loss of market value and the number of firms affected by that failure. Finally, we perform the analysis by industry level.[4]

5.1. Network Structure

To assess the strength and the extent of possible contagion, we estimate three characteristics of the network structure. Integration plays an essential role in the strength of the contagion since it indicates how much firm's assets are exposed to other firms. Diversification accounts for the extent of the contagion by measuring the spread out in firms' cross-holdings and homophily measures the chance of connecting with a firm of the same industry.

Fig. 3 shows the frequency distribution of firms' diversification. The distribution is left-skewed with an average value of 1.071. The model proposes that if the expected diversification is below one, the number of failures tends to zero. In the figure, 30% of firms are below one. This value suggests that the number of failures will not tend to zero. Moreover, the network has a principal component, but it is not entirely connected, which means that cascades could affect a significant proportion of firms if they are sufficiently integrated to spread financial contagion.

Integration captures how exposed are the assets of a firm. Fig. 4 presents the distribution of firms' integration. The distribution is highly left-skewed, and the mean value is 0.19. In the network, 64% of firms have an integration below 0.05. This low level of integration indicates that firms are particularly exposed to their own assets. Consequently, the effect of contagion could be weak.

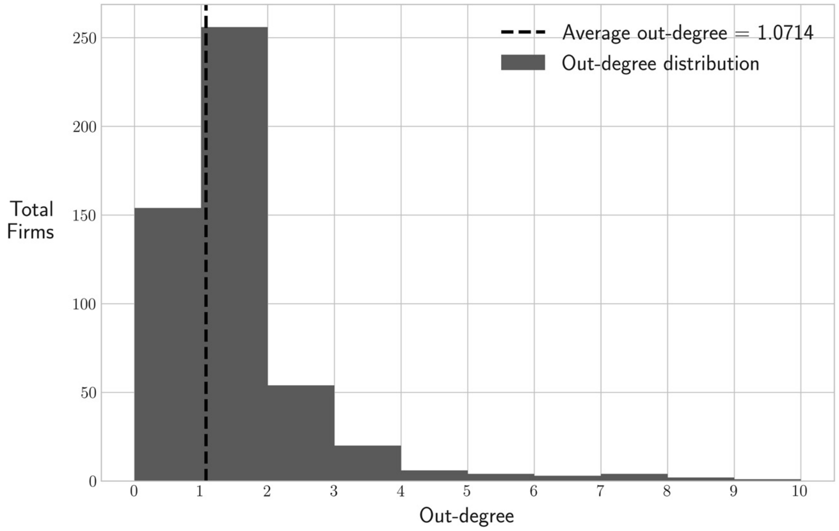

Fig. 3. Distribution of Firms at Different Levels of Diversification.

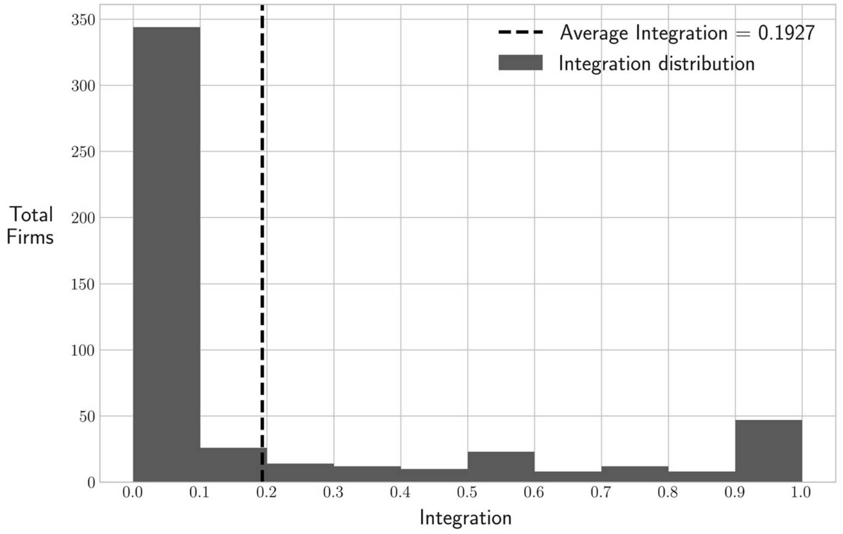

Fig. 4. Distribution of Firms at Different Levels of Integration.

Homophily also has significant consequences in financial contagion. In the cross-shareholding network, the assortativity coefficient is $r = 0.1635$. This result implies that this network is lowly assortative by industry (Newman, 2003). In other words, firms invest their money in same-industry firms more often than expected by pure chance. The standard deviation of the assortativity coefficient is calculated using the jackknife method, which gives a result of 0.023. Our finding of assortative mixing is statistically significant at 99% of confidence. Although diversification is not high, results suggest that we have enough conditions for a contagion event to occur. Also, firms are integrated at a low percentage. For instance, if an external shock affects a firm in the network, the low exposure will attenuate the effects of that shock. We assess the relationship between diversification and integration using a correlation coefficient, and we found that the correlation is -0.53. Therefore, firms that diversify less are more integrated with these few firms. These findings confirm that shocks in the network will produce contagion, but not at a large-scale level. Finally, given that the presence of positive homophily, once a firm is affected by a shock, there is a higher possibility that, firms belonged to the same industry, would be rapidly affected.

5.2. Cascades Effects: One Firm at a Time

To illustrate the methodology, we execute the algorithm for each set of parameters defined in the previous sections. Tables 2 and 3 show the number of firms that fail in each wave, when those failures are caused by firms that belong to a particular industry.[5] We display results for each combination of parameters. For instance, Table 2 shows that 55 firms belonging to the trade industry are infected

Table 2. Distribution of Firms Affected by Waves and Industries When $\alpha = 100\%$.

	Financial Activities	Commerce	Manufacturing	General Services	Real Estate	Construction	Transportation	Agriculture
				$\theta = 0.95$, $\beta = 30\%$				
Wave 1	54	55	45	61	23	11	12	8
Wave 2	5	2	0	4	1	0	2	6
				$\theta = 0.90$, $\beta = 30\%$				
Wave 1	43	43	39	40	16	8	9	7
Wave 2	2	1	2	1	3	0	0	0
				$\theta = 0.85$, $\beta = 30\%$				
Wave 1	35	38	30	29	13	8	7	6
Wave 2	0	0	0	3	1	0	1	0
				$\theta = 0.95$, $\beta = 20\%$				
Wave 1	54	55	45	61	23	11	12	8
Wave 2	4	2	0	4	0	0	1	5
				$\theta = 0.90$, $\beta = 20\%$				
Wave 1	43	43	39	40	16	8	9	7
Wave 2	0	0	1	0	3	0	0	0
				$\theta = 0.85$, $\beta = 20\%$				
Wave 1	35	38	30	29	13	8	7	6
Wave 2	0	0	0	3	1	0	1	0

Table 3. Distribution of Firms Affected by Waves and Industries When $\alpha = 50\%$.

	Financial Activities	Commerce	Manufacturing	General Services	Real Estate	Construction	Transportation	Agriculture
				$\theta = 0.95$, $\beta = 30\%$				
Wave 1	43	43	39	40	16	8	9	7
Wave 2	2	1	2	2	3	1	1	0
				$\theta = 0.90$, $\beta = 30\%$				
Wave 1	32	32	26	24	10	6	6	3
Wave 2	0	0	0	2	0	0	0	0
				$\theta = 0.85$, $\beta = 30\%$				
Wave 1	19	21	21	15	7	5	4	3
Wave 2	0	1	3	1	0	0	0	0
				$\theta = 0.95$, $\beta = 20\%$				
Wave 1	43	43	39	40	16	8	9	7
Wave 2	2	1	2	1	3	1	0	0
				$\theta = 0.90$, $\beta = 20\%$				
Wave 1	32	32	26	24	10	6	6	3
Wave 2	0	0	0	1	0	0	0	0
				$\theta = 0.85$, $\beta = 20\%$				
Wave 1	19	21	21	15	7	5	4	3
Wave 2	0	1	3	1	0	0	0	0

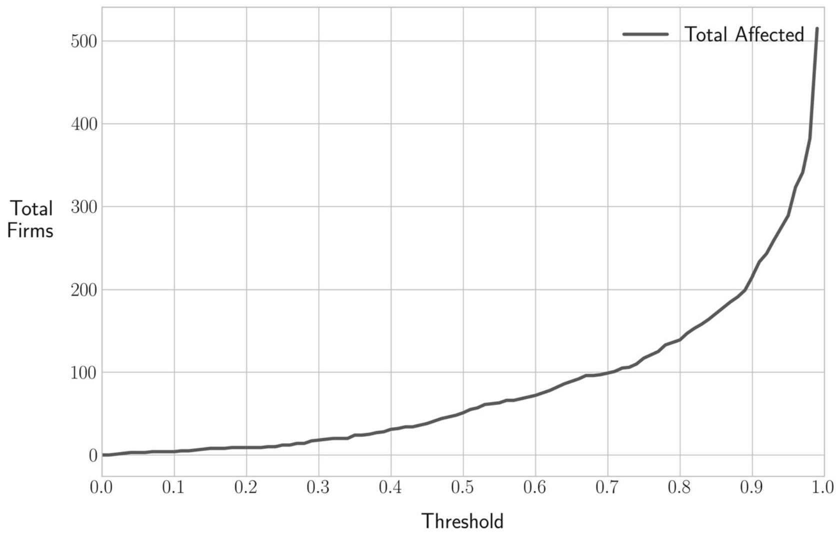

Fig. 5. Number of Firms Affected for Different Threshold Values.

in the first wave (more than 50% of firms in that industry), when $\alpha = 100\%$, $\beta = 20\%$, and $\theta = 0.95$.

Results suggest that the model behaves as expected when we change the simulation parameters. For instance, when the threshold (θ) increases, more firms become affected, for any combination of drop market value (α) and failure cost (β). Usually, the first cascade causes more firms to fail than that of the second wave. After that, no more firms are affected. This result is expected since increasing θ further would cause more firms to fail at earlier waves (see Tables 2 and 3).

We illustrate the sensitivity analysis on the threshold value in figure 5. We allow the parameter θ to vary from 0 to 1, and we count the total number of failures that each firm causes. By pushing θ above 0.7, we observe that the total firms affected increase exponentially. In addition, pushing α down from 100% to 50% leads to a similar sequence. Fewer firms are affected because assets are dropped to a lower degree such that they can keep running. In the worst-case scenario, they fail at later waves. Results also suggest that pushing the failure cost up causes more firms to be affected in the second wave. This outcome is expected since the liquidation cost reduces the value of assets of the other firms.

Findings also reveal that firms belonging to financial activities, trade, manufacturing, and general services can cause more contagion than other firms. As explained by Elliott et al. (2014), the strength and the extent of cascades depend on the integration and diversification of the network. The average integration of firms in these industries is 0.1914, which is statistically equal to the average integration of the remaining firms.[6] Furthermore, when we compared the average diversification between both groups, we found statistical differences.[7]

This evidence indicates that the group formed by the financial activities, trade, manufacturing, and general services industries are more spread out than the others. This situation could explain why the cascades propagate more when the referred industries originate it. When analyzing the characteristics of the network, we observe that it contains a giant connected component (around 270 firms) and many small components. However, the links of the network are weak, and it is unlikely to see stronger effects of a single firm's failure in most of the cases.

Figs. 6–9 show the 20 companies that generate the greatest contagion and the total number of failures they cause for each combination of parameters. Table 4 shows the measures of diversification and integration for firms present in previous graphs. For example, when $\alpha = 100$, $\beta = 30\%$, and $\theta = 0.95$ (see figure 7), these 20 firms cause 121 firms to fail. Although average diversification for this group is 0.90, lower than the mean (1.07), they exhibit a high average integration (0.47) relative to the mean (0.193). The low level of diversification makes firms to be highly sensitive to a few companies. Results show that the greatest contagion affects between 57 and 121 firms, which is less than 25% of firms in our sample.

Results also indicate that two firms coming from the finance and trade industry cause the highest contagion. For all the combinations of parameters, firms 49 and 65 affect between 13 and 38 firms, which represents less than 8% of firms in our sample. Both firms show a high diversification (6 and 8, respectively) with respect to the mean (1.07). However, firm 49 exhibits a higher integration (0.51) than that of firm 65 (0.04), which suggests that its higher level of exposure may cause more firms to fail.

5.3. What if an Entire Industry Collapses?

Same-industry firms have a higher probability of failing together, and an external shock is more likely to affect multiple firms rather than one. Hence, we assess the extent of contagion in the network when a shock on market values affects a particular industry.

Fig. 10 shows the number of firms affected once all same-industry firms suffer a drop in their market value. For any threshold value, we note that the trade and manufacturing industries cause more failures than other industries. In the worst-case scenario, both industries affect more than 80 firms in other industries, if the drop market value is 100%. The trade industry is one of the largest groups with 100 firms. In contrast, the manufacturing industry is the most systemically important, although it only has 57 firms.

In Ecuador, the manufacturing industry is a relevant economic sector since the government is continuously developing policies to improve its productivity. Furthermore, this industry substantially contributes to Ecuador's GDP, and here lies the importance of evaluating financial contagion, particularly, when the sector is both risky and relevant for the economic development of Ecuador.

Tables 5 and 6 display results for each combination of parameters when an entire industry suffers a shock. For any combination of parameters, the trade and manufacturing industries cause more failures. This result could be explained

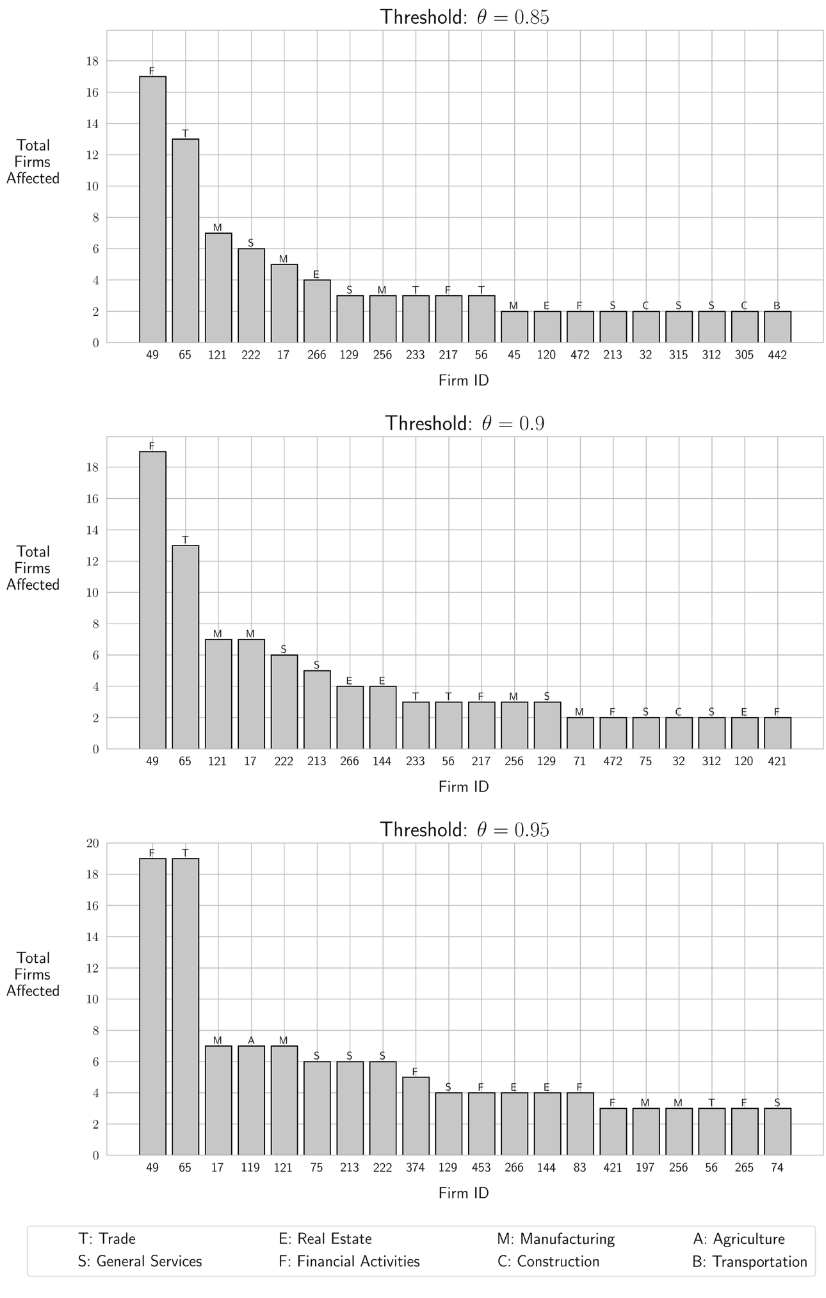

Fig. 6. The 20 Companies that Generate the Greatest Contagion. Drop Market Value=100% and Failure Cost = 20%.

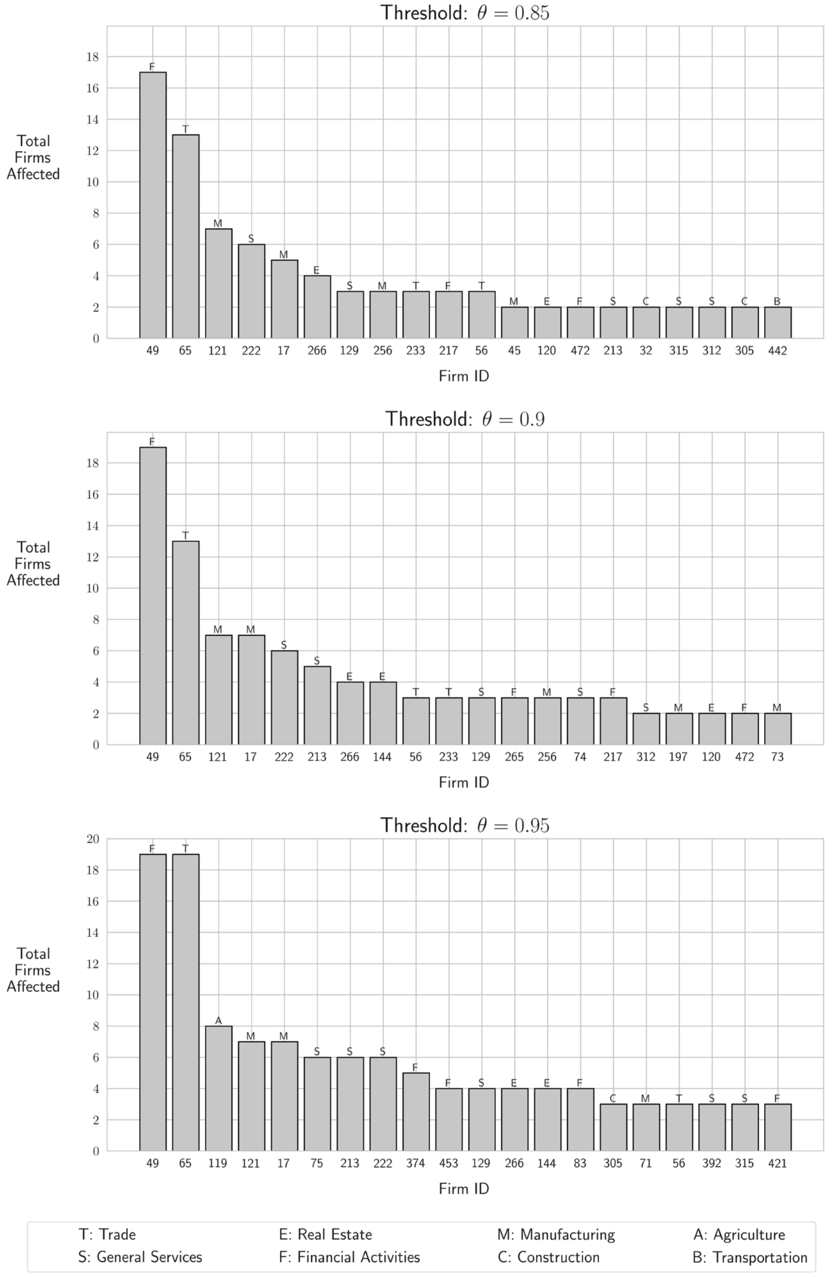

Fig. 7. The 20 Companies that Generate the Greatest Contagion. Drop Market Value=100% and Failure Cost = 30%.

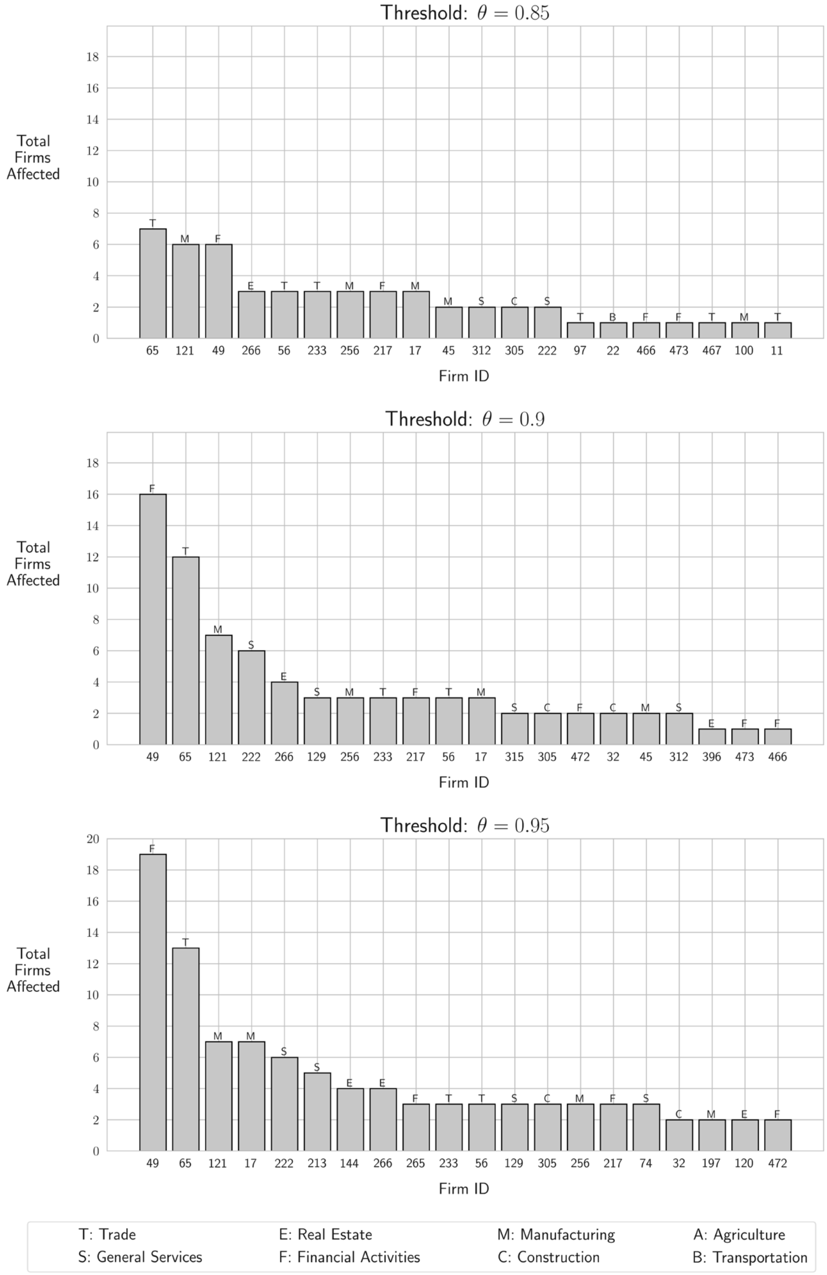

Fig. 8. The 20 Companies that Generate the Greatest Contagion. Drop Market Value=50%, Failure Cost = 20%.

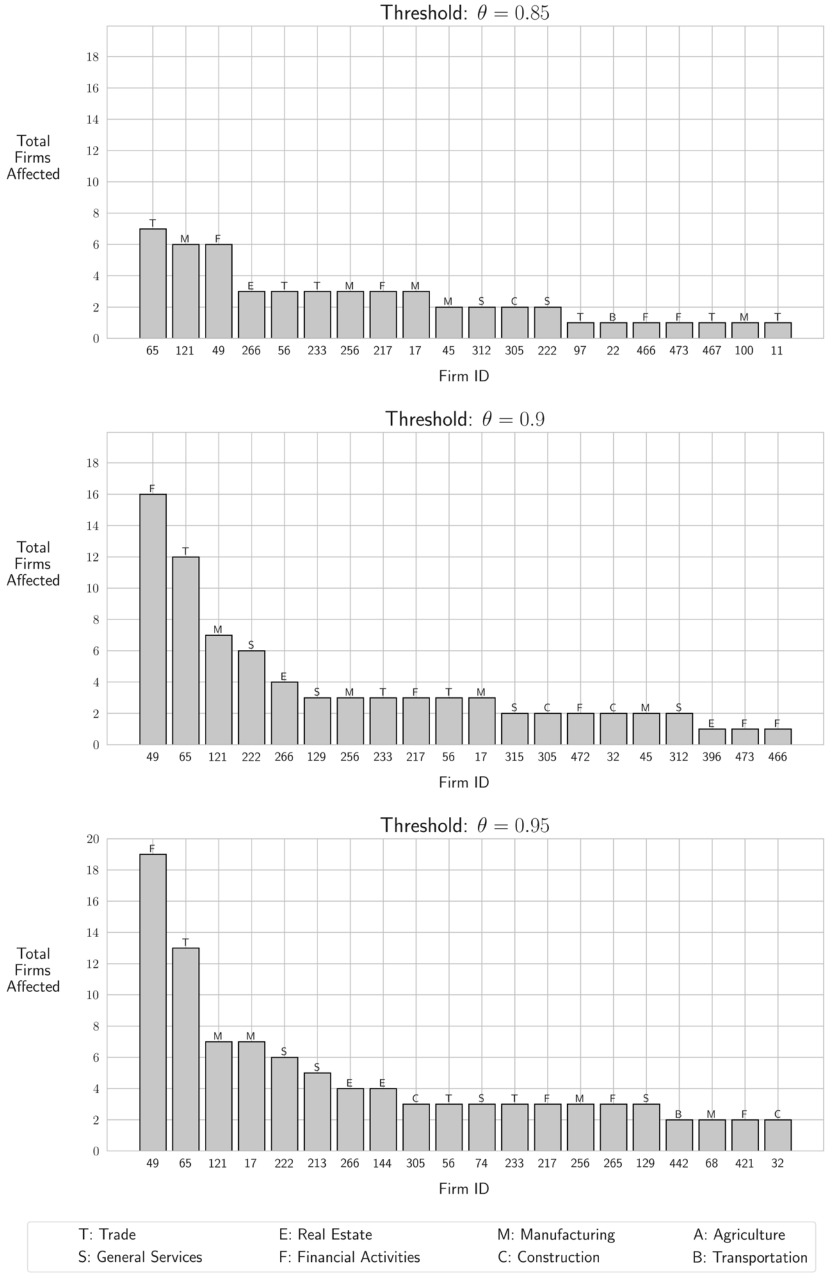

Fig. 9. The 20 Companies that Generate the Greatest Contagion. Drop Market Value=50% and Failure Cost = 30%.

Table 4. Firms Affected Based on Simulation Results Display in Figs. 6–9.

ID	Industry	Assets (USD)	Integration	Diversification
119	Agriculture	81,649	0.28	0
32	Construction	1,933	1.00	0
305	Construction	51,565	1.00	1
49	Financial activities	6,988	0.51	6
83	Financial activities	7,273	0.81	0
217	Financial activities	56,126	0.56	4
265	Financial activities	1,292	0.99	0
374	Financial activities	19,760	0.51	1
421	Financial activities	42,829	0.25	1
453	Financial activities	27,315	0.25	1
466	Financial activities	13,182	1.00	0
472	Financial activities	7,340	0.06	0
473	Financial activities	10,079	0.25	0
74	General services	628	0.75	2
75	General services	42,480	0.06	0
129	General services	80,362	0.01	0
213	General services	44,973	0.03	0
222	General services	34,396	0.96	1
312	General services	3,154	0.83	0
315	General services	10,371	0.01	3
392	General services	17,676	0.13	1
17	Manufacturing	193,386	0.08	2
45	Manufacturing	24,791	0.18	0
68	Manufacturing	19,668	0.66	0
71	Manufacturing	80,876	0.01	0
73	Manufacturing	32,600	0.06	0
100	Manufacturing	219,853	0.00	0
121	Manufacturing	132,974	0.65	1
197	Manufacturing	584	0.63	0
256	Manufacturing	96,813	0.09	0
120	Real estate	883	0.80	3
144	Real estate	10,918	0.96	0
266	Real estate	1,409	0.80	0
396	Real estate	10,732	0.50	0
11	Commerce	8,541	0.15	1
56	Commerce	27,506	0.09	0
65	Commerce	1,440,143	0.04	8
97	Commerce	72,373	0.48	1
233	Commerce	65,105	0.99	0
467	Commerce	3,889	0.50	0

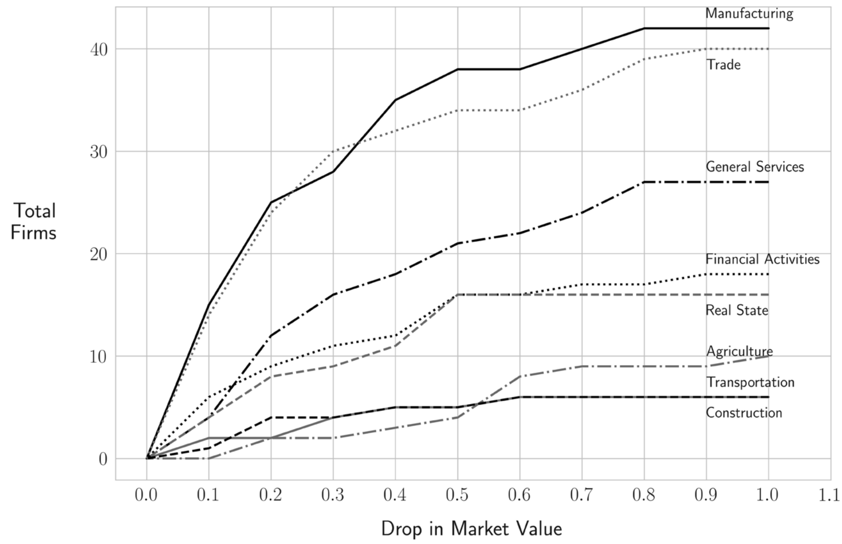

Fig. 10. Number of Firms Affected When an Entire Industry Receives the Shock.

by the fact that these industries contain 31% of firms in our sample not by their average integration and diversification (see Table 7). For instance, we can observe that the manufacturing industry has the lowest integration and diversification measures.

The construction, transportation, and agriculture industries cause fewer firms to fail because these sectors contain a small number of firms. These industries are characterized by low diversification and high integration. A potential limitation is that the estimated effects for industries could not be representative due to the small sample of firms. Despite this limitation, in most industries, the proportion of assets goes from 10% to 18%.

The practicality and simplicity of the model enable us to simulate single and multiple shocks throughout the network of cross-shareholdings. Figs. 11 and 12 show how the shock in a firm, using a threshold of 95% of the assets, affects the market value of other companies throughout the network. Policymakers can monitor the market at a certain period in time, using this methodology in multiple scenarios.

6. CONCLUSIONS

We apply the financial contagion model proposed by Elliott et al. (2014) to a cross-shareholding network of firms in Ecuador. We use a novel dataset provided by SUPERCIAS. Only 1.02% of firms have cross-holdings of shares among them,

Table 5. Distribution of Firms Affected by Waves and Industries When $\alpha = 100\%$.

	Financial Activities	Commerce	Manufacturing	General Services	Real Estate	Construction	Transportation	Agriculture
				$\alpha = 100\%, \theta = 0.95, \beta = 30\%$				
Wave 1	17	40	42	27	16	6	6	5
Wave 2	1	0	0	0	0	0	0	5
				$\alpha = 100\%, \theta = 0.90, \beta = 30\%$				
Wave 1	15	34	37	21	13	4	5	4
Wave 2	1	0	1	0	3	0	0	0
				$\alpha = 100\%, \theta = 0.85, \beta = 30\%$				
Wave 1	11	31	30	14	10	4	4	3
Wave 2	0	0	1	2	1	0	0	0
				$\alpha = 100\%, \theta = 0.95, \beta = 20\%$				
Wave 1	17	40	42	27	16	6	6	5
Wave 2	1	0	0	0	0	0	0	5
				$\alpha = 100\%, \theta = 0.90, \beta = 20\%$				
Wave 1	15	34	37	21	13	4	5	4
Wave 2	0	0	0	0	3	0	0	0
				$\alpha = 100\%, \theta = 0.85, \beta = 20\%$				
Wave 1	11	31	30	14	10	4	4	3
Wave 2	0	0	1	2	1	0	0	0

Table 6. Distribution of Firms Affected by Waves and Industries When $\alpha = 50\%$.

	Financial Activities	Commerce	Manufacturing	General Services	Real Estate	Construction	Transportation	Agriculture
				$\alpha = 50\%, \theta = 0.95, \beta = 30\%$				
Wave 1	15	34	37	21	13	4	5	4
Wave 2	2	0	1	0	3	1	1	0
				$\alpha = 50\%, \theta = 0.90, \beta = 30\%$				
Wave 1	9	29	27	11	8	2	4	2
Wave 2	0	0	0	1	0	0	0	0
				$\alpha = 50\%, \theta = 0.85, \beta = 30\%$				
Wave 1	8	19	24	5	7	2	2	2
Wave 2	0	1	1	0	0	0	0	0
				$\alpha = 50\%, \theta = 0.95, \beta = 20\%$				
Wave 1	15	34	37	21	13	4	5	4
Wave 2	1	0	1	0	3	1	0	0
				$\alpha = 50\%, \theta = 0.90, \beta = 20\%$				
Wave 1	9	29	27	11	8	2	4	2
Wave 2	0	0	0	1	0	0	0	0
				$\alpha = 50\%, \theta = 0.85, \beta = 20\%$				
Wave 1	8	19	24	5	7	2	2	2
Wave 2	0	1	0	0	0	0	0	0

Table 7. Average Integration and Diversification by Industry.

Industries	Integration	Diversification
Financial activities	0.170	1.759
Real estate	0.173	1.073
Commerce	0.194	1.070
General services	0.212	1.008
Agriculture	0.191	0.963
Construction	0.255	0.880
Manufacturing	0.169	0.684
Transportation	0.195	0.517

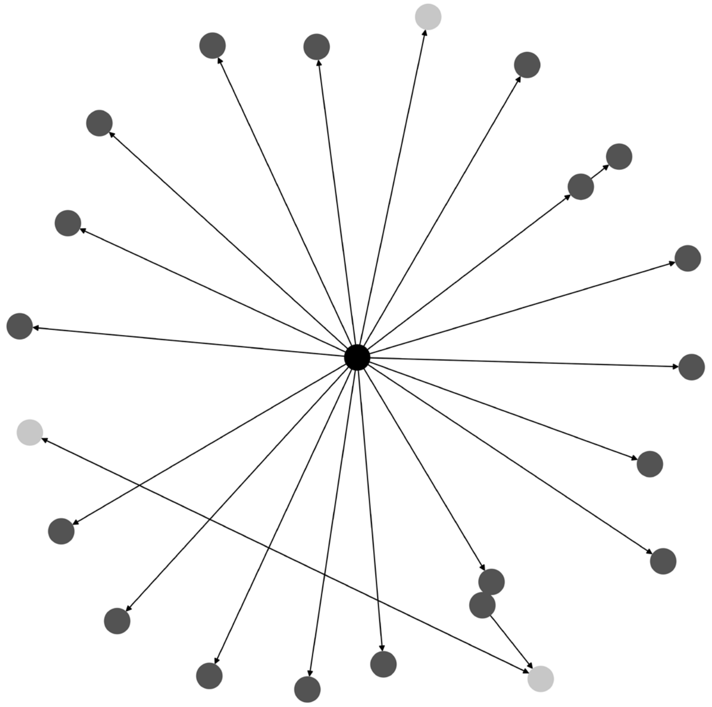

Fig. 11. Contagious Effect of Firm 49. The Black Node Represents Firm 49, Nodes Gray Those Firms That Are Affected by Firm 49, and White Nodes Are Firms That Were Not Affected even though They Are Directly Related to.

which is not a representative sample, although the proportion of assets represented in this sample is around 12%. The financial contagion model uses a network of financial interdependencies among firms in a dependency matrix, where each element represents the cross-shareholding. In this context, we study how a negative shock that affects one firm propagates through the network and generates a cascade of failures.

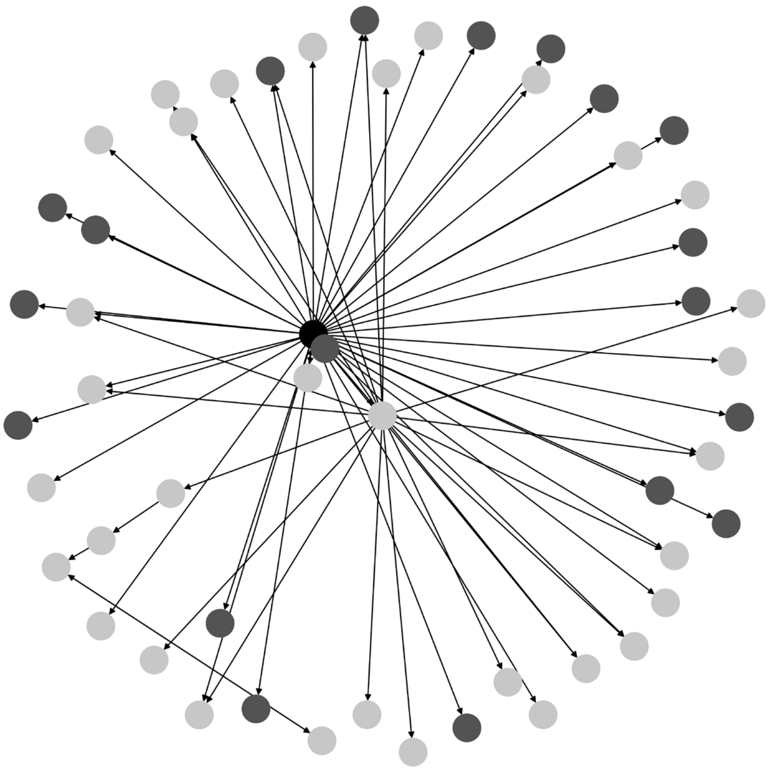

Fig. 12. Contagious Effect of Firm 65. The Black Node Represents Firm 65, Nodes Gray Those Firms That Are Affected by Firm 65, and White Nodes Are Firms That Were Not Affected even though They Are Directly Related to.

Our results indicate that the Ecuadorian market exhibits low levels of diversification and integration, which means that the effects of cascades cannot be amplified throughout the network. Low integration implies the presence of weak links in the network. Results also show the presence of a giant weakly connected component (40% of the total firms) because diversification is moderate, which suggests cascade effects are still weak.

Furthermore, we conduct a sensitivity analysis to determine which parameter mostly contributes to firm's failure. When we allow: the threshold, the failure cost, and the drop market value to vary, only two waves of contagion are noticeable in the simulations and no additional companies are affected in subsequent waves. Hence, pushing those parameters up cause more firms to fail at earlier waves. Findings also imply that specific industries can cause more contagion than other firms, and this is related to the level of diversification. Even though two industries are composed of firms with an equal level of integration, the group with high diversification tends to affect the most. Moreover, two firms coming from the finance and trade industry cause the highest contagion. When a shock affects an entire industry, we find that the trade and manufacturing industries cause more failures than other industries. In general, we note that all industries have the same behavior once the parameters change.

Our results are especially relevant for policymakers since they can monitor the market and anticipate future losses. For instance, policymakers can calculate the marginal effect of saving different levels of a firm's assets. Acemoglu et al. (2015) mention that a fundamental goal for policymakers would be to increase the stability of the system by financial linkages from an *ex ante* perspective. For *ex post* policy interventions, they suggest to bail out systemically relevant financial institutions once a shock occurs. Our study is a first step toward understanding the financial contagion and estimating losses to inform policymakers.

NOTES

1. SUPERCIAS stands for Superintendencia de Compañias, Valores y Seguros del Ecuador (*https://www.supercias.gob.ec*).
2. We used the jackknife method to estimate the expected statistical error of r.
3. Refer to Appendix 1 for matrix representation of equations shown in Section 3.
4. Appendix 2 shows the financial contagion algorithm used to derive our results.
5. Once the value of an asset for each firm is dropped in α%, we group them according to the industry where they belong to, and we count the number of firms that they cause to fail.
6. We executed a two-sample student's t-test with unequal variances and two-tailed. The statistic was 0.1445 and the p-value was 0.88.
7. The t-statistic was 1.966.
8. It can be thought as a shock that affects only firm i, while the value other firms' asset remains the same.

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APPENDIX 1: MATRIX REPRESENTATION

In this appendix, we summarize the algorithm developed by Elliott et al. (2014), which is the one we use to measure the financial contagion. First, we express equation from Section 3 in a matrix form.

We consider a set of N firms, which form a network G. Let the $N \times K$ matrix **D** be formed by the elements D_{ik}. The K-vector **p** contains the element p_k, the market price of the asset k. The $N \times N$ matrix **C** contains the elements C_{ij}.

In a matrix form, the off-diagonal entries of $\hat{\mathrm{C}}$ are 0.

Equation (1):

Using the previous matrix notation, equation (1) can be written as

$$\mathbf{V} = \mathbf{Dp}+\mathbf{CV}=(\mathbf{I}-\mathbf{C})^{-1}\,\mathbf{Dp} \tag{7}$$

Equation (2):

Defining $\hat{\mathrm{C}}$ as a $N \times N$ diagonal matrix formed by the elements $\hat{C}_{ii}$, we can express equation (2) in matrix notation,

$$\mathbf{v} = \mathbf{Dp}+\mathbf{CV}-\left(\mathbf{I}-\hat{\mathbf{C}}\right)\mathbf{V} \tag{8}$$

Equation (3):

Expressing equation (3) in matrix form, and substituting **V** from equation (7),

$$\begin{aligned} \mathbf{v} &= \mathbf{Dp}+\mathbf{CV}-\left(\mathbf{I}-\hat{\mathbf{C}}\right)\mathbf{V}-\mathbf{b}(\mathbf{v}) \\ &= \mathbf{A}\left(\mathbf{Dp}-\mathbf{b}(\mathbf{v})\right) \\ &= \mathbf{ADp}-\mathbf{Ab}(\mathbf{v}) \end{aligned} \tag{9}$$

where the matrix $\mathbf{A} = \hat{\mathbf{C}}(\mathbf{I}-\mathbf{C})^{-1}$. This is a $N \times N$ matrix whose elements A_{ij} represents the share of firm j owned by the firm i. This is a type of dependency. The first term on the right-hand side, **ADp**, is $N \times 1$ vector. Its i element $\sum_j A_{ij}\left(\sum_k D_{jk}\,p_k\right)$ represents the value of firm i's assets as the sum of what firm i owns of all firms. The second term, $-\mathbf{Ab}(\mathbf{v})$, is a $N \times 1$ vector whose i element is the failure cost that firm i bears when firms j' fail.

APPENDIX 2: PSEUDOCODE OF THE FINANCIAL CONTAGION MODEL

This appendix explains specific tasks that we follow to generate results shown in Appendix 1, which is the one we use to measure the financial contagion.

We start setting values for threshold θ and failure cost β. These are identical for all i. We calculate the threshold value $\underline{\mathbf{v}} = \theta \mathbf{v}^{(0)}$, where $\mathbf{v}^{(0)} = \mathbf{ADp}^{(0)}$ is the initial market value.

Step 0. We pick a firm i:

- We drop the value of firm i's asset by α%. That is, we take the product between the i-element of the vector $\mathbf{ADp}^{(0)}$ and $(1 - \alpha)$.[8]
- We generate a new vector $\mathbf{ADp}^{(1)}$, which is the same as $\mathbf{ADp}^{(0)}$ except for i-th element.

Step 1. The first *wave*:

- We compute the new market value, $\mathbf{v}^{(1)} = \mathbf{ADp}^{(1)}$ for all firms.
- We count how many firms satisfy the condition $\mathbf{v}^{(1)} < \mathbf{v}$. This number represents how many firms should liquidate their assets.

Step 2. The second *wave*:

- We compute the new market value, $\mathbf{v}^{(2)} = \mathbf{ADp}^{(1)} - \mathbf{Ab}(\mathbf{v}, \mathbf{p})$. Remember that firms affected in wave one incurs in a failure cost.
- We count how many firms satisfy the condition $\mathbf{v}^{(2)} < \mathbf{v}$.
- We repeat the process (i.e. we reach another wave) until no more firms incur in a failure cost (or are not affected).

Once we stop, we can estimate the total number of firms that were affected when firm i gets the shock. We repeat the same procedure for all firms in the network.