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Three Essays in Financial Crises

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Preface

The dictionary defines a crisis as *a time of intense difficulty or danger.* Financial crises fully satisfy this definition. Financial turmoils raise the cost of intermediation and restrict credit. In turn, the activity in the real sector contracts causes recessions. During recessions, the firms' profits decline, investments slow down, and the survival of the most fragile agents in the economic system is in danger. The fact that financial crises have such catastrophic effects gives a Ph.D. student dealing with this topic a significant advantage: research questions are easy to motivate!
The drawback is that financial crises have been extensively analysed in the economic literature. Therefore, making academic contributions that are sufficiently original and interesting is not an easy task.
In these opening pages, I try to briefly explain where this thesis comes to be original and why the results reported are - hopefully! - interesting.

Chapter I: Financial Contagion in Inter-Bank Lending Network With Overlapping Portfolios

In modern economies, individual banking crises are pretty rare. Financial innovation and deregulation have increased interconnections between financial institutions. These links serve as channels for financial contagion. Allen and Gale (2009) defines financial contagion as the process by which a crisis originating in one institution spreads to an economically linked institution. How the severity of financial contagion depends on the pattern of connections?
Financial contagion cannot occur in a system in which there are no links across financial operators. However, it is equally clear that this would be a highly inefficient system. In fact, in their seminal paper, Allen and Gale (2000) showed that banks facing uncertainty about liquidity demand could reach the efficient allocation by implementing a network of inter-bank deposits.
So, financial links are needed. How many links should be established? Literature answers to this question by discussing - mainly - a specific economic link: loan relationship.
Pioneering contributions highlight that complete inter-bank lending networks (i.e., networks in which each bank lends to all the other) are less prone to financial contagion (Freixas et al., 2000; Allen and Gale, 2000). However, the question is debated. Blume et al. (2011) suggested the opposite result. That is,

the severity of financial contagion tends to increase as the number of loan links increase. Currently, the prevailing wisdom is to consider the relationship between the completeness of the inter-bank lending network and financial stability as non-monotonic (Nier et al., 2007). In this spirit, Haldane (2013) proposed the terms *complete-yet-fragile*. Acemoglu et al. (2015) showed that the network structure minimising the severity of financial contagion depends on the size of the shock affecting the economy. For a small shock size, the complete network is the structure less prone to contagion. However, if the shock size is above a critical threshold, the complete exhibits a transition phase becoming the structure in which contagion has the most severe effects.

Hence, for its own sake, the pattern of inter-bank liabilities does not provide much information on the system's ability to stem financial contagion. It is the combination between the network structure and other variables that define fragility (Glasserman and Young, 2015).

I contribute to this debate by discussing how the inter-bank network structure minimising the severity of financial contagion depends on the level of overlapping portfolios in the banking system. The main result of my discussion shows that once we fix the level of overlapping portfolios in the banking system, there is no unique completeness degree that maximises the banking system's resilience. There are many.

The architecture of the inter-bank lending market evolves constantly. Interbank lending is, for the most part, overnight; the general level overlapping portfolios also could change rapidly. These changes are often beyond the control of policymakers and authorities. What changes should set alarm bells ringing? The first chapter helps to answer this question.

Chapter II: Risk Diversification and Liquidity Risk

Risk diversification pays. The idea that *putting eggs in different baskets* reduces the chances of losing all the eggs is easily understood, even by those who did not study finance. Sometimes, individual risk diversification pursuits clash with social interests. Consider a group of financial institutions, each of them endowed with a specific risky asset. Given a sufficiently high degree of independence between assets, institutions may succeed in eliminating the idiosyncratic risk embedded in their portfolios by forming a joint mutual portfolio. The drawback for society is the surge in systemic risk. That is, if the market portfolio has poor returns, all institutions wobble at the same time.

In general, the realisation of systemic crises induces economic and social costs beyond individual bank failure. Individual institutions fail to internalise such extra costs. Given this externality, it is widely accepted in the literature that personal investment decisions lead financial institutions to invest an excessive amount of capital in the market portfolio.

We suggest that the opposite result could also be an equilibrium. That is, individual investment decisions could lead financial institutions to invest in the market portfolio a share of capital which is *below* the first best. The economic mechanism lies on two assumptions: (i) banks are opaque entities, and (ii) systemic crises enhance the costs of raising liquidity.

Opacity entails liquidity risk. Banks' liabilities are mainly short-term liabilities or payable on demand. External creditors may decide not to roll over their credits or withdraw their funds in response to negative signals about the fundamental value of the bank. If banks are opaque, signals could be biased, and running on healthy institutions are possible. In such cases, banks are illiquid rather than bankrupt.

Whether banks survive liquidity crises depends on the costs of raising liquidity. Since - by assumption - systemic crises boost the expenses of raising liquidity, banks who are illiquid during widespread turmoils incur higher losses and - in extreme cases - they could go bust. By anticipating this risk, financial firms that are more likely to be illiquid find it optimal to reduce their investments in the market portfolio to be more counter-cyclical.

If liquidity risk is sufficiently high, the investment in the market portfolio turns to be lower than the social optimum. By reducing investments in the market portfolio, banks increase the idiosyncratic risk embedded in their portfolios. Financial institutions trade off this increase in riskiness with a lower probability of being illiquid during systemic crises. However, there is a loss that they fail to internalise. When the banks' riskiness increases, the creditors' expected profits decline.

We see this chapter as the first step of a broader discussion. Although the model we present is too stylised to describe real banking sectors fully, some empirical predictions emerge.

We suggest that the level of asset commonality in the banking system reacts to market liquidity conditions and banks' opacity/transparency.

Chapter III: The Economic Complexity Index and the Financial Fragility

Why is there cross-country heterogeneity in the frequency of financial crises? The last chapter investigates this question. In detail, we ask whether the characteristics of the bundle that countries' export could explain cross-country heterogeneity both in the frequency of financial crises and their effects. In our idea, countries exporting products only produced by a handful of other countries should exhibit superior market power. The market power should reduce domestic firms' cash flow volatility, decrease the default's probability, and increase the banks' domestic asset quality. Broadly, countries having market power on the global trade market should better absorb shocks originating from abroad and should face more stable foreign demand concerning countries that are less competitive.
To measure the competitiveness of bundle of products countries export, we use the the Economic Complexity Index proposed by Hidalgo and Hausmann (2009). The index summarises countries' economies into two dimensions: diversity and ubiquity.

Liquidity risk: risk of a default due to a run when the institution would otherwise have been solvent (Morris and Shin, 2009)

Diversity captures the number of products a country can export competitively. Ubiquity, instead, refers to the number of countries exporting such products. Loosely speaking, sophisticated countries export a diversified bundle of products, and such products are shipped only by a handful of other countries. In contrast, simple economies export a few different types of products that many other countries export. Evidence suggests that complex economies exhibit superior financial resilience. However, the statistical significance disappears once we interact the Economic Complexity Index with the openness' degree of the economy while the interaction term' s coefficient is negative and statistically significant. We interpret this evidence as follows. Having superior production capabilities that allow producing rare products - for its own sake - should not affect financial stability. Nevertheless, these products entail a dominant position on the global trade market. The beneficial effects of such market-power increase as relevance of the international trade for the economy increases.

The chapter contributes to the literature along two dimensions. First, scholars documented the real effects of the Economic Complexity Index. The sophistication gap between countries seems to be very efficient in explaining heterogeneity cross-country in terms of GDP per capita, prosperity, and growth (Hidalgo and Hausmann, 2009; Abdon and Felipe, 2011; Hartmann et al., 2017). The intuition lies in unexploited potential. An emerging country whose complexity index is identical to the one of the riches is likely to exploit all its technology to jump-start economic development in the next future. Up to our knowledge, no contributions are exploring the financial effects of the Economic Complexity Index. This paper starts to fill this gap.
Second, the chapter contributes to the literature assessing the determinants of financial fragility. That is, we claim that the composition of the trade openness degree matters. Broadly, we suggest that the characteristics of the bundle of products a country exports could explain the likelihood of experiencing a financial crisis.

Contents

Chapter 1

Financial Contagion in Inter-Bank Lending Network With Overlapping Portfolios

Abstract

It is common wisdom that the architecture of the inter-bank lending market has a fundamental role in cushioning/promoting financial contagion across banks. In this paper, we show that - for its own sake - the architecture of the inter-bank lending market does not define the extent to which a banking system is prone to financial contagion. That is, two banking systems can exhibit different architectures but similar resilience. We suggest that the interaction between the architecture of the inter-bank market and the extent to which banks' portfolios overlap defines the fragility/resilience of the system. Our model connects financial institutions through mutual claims and overlapping portfolios. The theoretical result suggests that many architectures allow the banking system to reach financial stability and not just the complete. From a macro-prudential perspective, we suggest that sudden freezes in the inter-bank lending market that accompanies spikes in the portfolios similarity or drops in the market liquidity are the primary sources of financial fragility.

1.1 Introduction

The intertwined nature of the banking system makes banks vulnerable to financial contagion. Idiosyncratic shocks could spread up to the entire banking sector generating financial dislocations and large economic fluctuations (Bernanke, 1983; Kindleberger et al., 1996; Allen and Gale, 2009).

An essential economic link connecting banks is inter-bank lending. Through the inter-bank market, banks can insure against idiosyncratic liquidity shocks and improve welfare (Allen and Gale, 2000; Dasgupta, 2004). Nonetheless, inter-bank claims expose creditor banks to contagion risk. When a bank defaults on its inter-bank liabilities, creditors suffer liquidity losses that may, in turn, push them to default. Thus, following the first failure, a cascade of bankruptcy is possible.

The distribution of the inter-bank claims defines the architecture of the inter-bank lending market (henceforth, inter-bank market). There are conflicting views about which architectures are resilient to financial contagion. In a multi-regional economy à la Diamond and Dybvig (1983), Allen and Gale (2000) argued that the architecture of the inter-bank market does not have any significance as far as achieving the full insurance against fluctuations in the regional liquidity demand is concerned. However, the pattern of the inter-bank claims defines the size of bilateral agreements needed to reach full insurance. In a complete architecture, such size is smaller concerning incomplete structures.[1] Thus, the complete inter-bank market is always more resilient concerning incomplete structures since a more homogeneous distribution of the inter-bank claims restrains the liquidity losses due to individual defaults.

Later on, Acemoglu et al. (2015) proposed a model in which banks hold stochastic portfolios whose returns' realisation define the amount of liquidity available to meet banks' liabilities. Conditioning on the first default, authors showed that if the portfolio's return of the distressed bank is not so poor, the complete structure ensures the maximum resilience against financial contagion, as in Allen and Gale (2000). Nonetheless, as the portfolio's return of the distressed bank falls below a critical threshold, the complete structure becomes the most fragile architecture, and lowering the completeness of the inter-bank market will lead to less severe contagion effects.

The models proposed by Allen and Gale (2000) and Acemoglu et al. (2015) connect banks only through inter-bank lending and conclude that there is a unique resilient architecture for the inter-bank market. Nonetheless, inter-bank lending does not exhaust all possible links across banks. Overlapping portfolios - in fact - are a prominent inter-bank connection (Greenwood et al., 2015). Common asset holdings represent a threat to financial stability because of fire sales propagation mechanisms. That is, when distressed banks liquidate their assets into markets, the liquidation process has a price impact leading to mark-to-market losses for banks holding assets that the distressed banks are liquidating (Shleifer and Vishny, 1992; Cifuentes et al., 2005; Ellul et al., 2011).[2] The

[1] Formally, the inter-bank market could be understood as a directed weighted graph where each node is a bank and an edge starting from node i and pointing in the direction of node j is present if the i lends to j. The weights assigned to each edge represent the nominal value of the debt. A directed weighted graph is *complete* if: (i) for any node there is an edge starting from the node and pointing towards all the other, and (ii) all edges have the same weight (Jackson, 2010). Thus, an *incomplete* directed weighted graph does not satisfy one between (i) and (ii).

[2] Besides fire sales mechanisms, common asset holdings represent a source of systemic risk simply because banks' exposition to the same risk factor (Acharya and Yorulmazer, 2007;

relevance of common asset holdings in explaining the severity of financial contagion is well documented in the empirical literature (Caccioli et al., 2013, 2014; Poledna et al., 2021).

Thus, we propose a model where banks connect each other via overlapping portfolios in addition to inter-bank claims. When both connections are at work, we show that the inter-bank market's architecture ensuring resilience to financial contagion is no more unique. That is, we identify a continuum of inter-bank market structures such that the first default does not trigger additional waves of bankruptcy. The fact that we identify a range of resilient architectures could have some implications. Increasing resilience to financial contagion is a primary interest for authorities and policymakers. A model identifying a unique resilient architecture imposes a demanding task to regulators. Suppose n banks populate the banking system, the number of different possible structures for the inter-bank market is $2^{n(n-1)/2}$.[3] As a further complication, most of the inter-bank lending occurs at the overnight frequency where bilateral agreements are due to liquidity deficit and surplus that cannot be easily predicted. Therefore, implementing policies targeting a unique architecture could be unfeasible. In this perspective, identifying a set of resilient structures could impose a less demanding task for authorities who aim to increase financial stability. By monitoring the tightness of the set of resilient structures, regulators could infer whether the banking system is resilient. Statistically speaking, the tighter is the set, the lower is the probability that the inter-bank market lies on the set. Our comparative static exercises help to understand the determinants of the set's measure.

Moreover, the non-uniqueness of the resilient architecture implies that - for its own sake - the structure of the inter-bank market does not define the fragility/resilience of a banking system. That is, two banking systems could exhibit a different architecture of the inter-bank market but similar fragility/resilience. What defines the fragility/resilience of a banking system is how the architecture of the inter-bank market interacts with other variables (Glasserman and Young, 2015).

More concretely, we consider a three-period banking system in which n banks have economic connections via unsecured debt contracts and via overlapping portfolios. In the initial period, banks invest over the economy's assets and in the inter-bank market. The distribution of the inter-bank claims defines the architecture of the inter-bank market. As in Acemoglu et al. (2015), we consider two extreme architectures - the ring and the complete - and their linear convex combinations. In the ring architecture, each bank has one creditor and one debtor in the inter-bank market, and all banks are connected through a unique cycle. In the complete network, banks spread their inter-bank claims homogeneously over the remaining $n-1$ banks in the system. In an architecture that is a linear convex combination between the two, the distribution of the inter-bank claims depends on a parameter - π - varying in the interval $[0, 1]$. As

Ibragimov et al., 2011)

[3] That is, for $n = 10$ - a relatively modest number of banks - the number of possibilities is 35184372088832.

the parameter tends to zero, the inter-bank claims follow a distribution similar to the ring architecture. Instead, as the parameter tends to one, the inter-bank claims follow a distribution similar to the complete.[4]

In addition to inter-bank liabilities, banks have to make other payments with seniority to inter-bank debit. We interpret external liabilities as retail deposits. The presence of external liabilities payable on demand makes banks vulnerable to liquid risk (Morris and Shin, 2009). That is, banks could face unexpectedly high liquidity demand from depositors (Diamond and Dybvig, 1983). We assume that - at the interim period - one bank faces liquidity demand from depositors exceeding cash reserves. The distressed bank liquidates its assets into the markets to get the liquidity necessary to offset depositors' demand. Since markets are not perfectly liquid, the liquidation process has a price impact leading to mark-to-market losses for banks having common asset holding with distressed banks. Conditioning on a suitable parameterisation of the model, the liquidity shock causes the bankruptcy of the affected bank. Once a bank is in default, it is liquidated, and all creditors (retail depositors and inter-bank creditors) share the proceeds following the seniority and the proportion of their claims. Following the first default, spillover effects propagate in the banking sector. Such effects depend on (i) the market liquidity (market's ability to absorb market orders without significantly impacting the price of the asset), (ii) the extent to which banks' portfolios overlap, and (iii) the architecture of the inter-bank lending network. In this framework, we aim to understand which values of π the banking system is resilient to the first default and how the set of resilient architectures varies as market liquidity and the level of portfolios' overlay vary.[5]

The model identifies an interval for π such that any architecture in the range ensures resilience. As the market liquidity reduces or the level of portfolios' overlay in the banking system increases, the range of the set shrinks, meaning that architectures in which the distribution of inter-bank claims is the most extreme (too concentrated or too homogeneous) exit from the stable set. To see the economic intuition behind the result, note that as π approaches zero, the distribution of the inter-bank claims tends to be highly concentrated. That is, the liquidity losses due to the default of one bank, say bank i, is entirely transmitted to bank $i-1$, the unique creditor of bank i. When π approaches one, the liquidity losses due to default of bank i is transmitted - homogeneously - also to the remaining banks $j \neq i, i-1$. Thus, as π increases, the liquidity losses suffered by bank $i-1$ decrease while the liquidity losses suffered by all the other banks $j \neq i, i-1$ increases. Hence, it is possible to determine the lowest π at which bank $i-1$ can survive to the default of bank i and the highest π at which the all remaining banks $j \neq i, i-1$ can survive to the default of bank i. These two thresholds identify the range of resilient architectures. The ability of banks to resist liquidity losses depends on mark-to-market losses which are proportional to the market liquidity and the level of the portfolio's overlay. Hence, as the

[4]It is essential to note that, as π moves from zero, all banks lends to all the remaining banks in the system. Parameter π should be understood as a concentration measure for the inter-bank claims rather than an indicator for the number of bilateral contracts.

[5]Resilient architectures do not trigger additional waves of default once the first is realised

market liquidity reduces, mark-to-market losses become more severe, meaning that the lowest π ensures the survival of bank $i-1$ increases and - at the same time - the highest π ensuring the survival of all the other banks $j \neq i, i-1$ reduces. Thus, the range of resilient architectures shrinks.

Though stylised, our model provides some economic insights on macroprudential policy. Indeed, we suggest that how the architecture of the inter-bank market reacts to variations in market liquidity and the extent of common asset holdings between banks should set alarm bells. Squeezes in the inter-bank market activity joint to decline market liquidity threaten financial stability. Similarly, a spike in portfolios' overlay could be more or less worrying depending on how the architecture of the inter-bank market reacts. Monitoring systemic risk entailed by asset commonality is challenging. In recent years, financial innovation (and deregulation) has increased the number and complexity of financial products to which financial institutions have access. Although these instruments allow for a better allocation of risk, they strengthen the intertwining between portfolios' financial institutions. In this perspective, our model should be helpful to understand when inter-bank market freezes and increase in the asset commonality across financial institutions should set alarm bells.

Our paper is part of extensive literature discussing financial contagion. Pioneering contributions highlighted that lending networks in which the distribution of the credits is the more homogeneous are less prone to financial contagion (Freixas et al., 2000; Allen and Gale, 2000). The economic intuition lies in the loss distribution. A more homogeneous distribution of the inter-bank claims restrains the liquidity losses due to individual default. Yet, the literature is not unanimous. Recently, the *complete-yet-fragile* theory had become popular. The theory claims that under some circumstances, complete inter-bank markets cushion spillover effects across institutions. Yet, under other circumstances, completeness favour shock transmission leading to widespread losses in the system (Haldane, 2013). In this spirit, Acemoglu et al. (2015) showed that complete inter-bank markets exhibit a phase of transitions - moving from the most resilient architecture to the most fragile - as the shock size exceeds a critical threshold. Mistrulli (2011) found evidence supporting the Acemoglu et al. (2015) conjecture in a simulation over the Italian banking system. Gai and Kapadia (2010) described a similar result. They showed that complete architectures are less prone to systemic crises but the most fragile once crises begin. In a simulation, Nier et al. (2007) showed the existence of a non-monotone relation between financial resilience and density of the inter-bank market.

Besides inter-bank lending, the literature investigated also other financial contagion channels. Our paper relates to contributions assessing the role of overlapping portfolios. In addition to the fire sales mechanisms we cite above, Allen et al. (2012) showed that the extent of overlapping portfolios determines the degree of information transmission and further the possibility of a systemic crisis. Only a few contributions discuss both direct and indirect contagion channels. Tasca and Battiston (2016) argued that when both channels are present, a pro-cyclical loop between assets' prices and banks' leverage ratio emerges. In an empirical study on the Austrian banking system, Caccioli et al. (2014) con-

cluded that the existence of counter-party risk contagion significantly amplifies the contagion effects of portfolios' overlay.
In a recent contribution, Shen and Li (2020) simulated a banking system similar to the one that we discuss in this paper. They studied the severity and the probability of contagion as a function of individual institutions' diversification and the architecture of the inter-bank market. Their results highlight the existence of a U-shaped relationship between financial resilience and the extent to which banks' portfolios are diversified.

1.2 Theoretical Framework

The economy lasts three periods: initial, interim, and final. Define two sets $N = \{1, \dots, i, \dots, n\}$ and $M = \{1, \dots, k, \dots, m\}$ representing the set of banks and the set of the available assets in the economy, respectively. In this framework, assets are illiquid long-run maturity investments. For the sake of simplicity, I assume that all assets have the same deterministic fundamental value: $V > 1$.

Table 1.1: Balance-Sheet at the End of the Initial Period

Asset	**Liabilities**
$(1-c)V$ (Portfolio's Market Value)	e (Equity)
c (Cash Reserves)	d (Deposits)
X (Inter-Bank Claims Market Value)	Y (Inter-Bank Liabilities)

1.2.1 Initial Period

In the initial period, banks collect one unit capital of which a fraction $d \in (0,1)$ represents retail deposits and a fraction $e = 1-d$ represents equity. Banks store a fraction c of the capital as cash reserves and invest the remaining fraction over the assets.

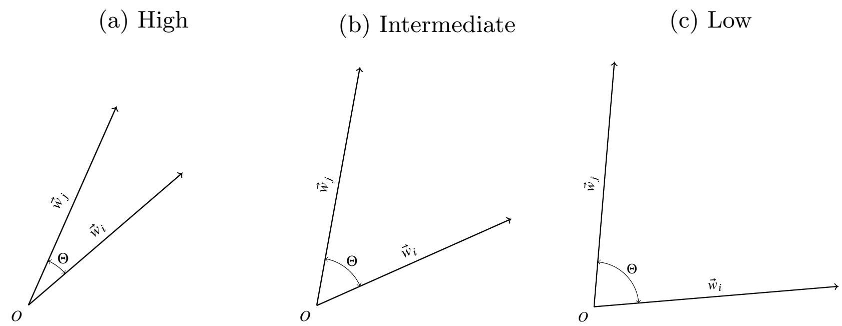
Portfolios and Common Asset Holdings

Define $w_{i,k} \in [0,1]$, the fraction of capital invested by bank i in asset k. On aggregate, banks investments are as follows:

$$B = \begin{bmatrix} w_{1,1} & \dots & w_{1,m} \\ \vdots & \vdots & \vdots \\ w_{n,1} & \dots & w_{n,m} \end{bmatrix} \tag{1.1}$$

Bank i' s portfolio is the i^{th} row of the matrix B: $\vec{w}_i = [w_{i,1}, \dots, w_{i,m}]$. For our scope, it is helpful to introduce a measure allowing us to capture to which extent bank i and j' s portfolios overlap. Since vectors represent portfolios, a natural measure will be to consider the angle between them. Define $\Theta_{i,j} \in [0, 90°]$ the degree of the angle between $\vec{w}_i$ and $\vec{w}_j$. As $\Theta_{i,j}$ shrinks, $\vec{w}_i$ tends to coincide with $\vec{w}_j$. Instead, as $\Theta_{i,j}$ increases, the two vectors tend to be orthogonal each other. Therefore, $\Theta_{i,j}$ is a suitable - inverse - measure of the extent to which the i and j 's portfolios overlap. As an illustrative example, Figure 1.1 provides a graphical representation for $m = 2$.

Figure 1.1: The Measure of Common Asset Holdings



Inter-Bank Market

In the initial period, banks could also invest in the inter-bank market. Inter-bank lending occurs through a standard debt contract in which the interest rate is fixed to zero to save notation. The vast majority of the inter-bank loans are overnight. Thus, we assume that the maturity of inter-bank loans is at the interim period.

Define Y_{i_L} and Y_{i_B} as the total amount of capital that bank i lends and borrows from other banks, respectively. Formally, it is possible to represent the inter-bank lending market via a directed weighted graph where each node is a bank and an edge starting from i and pointing in the direction of $j \in N$ is present if i has a credit towards j. The weights assigned to each edge represent the nominal value of the debt. The adjacency matrix of such graph is defined as follows:

$$\mathcal{Y} = \begin{bmatrix} 0 & \dots & y_{1,n} \\ \vdots & \vdots & \vdots \\ y_{n,1} & \dots & 0 \end{bmatrix} \tag{1.2}$$

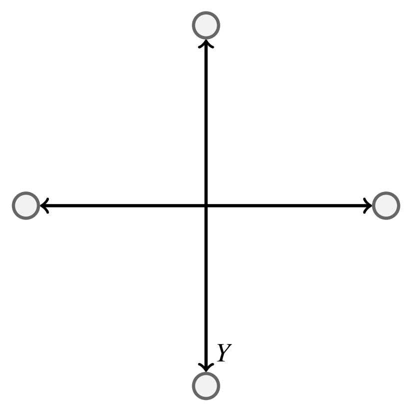
Where $y_{j,i}$ is the amount of capital that bank i lends to bank j. Following this notation, we have that: $Y_{i_L} = \sum_{j \neq i} y_{j,i}$ and $Y_{i_B} = \sum_{j \neq i} y_{i,j}$

For tractability reasons, we impose the standard restrictions on the inter-bank lending market (Acemoglu et al., 2015). Specifically, we assume that there are not net creditors and that the amount of inter-bank claims is equal across banks. That is: $Y_{i_L} = Y_{i_B} = Y_i = Y$ for any i.[6]

[6]Inter-bank markets are far away to satisfy these restrictions. Yet, in a simplified environment in which our assumptions hold, we can still get interesting economic insight concerning the way in which inter-bank claims are distributed.

Moreover, we restrict our attention to connected graph. A graph is connected if - for any two nodes - there is always a path connecting them (Jackson, 2010). In terms of financial fragility, connectivity is a crucial property. In fact, in a connected network - potentially - all nodes could be affected by individual shocks. As an example, let us consider the network in Figure 1.2. Here, the distribution of the inter-bank claims is as in the ring architecture. Nevertheless, there are two distinct clusters of banks. If a bank in one cluster cannot meet its liabilities, there are no losses for banks in the other cluster.

Figure 1.2: A Not-Connected Graph



Among connected graphs, there are two extreme structures: the complete and the ring. The complete network is the architecture with the more evenly distribution of the inter-bank claims. Each bank borrows from all the others, and the weight assigned to each edge is equal to $Y/(n-1)$. On the right side, there is a ring network structure. The ring network is the connected network with the sparsest distribution of the inter-bank claims. In the ring network, each bank has exactly one debtor and one creditor. The weight assigned to each edge is equal to Y.

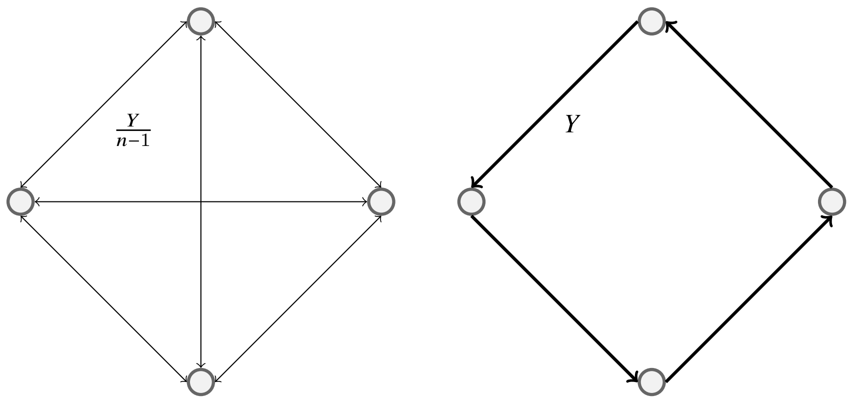
Between the ring and the complete architectures, there are intermediate claims' distributions. To capture them, we introduce the following definition:

Definition 1.1. (Acemoglu et al., 2015) An inter-bank market $\mathcal{Y}(\pi)$ is a linear convex combination of the complete - $\mathcal{Y}^C$ - and the ring - $\mathcal{Y}^R$ - if there exists $\pi \in [0,1]$ such that:

$$\mathcal{Y}(\pi) = \pi\mathcal{Y}^C + (1-\pi)\mathcal{Y}^R \tag{1.3}$$

It is essential to note that - as π moves from zero - each bank lends to all the other. Thus, π should be understood as a concentration measure for the inter-bank claims rather than an indicator for the number of bilateral contracts.

Figure 1.3: Two Extreme Architectures



In the complete network - left - all banks lend to all the remaining $n-1$ banks in the system. In the ring network - right - banks have only one creditor and one debtor. Arrows point in direction of the debtor. The more the edge is thick the higher is its weight

As an example, suppose that $Y = 1$ and $n = 4$.

$$\mathcal{Y}^C = \begin{bmatrix} 0 & .33 & .33 & .33 \\ .33 & 0 & .33 & .33 \\ .33 & .33 & 0 & .33 \\ .33 & .33 & .33 & 0 \end{bmatrix} \quad \mathcal{Y}^R = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 \end{bmatrix}$$

Consider two inter-bank markets: $\mathcal{Y}^A$ and $\mathcal{Y}^B$.

$$\mathcal{Y}^A = \begin{bmatrix} 0 & .9866 & .0066 & .0066 \\ .0066 & 0 & .9866 & .0066 \\ .0066 & .0066 & 0 & .9866 \\ .9866 & .0066 & .0066 & 0 \end{bmatrix} \quad \mathcal{Y}^B = \begin{bmatrix} 0 & .9 & .07 & .03 \\ .1 & 0 & .85 & .05 \\ .2 & .2 & 0 & .6 \\ .98 & .01 & .01 & 0 \end{bmatrix}$$

It is immediate that $\mathcal{Y}^A = \pi\mathcal{Y}^C + (1-\pi)\mathcal{Y}^R$ holds for $\pi = .02$. However, there is no π such that $\mathcal{Y}^B = \pi\mathcal{Y}^C + (1-\pi)\mathcal{Y}^R$. Thus, inter-bank market $\mathcal{Y}^A$ is a linear convex combination between the ring and the complete while $\mathcal{Y}^B$ is not.

In accordance to the notation that we introduced, the matrix B and the parameters π and Y define our banking system. Thus, we label a generic banking system as: $\mathcal{B}(B, \pi, Y)$

1.2.2 Interim Period

A liquidity shock of size $\varepsilon \in]c, d]$ hits one bank at the interim period. We interpret the liquidity shock as an unexpected withdrawal by depositors. Let us label as i the bank hit by a shock.

Because $\varepsilon > c$, bank i is illiquid. The liquidity shortage is offset by selling assets in the markets. Because of market illiquidity, asset sales result in a decline in the market prices (Shleifer and Vishny, 1992, 2011). As standard in the related literature, we assume a non-linear price impact described as follows (Cont and Schaanning, 2019):

$$p_k = \max\left\{V\left(1 - \frac{s_{i,k}}{\lambda}\right), 0\right\} \tag{1.4}$$

Where $s_{i,k}$ is the amount of asset k sold by bank i at the interim period and λ is a measure for the market liquidity. The higher the term λ, the lower is the price impact of market orders for asset k. Henceforth, we assume that the market liquidity is such that bank i defaults and assets prices are all strictly positive.

When bank i defaults, it is fully liquidated. Thus, $s_{i,k} = (1-c)w_{i,k}$ for any k.

Loss Given Default

The default of bank i has two detrimental effects for the remaining banks of the economy: mark-to-market effects and liquidity effects.

The mark-to-market losses suffered by bank j equal the portfolio depreciation concerning the initial period. At the initial period, the portfolio market value for all banks was $\sum_k V(1-c)w_{j,k} = V(1-c)$. Following bank i liquidation, prices fall to:

$$p_k = V\left(1 - \frac{w_{i,k}(1-c)}{\lambda}\right)$$

Thus, mark-to-market losses for bank j is equal to:

$$\begin{aligned}
(1-c)V - \sum_k p_k w_{j,k} =& (1-c)V - V(1-c)\sum_k \left(1 - \frac{w_{i,k}(1-c)}{\lambda}\right) w_{j,k} \\
&= V(1-c)\left[1 - \sum_k w_{j,k} + \frac{1-c}{\lambda}\sum_k w_{j,k}w_{i,k}\right] \\
&= V(1-c)^2\left[\frac{1}{\lambda}\sum_k w_{j,k}w_{i,k}\right]
\end{aligned}$$

Mark-to-market losses are proportional to the term: $\sum_k w_{j,k}w_{i,k}$.
It is well known that:

$$\sum_k w_{j,k}w_{i,k} = \vec{w}_i \bullet \vec{w}_j = \left\|\vec{w}_j\right\| \left\|\vec{w}_i\right\| \cos(\Theta_{i,j}) = \rho(\Theta_{i,j})$$

Recall that $\Theta_{i,j}$ is an inverse measure of portfolios' overlay. If two banks i and j hold the same portfolio, $\Theta_{i,j} = 0$ and $\cos(0) = 1$. If banks hold orthogonal portfolios, $\Theta_{i,j} = 1$ and $\cos(1) = 0$. As an illustrative example, let us consider the case in which $m = 2$. Suppose that:

$$\vec{w}_i = [\theta, 1-\theta]; \;\; \vec{w}_j = [1-\theta, \theta]$$

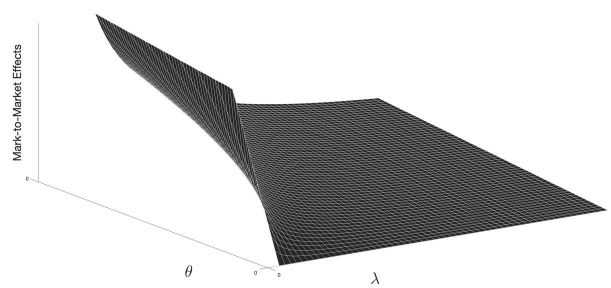
Where $\theta \in [0, \frac{1}{2}]$. In this example, we have that:

$$\rho(\Theta_{i,j}) = 2\theta(1-\theta)$$

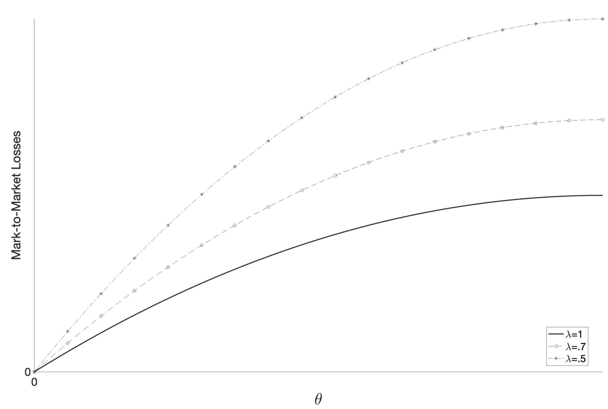
Thus, mark-to-market losses are proportional to the term: $\frac{2\theta(1-\theta)}{\lambda}$. Figure 1.4 provides an illustration of mark-to-market losses as function of θ and λ.

Figure 1.4: Mark-to-Market Effects

(a)



(b)



Liquidity Effects

The creditors of the default bank - retail depositors and other banks - share the proceeds obtained by the liquidation of bank i. All creditors must receive the same treatment following the seniority of their claims. Following Acemoglu et al. (2015), I assume that depositors have seniority concerning inter-bank creditors.

The bank i liquidation value is equal to:

$$\sum_k p_k w_{i,k} + c + X_i$$

The first term refers to the proceeds obtained from the markets, the second term refers to the cash reserves, and the third is the repayment made by the i's inter-bank debtor.
In principle, X_i could be different from Y because some borrowers may be insolvent. However, we compute the liquidation value in the best possible scenario where all banks but i can meet their liabilities. Under this assumption, the bank i liquidation value is equal to:

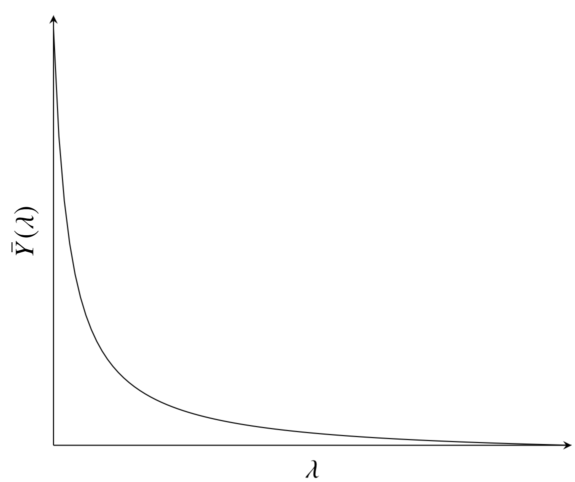
$$V\bigg(1-c\bigg)\left[1-(1-c)\frac{\|\vec{w}_i\|^2}{\lambda}\right]+c+Y$$

Since retail depositors have senior claims, inter-bank creditors get positive repayments if and only if the liquidation value is larger than d:

$$Y > \bar{Y}(\lambda) = d - V\bigg(1-c\bigg)\left[1-(1-c)\frac{\|\vec{w}_i\|^2}{\lambda}\right]-c \tag{1.5}$$

For the remainder of the discussion, we assume that the above condition is satisfied. Therefore, $\bar{Y}(\lambda)$ is the liquidity loss for the inter-bank creditors. In fact, against a credit of Y they will receive only $Y - \bar{Y}(\lambda)$

Figure 1.5: Liquidity Losses



1.2.3 The Resilient System

The sum between the mark-to-market losses and the liquidity losses provides the total losses suffered by bank j given the default of bank i. These losses cause a shrinkage in the asset side of bank j' s balance-sheet. If the shrinkage is such that the market value of j's equity turns negative, bank j is in default. This section provides conditions ensuring that the banking system is resilient to the default of bank i.

Definition 1.2. A banking system $\mathcal{B}(B, \pi, Y)$ is resilient to the default of bank i if the default of bank i does not trigger other defaults.

Our main interest is to understand how the architecture of the inter-bank market leading to a resilient banking system varies as the level of portfolios' overlay in the banking system changes. In principle, mark-to-market losses could be so high that the liquidation of i's portfolio leads to the default of a bank $j \neq i$ regardless the architecture of the inter-bank market.

Proposition 1.1. *If the following condition on $\Theta_{i,j}$ holds, the liquidity shock that affects bank i causes the default of bank j regardless the architecture of the inter-bank market.*

$$\rho(\Theta_{i,j}) > \frac{\lambda}{(1-c)^2}\left[(1-c) - \frac{d-c}{V}\right] = \bar{\rho}(\lambda) \tag{1.6}$$

Proof. Since there are no net creditors in the inter-bank market, a sufficient condition for j being in default is:

$$(1-c)\sum_k p_k w_{j,k} + c < d$$

If we expand the term p_k and re-arrange the inequality, we get Condition (1.6) □

Therefore, we cannot construct a resilient banking system if there exists a pair of banks i, j such that the extent to which their portfolios overlay exceeds the threshold $\bar{\rho}(\lambda)$. It is then necessary to introduce the following restriction:

Assumption 1.1. For any pair i, j of banks, we have that: $\rho(\Theta_{i,j}) \leq \bar{\rho}(\lambda)$

Losses given the default of bank i involve also liquidity losses. Hence, Assumption (1.1) is not sufficient to ensure that the banking system is resilient to the default of bank i. Since liquidity losses suffered by bank $j \neq i$ depends by the architecture of the inter-bank market, we need also conditions on π.

Proposition 1.2. *If n is sufficiently large, Assumption (1.1) and Condition (1.5) hold, there exists a non empty interval S such that, for any $\pi \in S$ the banking system $\mathcal{B}(B, \pi, Y)$ is resilient to the default of bank i*

$$S = \left[\pi_1(\lambda, \Theta_{i-1,i}), \pi_2(\lambda, \Theta_{j^\star(i),i})\right] \tag{1.7}$$

Where $j^\star(i)$ is the bank with the highest portfolio overlays with bank i

Proof. When the bank i is in default, the bank $i-1$ is the bank that suffers the highest liquidity losses for any $\pi \in [0,1)$.
The bank $i-1$ avoids the default if the following condition holds:

$$\sum_k p_k w_{i-1,k} + c + \frac{\pi}{n-1}\Big[(n-1)Y - \bar{Y}(\lambda)\Big] + (1-\pi)\Big[Y - \bar{Y}\Big] \geq d + Y$$

The above conditions ensure that the equity market value is no-negative. The left-hand side has three components:

(i) The market value of the portfolio: $\sum_k p_k w_{i-1,k}$

(ii) The cash reserves: c

(iii) The liquidity from the inter-bank market: $\frac{\pi}{n-1}[(n-1)Y - \bar{Y}(\lambda)] + (1-\pi)[Y - \bar{Y}]$

To see why the liquidity that bank $i-1$ gets from the inter-bank market is as in bullet (iii), note that - if the inter-bank market is complete - the bank $i-1$ receives a repayment of $\frac{Y}{n-1}$ from $n-2$ banks and a repayment of $\frac{Y-\bar{Y}(\lambda)}{n-1}$ from bank i. If the architecture of the inter-bank market was the ring, the bank i is the unique debtor of the bank $i-1$. Hence, the amount of liquidity that bank $i-1$ receives from the inter-bank market is equal to $Y - \bar{Y}(\lambda)$. Since in the banking system $\mathcal{B}$ banks distribute inter-bank claims as a linear convex combination between the ring and the complete, we have bullet (iii).

Note that the liquidity that bank $i-1$ gets from the inter-bank market increases in π. Hence, we can find a threshold such that if π is below such threshold, bank $i-1$ is in default. We define such threshold as π_1 By re-arranging the above condition, we get:

$$\pi \geq \pi_1(\lambda, \Theta_i) = \frac{n-1}{n-2}\left[1 - \Gamma(\lambda)\Big(\bar{\rho}(\lambda) - \rho(\Theta_{i,i-1})\Big)\right] \tag{1.8}$$

Where $\Gamma(\lambda) = \frac{V\lambda}{(1-c)^2\bar{Y}(\lambda)}$.
Let us now discuss conditions ensuring that bank $j \neq i, i-1$ survives to the default of bank i.

$$\sum_k p_k w_{j,k} + c + \frac{\pi}{n-1}\Big[(n-1)Y - \bar{Y}(\lambda)\Big] + (1-\pi)Y \geq d + Y$$

The difference concerning the previous case is that the liquidity that bank j gets from the inter-bank market decreases in π. Therefore, we can find a threshold such that if π is above such threshold, bank j is in default. We define the threshold as π_2.
By re-arranging the above condition, we get:

$$\pi \leq \pi_2(\lambda, \Theta_{i,j}) = (n-1)\Gamma(\lambda)\Big[\bar{\rho}(\lambda) - \rho(\Theta_{j,i})\Big]$$

Note that the higher is the level of portfolios' overlay between bank i and bank j, the lower will be the threshold π_2. Hence, a sufficient condition ensuring that all banks $j \neq i, i-1$ avoid the default is:

$$\pi \leq \pi_2(\lambda, \Theta_{i,j}) = (n-1)\Gamma(\lambda)\Big[\bar{\rho}(\lambda) - \rho(\Theta_{j^\star(i),i})\Big] \tag{1.9}$$

Where:

$$\Theta_{j^\star,i} = \min\Big\{\Theta_{1,i}, \ldots, \Theta_{i-2,i}, \Theta_{i+1,i}, \ldots, \Theta_{n,1}\Big\}$$

Finally, note that as n increases the threshold π_2 increases while the threshold π_1 tends to a constant term. Therefore, there exists a sufficiently large n labelled $\bar{n}$ such that for any $n \geq \bar{n}$ we have that: $\pi_1 \leq \pi_2$. □

Proposition (1.2) claims that resilience requires a distribution of the inter-bank claims that is both not too concentrated ($\pi \geq \pi_1$) and not too homogeneous ($\pi \leq \pi_2$). The economic intuition is as follows. When the distribution of the inter-bank claims tends to be more concentrated (π decreases), the liquidity losses for bank $i-1$ increases. The threshold π_1 identifies the less connected architecture at which bank $i-1$ survives to default of bank i. If π is below π_1, the liquidity shock affecting bank i causes the default of bank $i-1$ Nonetheless, as the distribution of the inter-bank claims tends to be more homogeneous, the liquidity losses for bank $j \neq i-1$ increases. Among all possible banks different from i, the bank which is closest to the bankruptcy is the bank who suffers the highest mark-to-market losses ($j^\star$). The threshold π_2 identifies the most connected architecture at which bank ($j^\star(i)$) survives. If π exceeds π_2, the liquidity shock affecting bank i causes the default of bank $j^\star(i)$.
Hence, the Proposition identifies a range of architectures equivalent in terms of resilience.

In the next section, we discuss how this range depends on the extent to which banks portfolios overlap.

1.2.4 Resilience and Portfolios Overlay

In their seminal paper, Allen and Gale (2000) argued that the complete inter-bank market ($\pi = 1$) is the most resilient architecture whatever the conditions of the economy. It may not be the case in our framework since π_2 could be smaller than 1. We start our discussion by investigating when the complete network is not resilient.

Proposition 1.3. *Define $P_1(\lambda)$ as follows:*

$$P_1(\lambda) = \bar{\rho}(\lambda) - \frac{1}{(n-1)\Gamma(\lambda)} \tag{1.10}$$

Hence, if $\rho(\Theta_{j^\star,i}) \in \Big(P_1(\lambda), \bar{\rho}(\lambda)\Big)$ and $\rho(\Theta_{i-1,i}) < P_1(\lambda)$ we have that:

(i) The complete network is not resilient to the default of bank i

(ii) There is at least one resilient architecture. That is, S is not empty

Proof.

(i) The complete architecture is not resilient if $\pi = 1$ does not belong to the set S. Hence, if and only if $\pi_2 < 1$. Note that, π_2 is larger or equal to 1 if and only if $\rho(\Theta_{j^\star,i}) \leq P_1(\lambda)$. Thus, if $\rho(\Theta_{j^\star,i}) \in \Big(P_1(\lambda), \bar{\rho}(\lambda)\Big)$ we have that $\pi_2 < 1$

(ii) The set S is not empty if and only if $\pi_1 < \pi_2$. Note that π_1 is smaller to 1 if $\rho(\Theta_{i-1,i}) < P_1(\lambda)$. Thus, it is sufficient to take values for $\rho(\Theta_{j^\star,i})$ that are sufficiently close to P_1 to have the result.

□

Proposition (1.3) claims that there are some conditions for which the complete network is not resilient while other architectures, where inter-bank claims are not homogeneously distributed, are.
Proposition (1.3) marks a difference between our paper and Allen and Gale (2000). We find a condition for which the complete network is not resilient.
We reach the same conclusion of Acemoglu et al. (2015). Acemoglu et al. (2015) argued that the complete network moves from the most resilient architecture to the worst as the size of the initial liquidity shock affecting the banking system is above a critical threshold. We claim that the complete network exits from the resilient architectures for some conditions on the level of overlapping portfolios across banks. More concretely, Proposition (1.3) shows that if the level of common asset holdings between bank i and bank $i-1$ is sufficiently low and the level of common asset holdings between bank i and any other bank in the system is sufficiently high, resilience requires bank $i-1$ to bear the most fraction of the i' s inter-bank liabilities. Indeed, the low overlap between bank i and bank $i-1$ provides to the latter a high buffer to restrain significant liquidity losses. Other banks - with a high overlap - could not survive even to small liquidity losses.

Moreover, we can add another page to the story of Acemoglu et al. (2015). We can also investigate whether the ring network could be resilient.
The ring network belongs to the interval S if and only if:

$$\pi_1(\lambda, \Theta_{i-1,i}) \leq 0$$

$$\frac{n-1}{n-2}\left[1 - \Gamma(\lambda)\Big(\bar{\rho}(\lambda) - \rho(\Theta_i)\Big)\right] \leq 0$$

$$\rho(\Theta_{i-1,i}) \leq P_2(\lambda) = \bar{\rho}(\lambda) - \frac{1}{\Gamma(\lambda)} \tag{1.11}$$

Moreover, we can find conditions ensuring that the ring network is the only resilient architecture.

Proposition 1.4. *Under the assumptions of the model*

(i) If $\rho(\Theta_{i-1,i}) = P_1(\lambda) = \rho(\Theta_{j^\star,i})$*, the complete network is the unique resilient architecture*

(ii) If $\rho(\Theta_{j^\star,i}) = \bar{\rho}(\lambda)$ *and* $\rho(\Theta_{i-1,i}) \leq P_2(\lambda)$*, the ring network is the unique resilient architecture.*

(iii) If $\rho(\Theta_{i-1,i}) \leq P_2(\lambda)$ *and* $\rho(\Theta_{j^\star,i}) \leq P_2(\lambda)$*, any linear convex combination between the ring and the complete network is resilient*

Proof.

(i) If $\rho(\Theta_{i-1,i}) = P_1(\lambda) = \rho(\Theta_{j^\star,i})$, we have that $\pi_1 = \pi_2 = 1$. Hence, $S = \{1\}$

(ii) If If $\rho(\Theta_{j^\star,i}) = \bar{\rho}(\lambda)$ and $\rho(\Theta_{i-1,i}) \leq P_2(\lambda)$, we have that $\pi_1 = \pi_2 = 0$. Hence, $S = \{0\}$

(iii) If $\rho(\Theta_{i-1,i}) \leq P_2(\lambda)$ and $\rho(\Theta_{j^\star,i}) \leq P_2(\lambda)$, we have that $\pi_1 \leq 0$ and $\pi_2 \geq 1$. Hence, $S = [0, 1]$.

□

Our results suggest that the inter-bank market's architecture - for its own sake - is not prominent in defining the resilience of the banking system to financial contagion. Both the complete and the ring network can be resilient to the default of bank i. Moreover, there are conditions such that any linear convex combination between the two architectures is resilient. What matters for stability is the interaction between the architecture of the inter-bank market, the level of the portfolio overlays and market depth.

We can conclude that as the level of portfolio overlay between bank i and all other banks increases (i.e. $\rho(\Theta_{j^\star,i})$ and $\rho(\Theta_{i-1,i})$ increase) the set of resilient architectures shrinks, meaning that architectures where the inter-bank claims follow extreme distributions (very concentrated and very homogeneous) exit from the resilient set. Ceteris paribus, a decrease in the market depth has the same effect.

In light of this discussion, we suggest that incomplete inter-bank markets are not necessarily a threat to financial stability. Nevertheless, the slowdowns in the inter-bank activity followed by spikes in the portfolios similarity or drops in the market liquidity are the primary sources of financial fragility that must set alarm bells.

1.3 Conclusion

In this paper, we discussed the architecture of the inter-bank lending market less prone to financial contagion. We find that, once we fix the parameters of the economy, there could be many architectures ensuring that the banking system is maximally resilient to financial contagion. The measure of the set of stable architectures depends on the level of overlapping portfolios across banks. As similarity between portfolios increases, architectures characterised by extreme distributions of the inter-bank claims become fragile.

From a macroprudential perspective, the paper helps to set alarm bells. The slowdown in inter-bank lending activity should cause concern if it is accompanied by increases in portfolio overlap between financial institutions. Similarly, a spike in portfolios' overlay could be more or less worrying depending on how the activity of the inter-bank market reacts.

Chapter 2

Risk Diversification and Liquidity Risk

Abstract

Profits' maximisation purposes carry banks to diversify their idiosyncratic risk by investing a share of capital in the market portfolio. Such a strategy could have drawbacks for society. In fact, during widespread turmoils - i.e., when the market portfolio has poor returns - liquidation costs increase, worsening the payoffs of external creditors of failing banks. Since creditors' losses are not internalised ex-ante by banks, equilibrium asset allocation involves excessive correlation - from a social standpoint - between bank individual default probability and the market portfolio's return. This paper shows that banks exposed to liquidity risk find it optimal to forego diversification and decrease the exposition to the market portfolio. The economic mechanism lies in the costs of raising liquidity. Widespread turmoils raise the costs of obtaining liquidity by enhancing market illiquidity. Hence, illiquid banks during market downturns incur higher losses, and - in extreme cases - they could go bust. By anticipating this risk, banks whose liquidity risk is higher will reduce their investments in the market portfolio even at the cost of a lower diversification degree. From the standpoint of positive analysis, this paper suggests that portfolios' correlation in the financial sector declines when the bank panic is more likely. Moreover, we suggest the existence of a U-shaped relationship between market liquidity conditions and the level of portfolio overlays between banks.

2.1 Introduction

Risk diversification seems to be the goal for all rational economic agents.[1] Undergraduate students in finance soon learn that *putting eggs in different baskets* is - usually - a winning strategy for individual agents (Samuelson, 1967).

[1] With some exceptions. See Mayshar (1979)

However, individual risk diversification pursuits - sometimes - clash with social welfare. In the financial system, such tensions are evident. Suppose that each financial institution holds a specific risky asset. Given a sufficiently high degree of independence between the risky assets, the institutions may succeed in eliminating the idiosyncratic risks embedded in their portfolios by forming a joint mutual market portfolio, with each financial firm contributing its risky portfolio to the total and receiving back its proportional share of the total (Ibragimov et al., 2011; Allen et al., 2012). The drawback for society is a surge in systemic risk.[2]

When there is a widely spread asset - as the market portfolio - there are at least two sources of systemic risk. First, when the market portfolio has poor returns, all the institutions shake. An excellent example of that is the European sovereign debt crisis. Italian banks were (are) heavily exposed to the Italian government bonds. When the solvency of Italy was in doubt, the entire Italian financial system faltered.
Second, asset markets are - usually - less than perfectly liquid. Thus, small, idiosyncratic liquidity shocks could wipe out the entire financial system. Fire sales and deleveraging processes have a price impact leading to mark to market losses and destabilising feedback loops (Cifuentes et al., 2005; Ellul et al., 2011). When realised, the systemic risk generates - usually - super-additive costs. The losses suffered during systemic crises are more significant than the losses generated by individual defaults. Financial institutions fail to internalise such extra costs and - as a consequence - the equilibrium investment in the market portfolio exceeds the social optimum (Acharya and Yorulmazer, 2007; Wagner, 2010).

In contrast with this view, this paper claims that equilibria in which the individual investment in the market portfolio is below the social optimum are possible.
We consider a straightforward economy in which a representative financial institution (henceforth bank) can invest in two assets. The first asset represents the market portfolio whose performance defines the general conditions of the economy. If market portfolio's returns are below a critical threshold, the economy falls into a market crisis.
The other asset is bank specific, meaning that no other agents in the economy have access to it.[3] All assets' returns distributions are assumed to be mutually independent.
The independence assumption implies that the minimum variance portfolio requires investing half of the capital in the market portfolio and half in the exclusive asset.[4] In a simple mean-variance preferences framework, the minimum variance portfolio will be the equilibrium asset allocation.

If we - reasonably - assume that market crises dry market liquidity (Næs et al., 2011), it is not difficult to show that such equilibrium drives to a socially

[2]In this paper, we define systemic risk as to the risk - or probability - that an entire sector breakdown (Kaufman and Scott, 2003). However, it should be borne in mind that systemic risk is defined and interpreted in many ways in the literature. See Smaga (2014) for a survey.

[3]Exclusivity here may be due to legal barriers or to some bank' s competitive advantages

[4]For the sake of simplicity, all assets have the same returns' distributions

inefficient outcome. Bankrupted banks liquidate their portfolios in the asset markets and use proceeds to repay external investors. The investors' payoff is proportional to the market liquidity in case of bank failure. Hence, the investors' losses in case of bank default will be more significant if the bankruptcy occurs during a market crisis and lower if the bank is distressed when the market is in *business-as-usual* conditions. Banks do not internalises investors' losses during market crises. So, equilibrium asset allocation is inefficient.
More or less, this is the reasoning of the literature highlighting that individual bank risk is excessively correlated to the risk of the entire system.

Our contribution is to add liquidity risk to the story. The liquidity risk is the risk of a default due to a run when the institution would otherwise have been solvent (Morris and Shin, 2009). To model liquidity risk in the simplest possible way, we assume that banks are opaque. That is, banks' external investors cannot perfectly observe banks' fundamental value (Morgan, 2002). To see why opacity entails liquidity risk, note that banks' liabilities are mainly short-term liabilities or payable on demand. External investors may decide not to roll over their credits or withdraw their funds in response to negative signals about the fundamental value of the bank. If banks are opaque, the signals could be biased, and running on healthy institutions are possible. In such cases, banks are illiquid rather than bankrupt. Whether banks survive liquidity crises depends on the costs of obtaining liquidity. In our economy, illiquid banks have only one source for liquidity: asset markets. Illiquid banks sell their assets into the market to get the liquidity necessary to offset the liquidity demand from external investors. Selling prices are lower than fundamentals (Shleifer and Vishny, 1992, 2011). The gap between the fundamental price and the selling price depends on market liquidity (Allen and Gale, 2004; Gorton and Huang, 2004). Since during market crises, market liquidity is lower, illiquid banks have more chance - on average - to overcome liquidity crises if they are illiquid during *business-as-usual* conditions. Therefore, they are willing to deviate from the minimum variance portfolio by investing in a portfolio that is less correlated to the market conditions.

In a nutshell, the model shows that opacity (liquidity risk) brings financial institutions to invest in less diversified and more counter-cyclical portfolios. Concerning the literature, a different kind of inefficiency could arise. In fact, by deviating from the minimum variance portfolio, banks are increasing their idiosyncratic risk. Financial institutions trade off the increase in riskiness with a lower probability of being illiquid during market crises. However, the increase in riskiness reduces the external investors' expected payoffs. Since investors' losses are not internalised by banks, deviating from the minimum variance portfolio could be more costly for society than for individual banks. This reasoning could lead to a paradoxical result: individual investments in the market portfolio could be below the social best.

The model sketched in this paper is too stylised to dispense a realistic description of financial systems. Still, it offers some economic insights.
First, the model provides empirical predictions that could be helpful to monitor the level of overlapping portfolios in the banking system. Overlapping portfolios - or asset commonality - refers to the case in which two or more institutions

invest in the same risk factor: an asset. Currently, it is one of the main concerns for the stability of the financial sector (Caccioli et al., 2014; Greenwood et al., 2015; Poledna et al., 2021). Specifically, we suggest that asset commonality should be more pronounced in the banking system where liquidity risk is low and financial institutions are transparent.

Moreover, we also suggest a U-shaped relationship between the level of overlapping portfolios in the banking system and the market liquidity conditions. To see why the model leads to this last prediction, note that - in our framework - banks have no reasons for caring of liquidity crises when market liquidity is plentiful or when markets are very illiquid. When liquidity is plentiful, liquidity crises are harmless. Illiquid institutions sell their assets at fundamental prices, and liquidation costs tend to zero, so banks' losses. Instead, when markets are very illiquid, banks cannot overcome liquidity crises regardless of whether they are in a market crisis. In both cases, the best that banks can do is to minimise the portfolios' riskiness.
Second, in a famous paper Acharya and Yorulmazer (2007) discussed the *too-many-to-fail* problem. Small financial institutions have an incentive to invest in the market portfolio to increase the probability of being bailed out by the regulator during market downturns. If there are *too many* distressed institutions, the regulator implement rescue plans to avoid massive losses. Following the A&Y contribution, empirical investigations confirm that governments are less likely to take over or close a failing bank if the banking system is weak (Brown and Dinç, 2011). Despite that, we still observe that some financial institutions invest in portfolios that tend to be orthogonal to the market portfolio (Blei and Ergashev, 2014). This paper provides a rational explanation for this behavior.

2.2 Theoretical Framework

2.2.1 General Aspects, Assumptions and Definitions

The economy lasts three periods: initial ($t = 0$), interim ($t = 1$) and final ($t = 2$). The financial sector consists in n banks - indexed by i - and two assets: X_i and Y.
Asset X_i is exclusive of bank i. Instead, all financial institutions have access to asset Y, representing the market portfolio.
For the sake of interpretation, the reader could view asset X_i as commercial loans provided by bank i to its customers and the asset Y as the market portfolio.
In the initial period, banks collect capital of which a fraction $D < 1$ is in the form of deposits, and the remaining is equity. Banks use capital to invest in risky assets.

Assumption 2.1. Assets returns - $\tilde{X}_i, \tilde{Y}$ - are independent random variables uniformly distributed on the support $[0, R]$, where $R > 1$.

At the interim period, assets returns become known to the banks. In that period, the bank value is equal to:

$$v_i = (1 - \alpha_i)\tilde{X}_i + \alpha_i \tilde{Y} \tag{2.1}$$

Where α_i represents the investment in the market portfolio.
In the same period, depositors receive a signal about bank value.

Assumption 2.2. Depositors observe a biased bank value.

Equation (2.2) describes the value observed by depositors.

$$v_i^{obs} = \Phi_i v_i \tag{2.2}$$

Where Φ_i is a random variable uniformly distributed in the interval $[1 - \phi_i, 1 + \phi_i]$. The distribution of the depositors' bias is independent across banks. Furthermore, it is also independent of the realisations of the assets returns.
Parameter ϕ_i captures the standard error made by depositors in assessing the bank's fundamental value. Henceforth, we will interpret it as the bank i' s opacity.

If the observed value is lower than D, depositors run on the bank. We exclude other reasons for bank runs. Note that - conditioning on the signal - depositors always find it convenient to run on the bank during the interim period. In fact, by running at $t = 1$, depositors expect to receive a payoff equal to the liquidation value of v_i^{obs}. If they wait until the last period, they still expect to receive the liquidation value of v_i^{obs}. Hence, run at $t = 1$ should be preferred in any standard structure on consumption preferences over time.
Equation (2.3) describes the run condition in the economy

$$v_i^{obs} < D \tag{2.3}$$

Definition 2.1. When a bank run occurs, we define it:

(i) Inefficient, if it had not occurred in case of full observable fundamentals: $\phi_i = 0$,

(ii) Fundamental, otherwise

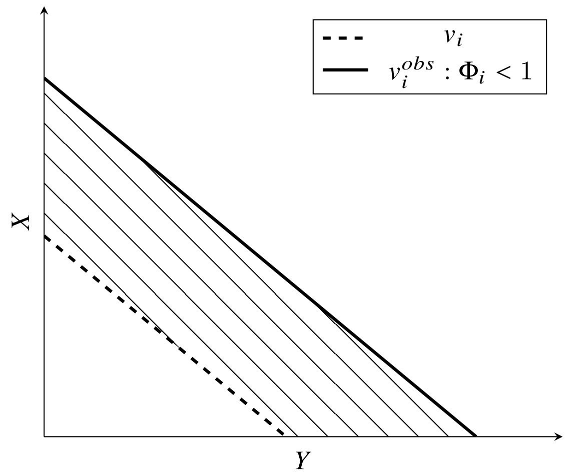
Definition 2.2. If $\tilde{Y} < \gamma$ we say that there is a market crisis. If $\tilde{Y} \geq \gamma$ we say that there are *business-as-usual* conditions.

Therefore, we anchor the state of health of the economy to the return of the market portfolio. The assumption's economic foundation is that when a widely spread asset - such as the market portfolio - has poor returns, the entire economy staggers. In our interpretation, parameter γ represents the threshold beyond which widespread turmoils arise. To avoid triviality, we will not consider extreme values for γ.

Assumption 2.3. All banks are identical: $\phi_i = \phi$

Given Assumption 2.3, we can suppress the index i. Henceforth, the discussion regards the representative bank of the economy.

Figure 2.1: Inefficient Runs



Liquidation Costs

In the case of inefficient runs, the bank is illiquid rather than insolvent. The bank can raise liquidity by selling its assets in the markets. Denote as p_k the price of asset $k = X, Y$.

$$p_k = \begin{cases} ck & \text{During Business as Usual Conditions} \\ qck & \text{During a Market Crisis} \end{cases}$$

Where k is the realised return.

Thus, if early liquidated, assets yield a fraction c of the fundamental value if the economy is at *business-as-usual* conditions and a fraction qc - with $q < 1$ - in case of systemic crises. Said differently, parameter q captures the effects on asset markets of a collapse in the market portfolio.
Parameters c and q describe market liquidity conditions.

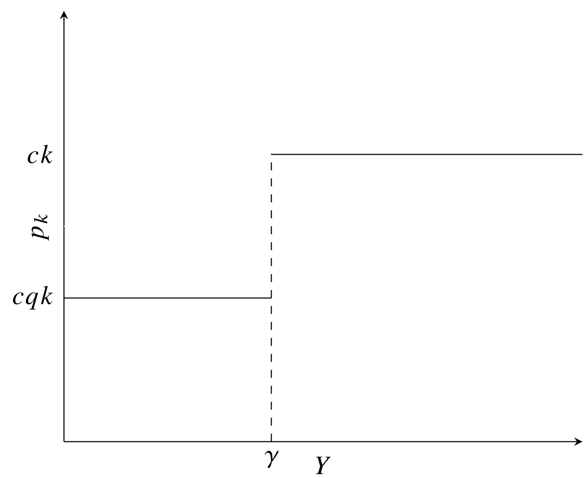
Expected Profits

In this section, we compute the returns that the bank should expect.

In case of fundamental run, the bank cannot get positive profits. Moreover, the bank makes zero profits also if there is no bank run but $v < D$. Hence, we need to compute bank's expected profits only when there is no bank run and $v \geq D$, and when there are inefficient runs.

Depositors do not run if $v^{obs} \geq D$. Ex-ante, we have that $v^{obs} = v$. Thus, when there are no runs, average profits are equal to the case of observable fundamentals. Because assets have identical distributions, they will have the same conditional return implying that banks' expected profits do not depend on asset allocation: $V = E[v|\text{No Run}] - D$.

Figure 2.2: Assets Prices and Market Portfolio' s Return



Computing bank's expected profits in the case of inefficient runs is more tricky because they depend by whether there is a market crisis. With a slight abuse of notation, we denote as IR, MC the event Inefficient Run $\wedge$ Market Crisis while with IR, BU we denote the event Inefficient Run $\wedge$ Business as Usual.

Lemma 2.1. *If $\gamma < \mathcal{D}(\phi) - D$, we have that:*

(i)

$$E[Y|IR, MC] = \frac{\gamma}{2} \tag{2.4a}$$

$$E[X|IR, MC] = \frac{D + \mathcal{D}(\phi) - \alpha\gamma}{2(1-\alpha)} \tag{2.4b}$$

(ii)

$$E[Y|IR, BU] = \frac{D + \alpha\gamma}{2\alpha} \tag{2.5a}$$

$$E[X|IR, BU] = \frac{\mathcal{D}(\phi) - \alpha\gamma}{2(1-\alpha)} \tag{2.5b}$$

Proof. We provide proof only for (i). Computations for (ii) follow similar steps.

An inefficient run can occur if and only if $\Phi < 1$. Because the assumption of uniform distribution, we have that:

$$E[\Phi|\Phi < 1] = 1 - \frac{\phi}{2}$$

$$\begin{cases} v \geq D \\ v^{obs} < D \end{cases}$$

$$X \geq x_1(\tilde{Y}) = \frac{D - \alpha\tilde{Y}}{1-\alpha}$$
$$X \leq x_2(\tilde{Y}) = \frac{\mathcal{D}(\phi) - \alpha\tilde{Y}}{1-\alpha}$$

Where: $\mathcal{D}(\phi) = \frac{D}{1-\frac{\phi}{2}}$.
The functions x_1 and x_2 - defined in $[0, \gamma]$ - describe the minimum and the maximum realisation of $\tilde{X}$ - as function of the realisation $\tilde{Y}$ - consistent to the event IR, MC. Since $\tilde{X}$ is uniformly distributed, we have that:

$$E[X|IR, MC] = \frac{x_1(\tilde{Y}) + x_2(\tilde{Y})}{2} = \bar{x}(\tilde{Y})$$

Similarly, we can define functions y_i and y_2 - defined in the interval $[0, \frac{\mathcal{D}(\phi)}{1-\alpha}]$ - describing the minimum and the maximum realisation of the market portfolio - as function of the specific asset - consistent to the event IR, MC

$$\begin{cases} \tilde{Y} \geq y_1(\tilde{X}) \\ \tilde{Y} \leq y_2(\tilde{X}) \end{cases}$$

In a market crisis, the upper bound for the realisation of the market portfolio is γ. The function y_2 takes values larger than γ if and only if:

$$\frac{\mathcal{D}(\phi) - (1-\alpha)X}{\alpha} > \gamma \implies \frac{\mathcal{D}(\phi) - \alpha\gamma}{1-\alpha} = x_2(\gamma) > \tilde{X}$$

The lower bound for the market portfolio is zero. The function y_1 turns negative if and only if:

$$\frac{D - (1-\alpha)X}{\alpha} < 0 \implies \frac{D}{1-\alpha} < \tilde{X}$$

Because $\gamma < \mathcal{D}(\phi) - D$, we have that:

$$\frac{D}{1-\alpha} < x_2(\gamma)$$

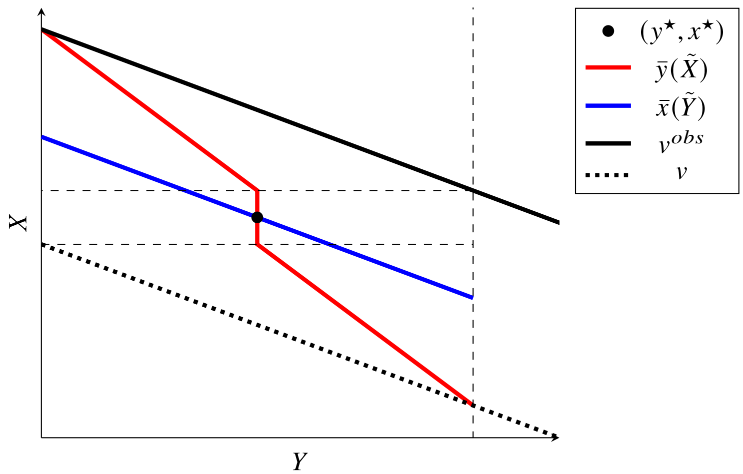
Thus, if $\tilde{X} \in [\frac{D}{1-\alpha}, x_2(\gamma)]$, we have:

$$E[Y|IR, MC] = \frac{\gamma}{2}$$

Thus:

$$E[Y|IR, MC] = \bar{y}(\tilde{X}) = \begin{cases} \frac{\gamma + y_1(\tilde{X})}{2} & \text{If } \tilde{X} \leq \frac{D}{1-\alpha} \\ \frac{\gamma}{2} & \text{If } \tilde{X} \in \left[\frac{D}{1-\alpha}, x_2(\gamma)\right] \\ \frac{y_2(\tilde{X})}{2} & \text{If } \tilde{X} \in \left[x_2(\gamma), \frac{\mathcal{D}(\phi)}{1-\alpha}\right] \end{cases}$$

Figure 2.3: Expected Returns During Market Crises



Function $\bar{x}/\bar{y}$ provides the expected return of asset X/Y consistent to the event IR, MC as function of the realisation of $\tilde{Y}$ / $\tilde{X}$. Thus, we need to find a pair $(x^\star, y^\star)$ such that:

$$\bar{x}(y^\star) = x^\star; \;\; \bar{y}(x^\star) = y^\star$$

It is straightforward to show that:

$$x^\star = \frac{D + \mathcal{D}(\phi) - \alpha\gamma}{2(1-\alpha)}$$

$$y^\star = \frac{\gamma}{2}$$

□

According to results described by Lemma 2.1, the maximum amount of liquidity that the bank can obtain in case of inefficient runs during business-as-usual conditions is equal to:

$$L_1(\phi, c) = cE[v|IR, BU] = \frac{c}{2}\Big[D + \mathcal{D}(\phi)\Big]$$

Similarly, the maximum amount of liquidity that the bank can obtain in case of inefficient runs during systemic crises is equal to:

$$L_2(\phi, c, q) = cqE[v|IR, MC] = \frac{cq}{2}\Big[D + \mathcal{D}(\phi)\Big]$$

The bank expects to not survive to liquidity crises when L_1 and L_2 are smaller than D. Whether the bank survives to inefficient runs depends by the liquidation costs.

Definition 2.3. Liquidation costs are said to be:

(i) *High*, if the bank can never survive - on average - to liquidity crises. That is, if: $L_1(\phi, c) < D$

(ii) *Intermediate*, if the bank can survive - on average - liquidity crises *only* during business-as-usual conditions. That is, if: $L_2(\phi, c, q) < D \leq L_1(\phi, c)$

(iii) *Low*, if the bank can always survive - on average - liquidity crises. That is, if: $L_2(\phi, c, q) \geq D$

Finally, we can compute the fundamental value of the residual bank portfolio. We assume that the bank liquidates the entire portfolio, uses the proceeds to offset the liquidity demand, and uses the residual liquidity - if any - to re-purchase assets at the same price. We further assume that the asset allocation in the residual portfolio keeps the same proportion between asset X and asset Y as the initial allocation. Under our assumptions, it is straightforward to show that bank' s expected profits coincide with the available liquidity minus the amount paid to depositors.

Denote as θ_{1_X} and θ_{1_Y} the share of asset X and asset Y in the bank residual portfolio when the bank survives liquidity crisis during business-as-usual conditions.

$$\theta_{1_X}(\phi, c) = \frac{2(1-\alpha)\Big[L_1(\phi, c) - D\Big]}{D + \mathcal{D}(\phi)} \tag{2.6a}$$

$$\theta_{1_Y}(\phi, c) = \frac{2\alpha\Big[L_1(\phi, c) - D\Big]}{D + \mathcal{D}(\phi)} \tag{2.6b}$$

Hence, the bank expected payoff when it survives to inefficient runs during business-as-usual conditions is equal to:

$$\theta_{1_X}(\phi, c)E[X|IR, BU] + \theta_{1_Y}(\phi, c)E[Y|IR, BU] = L_1(\phi, c) - D = v_1(\phi, c)$$

Similarly, denote as θ_{2_X} and θ_{2_Y} the share of asset X and asset Y in the bank residual portfolio when the bank survives liquidity crisis during systemic crises.

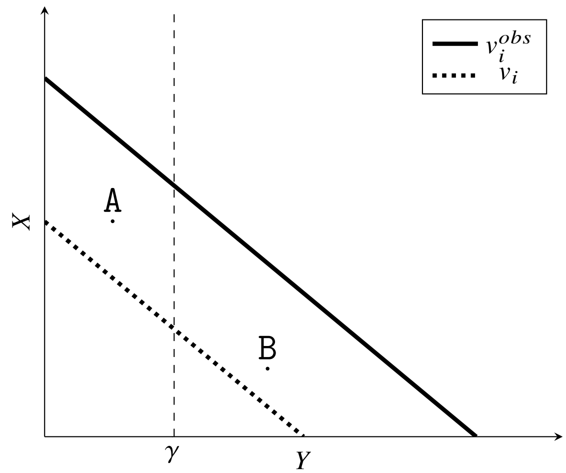
$$\theta_{2_X}(\phi, c, q) = \frac{2(1-\alpha)\Big[L_2(\phi, c, q) - D\Big]}{D + \mathcal{D}(\phi)} \tag{2.7a}$$

$$\theta_{2_Y}(\phi, c, q) = \frac{2\alpha\Big[L_2(\phi, c, q) - D\Big]}{D + \mathcal{D}(\phi)} \tag{2.7b}$$

Hence, the bank expected payoff when it survives to inefficient runs during market crises is equal to:

$$\theta_{2_X}(\phi, c, q)E[X|IR, MC] + \theta_{2_Y}(\phi, c, q)E[Y|IR, MC] = L_2(\phi, c, q) - D = v_2(\phi, c, q)$$

Figure 2.4: Probability of Inefficient Runs



Area A=Prob(IR,MC), Area B=Prob(IR,BU), Area A+B= Prob(IR)

Dead-weight Losses

In this section, we compute the amount of resources wasted in the liquidation process.
When the bank liquidates assets at the interim period, there is a waste of $1-c$ for each unit. If the bank does not survive the liquidity crisis, the entire portfolio is liquidated, and the deadweight loss is equal to $1-c$ or $1-cq$ depending on if there is a market crisis or not.
If the bank survives inefficient runs, there are some units that the bank can recover. Hence, if liquidation costs allow the bank to survive to inefficient runs, the resources wasted are equal to:

$$TC_1(\phi, c) = \left[1 - c\right]\left[1 - \frac{2v_1(\phi, c)}{D + \mathcal{D}(\phi)}\right] \tag{2.8a}$$

$$TC_2(\phi, c, q) = \left[1 - cq\right]\left[1 - \frac{2v_2(\phi, c, q)}{D + \mathcal{D}(\phi)}\right] \tag{2.8b}$$

Probabilities of Crises

We move to compute the probability of a bank run. We start by fundamental runs. When there is a fundamental run, we have that both v^{obs} and v are below D. Since $E[v^{obs}] = v$, the expected probability of a fundamental run is equal to:

$$\text{Prob(FR)} = \text{Prob}(v < D) = \int_0^{\frac{D}{\alpha}} \frac{D - \alpha\tilde{Y}}{(1-\alpha)} \frac{d\tilde{Y}}{R^2} = \frac{D^2}{2R^2\alpha(1-\alpha)} = \pi(\alpha) \tag{2.9}$$

Inefficient runs - instead - are possible only in states of the world in which depositors underrate the fundamental value of the bank. That is, if and only if $\Phi < 1$. Therefore, an inefficient run occurs with probability:

$$\text{Prob (IR)} = \int_0^{\frac{\mathcal{D}(\phi)}{\alpha}} \frac{\mathcal{D}(\phi) - \alpha\tilde{Y}}{1-\alpha}\frac{d\tilde{Y}}{R^2} - \int_0^{\frac{D}{\alpha}} \frac{D - \alpha\tilde{Y}}{1-\alpha}\frac{d\tilde{Y}}{R^2} = \pi(\alpha)f(\phi) \qquad (2.10)$$

Where: $f(\phi) = \phi\frac{1+\phi/2}{1-\phi/2}$.
Since liquidation costs differ depending on the return of the market portfolio, we need to split the overall probability of an inefficient run into the probability of an inefficient run during market crisis and the probability of an inefficient run during business-as-usual condition.

$$\text{Prob(IR,MC)} = \int_0^{\gamma} \frac{\mathcal{D}(\phi) - D}{1-\alpha}\frac{d\tilde{Y}}{R^2} = \frac{\gamma D}{R^2(1-\alpha)}\frac{\phi/2}{1-\phi/2} \qquad (2.11a)$$

$$\text{Prob(IR, BU)} = \pi(\alpha)f(\phi) - \frac{\gamma D}{R^2(1-\alpha)}\frac{\phi/2}{1-\phi/2} \qquad (2.11b)$$

2.2.2 Benchmark: $\phi = 0$

In the following sections, we compute the equilibrium asset allocation and the social efficient asset allocation. The scope of the bank is to maximize the return of equity capital. The scope of the social planner - instead - is to maximize the expected return both for bank owners and depositors.
We start from the benchmark case in which liquidity risk is null ($\phi = 0$). In this case, our framework is similar to Wagner (2010).

Proposition 2.1. *When fundamentals are fully observable* ($\phi = 0$) *and market crises have no effects on market liquidity conditions* ($q = 1$)*, the equilibrium asset allocation* α^E *coincides with the efficient asset allocation* $\alpha^\star$*. That is,* $\alpha^E = \frac{1}{2} = \alpha^\star$

Proof. The scope of the bank is to maximize the shareholders' expected return. Since assets follow identical distribution, and shareholders are risk-neutral, the task requires minimizing the portfolio's variance. Hence, $\alpha^E = 1/2$
Maximizing the welfare require to maximize the expected return of banks' shareholders and depositors. Since assets are identical distributed and agents are risk-neutral, maximizing the welfare requires minimizing liquidation costs. The bank liquidates only during runs. Hence, maximizing the welfare requires solving the following program:

$$\min \rightarrow \pi^{BU}(\alpha)(1-c) + \pi^S(\alpha)(1-cq) \qquad (2.12)$$

Where $\pi^{BU}(\alpha)$ and π^S are the probabilities of being hit by run during the *business-as-usual* conditions and market crisis, respectively.
By assumption, $q = 1$. Therefore, we have that:

$$\min \rightarrow \pi(\alpha)(1-c)$$

Given the strict convexity of $\pi(\cdot)$, the first order condition is necessary and sufficient to solve the welfare maximization problem.

$$\pi'(\alpha) = 0 \iff \alpha = \frac{1}{2}$$

Hence, $\alpha^\star = 1/2 = \alpha^E$ □

Proposition 2.2. *When fundamentals are fully observable by depositors* ($\phi = 0$) *and market crises dry up market liquidity* ($q < 1$)*, the equilibrium asset allocation involves an excess of portfolios correlation in the banking system. That is:* $\alpha^E = 1/2 > \alpha^\star$

Proof. When $\phi = 0$, parameter q does not affect banks' optimization program. Therefore, $\alpha^E = 1/2$.
To solve for the optimal asset allocation, start from (2.12). The objective function is equivalent to: $\pi(\alpha)[1-c] + c\pi^S(\alpha)(1-q)$.
A market crisis occurs when $\tilde{Y} < \gamma$. Therefore, the bank is hit by bank run during a systemic crises with probability:

$$\pi^S = \int_0^\gamma \frac{D - \alpha\tilde{Y}}{1-\alpha}\frac{d\tilde{Y}}{R^2} = \frac{1}{R^2}\left[\frac{D\gamma}{1-\alpha} - \frac{\alpha\gamma^2}{2(1-\alpha)}\right]$$

Note that:

$$\frac{\partial\pi^S}{\partial\alpha} = \frac{1}{R^2}\left[\frac{D\gamma}{(1-\alpha)^2} - \frac{\gamma^2}{2}\frac{1}{(1-\alpha)^2}\right] = \frac{\gamma}{R^2(1-\alpha)^2}\left[D - \frac{\gamma}{2}\right] > 0$$

Therefore, it must be that $\alpha^\star < \frac{1}{2}$.

□

Proposition 2.1 and 2.2 describe two standard results in the literature.
Proposition 2.1 claims that if market crises do not induce additional costs beyond individual failure, there are no tensions between private investment decisions and society. That is, the level of portfolios' correlation in the banking sector is efficient.
However, when market crises dry market liquidity, inefficiency comes.

2.2.3 Extension: $\phi > 0$

If banks are opaque, liquidity crises are possible. Depending on liquidity costs, the bank could also get profits in states of the world where (inefficient) bank runs occur. In such cases, the minimum variance portfolio cannot be an equilibrium. In fact, in a neighborhood of the minimum variance portfolio, the cost - in terms of lower diversification - of reducing the investment in the market portfolio is vanishing small. However, there is a strictly positive benefit since - by reducing the correlation with the market - the probability of being illiquid during market crises declines, and so expected liquidation costs.

Proposition 2.3. *If $\phi \in (0,1)$:*

(i) In case of high liquidation costs the equilibrium asset allocation coincides with the minimum variance portfolio: $\alpha^E = 1/2$

(ii) When market crises have no effects on market liquidity conditions ($q = 1$) the equilibrium asset allocation coincides with the minimum variance portfolio: $\alpha^E = 1/2$

(iii) If liquidation costs are not high and market crises dry market liquidity ($q < 1$) :

(iii.a) The equilibrium asset allocation does not coincide with the minimum variance portfolio: $\alpha^E(\phi, c, q) < 1/2$

(iii.b) The deviation from the minimum variance portfolio is larger when liquidation costs are intermediate

(iii.c) The deviation from the minimum variance portfolio increases as the liquidity risk increases: $\partial\alpha^E(\phi, c, q)/\partial\phi < 0$

Proof. (i) If liquidation costs are high, banks can never survive - on average - to liquidity crises. Therefore, the best that the bank can do is to minimize the portfolio's variance.

(ii) If $q = 1$, $v_1(\phi, c) = v_2(\phi, c)$. Hence, expected profits are equal to:

$$\Pi^e(\alpha) = (1 - \pi(\alpha))(E[v|\text{No Run}] - D) + \pi(\alpha) f(\phi) v_1(\phi, c)$$

Given the strictly concavity, the first order condition is necessary and sufficient to find the maximum point of Π^e. Note that the first order condition is satisfied if and only if $\pi'(\alpha) = 0$.

(iii.a) When $q < 1$ and liquidation costs are intermediate, the bank' s expected profits are equal to:

$$\Pi^e(\alpha) = (1 - \pi(\alpha))(E[v|\text{No Run}] - D) + \text{Prob(IR,BU)} v_1(c, \phi)$$

Taking the first order condition and evaluating at $\alpha = \frac{1}{2}$, we have that:

$$-4\gamma D \frac{\phi/2}{1 - \phi/2} v_1(\phi, c) < 0$$

Given the strictly concavity of the profit function, it must be that $\alpha^E < \frac{1}{2}$

(iii.b) This comes immediately from the fact that Prob(IR,MC) is an increasing function of α.

(iii.c) When liquidation costs are low, the first order condition is:

$$-(1-\alpha)^2\pi'(\alpha) = \gamma D \frac{\phi/2}{1-\phi/2}\left[\frac{v_1(\phi,c)-v_2(\phi,c,q)}{(E[v|\text{No Run}]-D)-f(\phi)v_1(\phi,c)}\right]$$

Note that the RHS is an increasing function of ϕ. Instead, the LHS is a decreasing function of α. Hence, we have the result.

□

The above proposition leads to the principal economic insights of the model. In a nutshell, when the liquidity risk is positive, the equilibrium asset allocation differs from the minimum variance portfolio. The minimum variance portfolio cannot be an equilibrium because - in a neighborhood of the minimum variance portfolio - to reduce the market portfolio's investment entails vanishing small costs in terms of diversification. Nevertheless, there is a strictly positive benefit. The reduction in the probability of being illiquid when market liquidity is poor. Although stylised, the proposition suggests some relationship between portfolios' correlation in the banking sector, market liquidity, and bank liquidity risk. In detail, we claim the existence of a U-shaped relationship between market liquidity conditions and the level of portfolios' correlation in the banking system. When market liquidity is poor, banks will never survive liquidity crises regardless of general system conditions. In such cases, there are no reasons for caring about liquidity crises. Hence, there are no reasons for deviating from the minimum variance portfolio. As a consequence, portfolios' correlation in the banking system is at its prime.[5]

When liquidation costs are intermediate, banks reduce their diversification degree, and portfolios' correlation in the banking system declines. Being illiquid during systemic crises is painful since illiquid banks will go bust despite their great fundamentals.
Still, if market liquidity further improves (low liquidation costs), diversification at the individual level and portfolios' correlation in the banking system come back to rise. Being illiquid during systemic crises involves losses but not bankruptcy. Thus, banks are willing to sacrifice more diversification when costs are intermediate.

Finally, when ϕ increases, investors' bias increases as well, meaning that liquidity crises are more frequent. As a consequence, banks' tendency to invest in imperfectly diversified portfolios rises as opacity increases. From this result, we claim that less in banking system in which bank panic are more frequent, banks should invest in portfolios that tend to be orthogonal to the market portfolio.

[5] The correlation between portfolios should also be at its prime when market liquidity conditions do not change during financial turmoils ($q = 1$). In such cases, expected profits during liquidity crises are the same regardless there is a market crisis or not. Therefore, banks will minimise the probability of being hit by a bank run, which requires, in turn, minimising the portfolios' variance.

Figure 2.5: Empirical Prediction: Portfolios’ Correlation and Market Liquidity

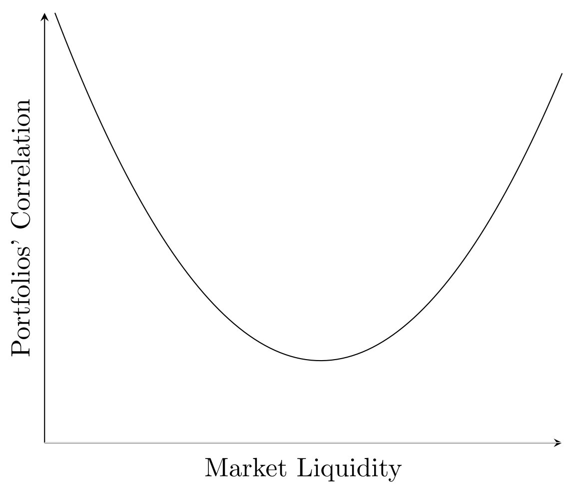
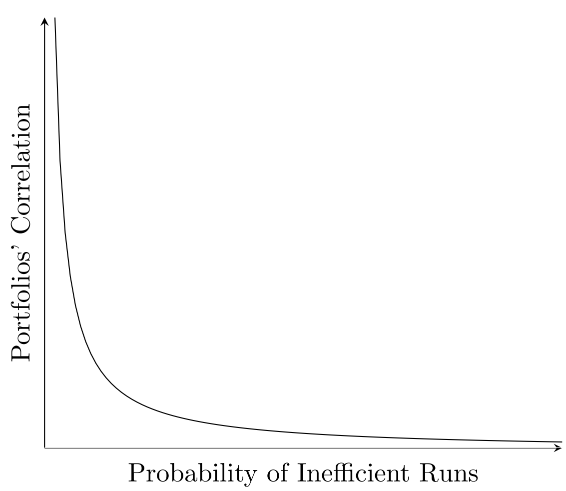


Figure 2.6: Empirical Prediction: Empirical Prediction: Portfolios’ Correlation and Opacity



2.3 Welfare Implication

In this section, we investigate tensions between the equilibrium and the efficient asset allocation when $\phi > 0$.
Two types of inefficiencies could emerge. The standard documented in the literature is that banks do not internalize the extra losses external investors incur when the bank is distressed during general turmoils. This externality leads to excessive investments in market portfolios.

The second type is the one discussed in this paper. By deviating from the minimum variance portfolio, the bank does not internalize the decline in investor expected returns due to the increase in the portfolio's riskiness. This externality could lead to poor diversification at the individual bank level and scarce aggregate investments in the market portfolio. The scope of this section is to identify the parameter space in which the second type of inefficiency emerges.

Proposition 2.4.

(i) If liquidation costs are intermediate, for any parameterization of the model satisfying the following condition, we have that $\alpha^E < \alpha^\star$.

$$\frac{\phi v_1(\phi, c)}{2\Big[V - f(\phi) v_1(\phi, c)\Big]} > \frac{c(1-q)(1-\frac{\phi}{2})(D-\frac{\gamma}{2}) - TC_1(\phi, c) D\phi/2}{\Big[(1-c) + TC_1(\phi, c) f(\phi)\Big]} \tag{2.13}$$

(ii) If liquidation costs are low, for any parameterization of the model satisfying the following condition, we have that $\alpha^E < \alpha^\star$.

$$\frac{\phi\Big[v_1(\phi, c) - v_2(\phi, c, q)\Big]}{2\Big[V - f(\phi) v_1(\phi, c)\Big]} > \frac{c(1-q)(1-\phi/2)(D-\gamma/2) - D\frac{\phi}{2}\Big(TC_1(\phi, c) - TC_2(\phi, c, q)\Big)}{D\Big[(1-c) + TC_1(\phi, c) f(\phi)\Big]}$$

Proof. We prove only statement (i). The proof for statement (ii) follows similar steps.
If liquidation costs are intermediate, the planner's objective function is:

$$\pi(\alpha)[1-c] + c\pi^S(\alpha)(1-q)] + \text{Prob(IR,BU)} TC_1(\phi, c) + \text{Prob(IR,MC)}[1-cq]$$

The first order condition is satisfied when:

$$\frac{1-2\alpha^\star}{(\alpha^\star)^2} = 2\frac{c(1-q)\gamma(D-\gamma/2) - TC_1(\phi, c)\gamma D\frac{\phi/2}{1-\phi/2}}{D^2\Big[(1-c) + TC_1(\phi, c) f(\phi)\Big]} \tag{2.14}$$

Instead, the bank's objective function is:

$$\left[1-\pi(\alpha)\right]V+\left[\pi(\alpha)f(\phi)-\frac{\gamma D}{R^2(1-\alpha)}\frac{\phi/2}{1-\phi/2}\right]v_1(\phi,c)$$

The first order condition is satisfied when:

$$\frac{1-2\alpha^E}{(\alpha^E)^2}=\frac{\gamma\phi v_1(\phi,c)}{D(1-\phi/2)\left[V-f(\phi)v_1(\phi,c)\right]} \tag{2.15}$$

Note that the function $(1-2x)/x^2$ is a decreasing function for $x\in[0,1]$. Hence, we have that $\alpha^E<\alpha^\star$ if and only if the R-H-S of Equation (2.14) is smaller than the R-H-S of Equation (2.15). □

Conditions stated in Proposition 2.4 provide a characterisation for the parameters of the economy, allowing for the rise of an equilibrium in which the bank invests in the market portfolio a share of capital that is below the social optimum. Since our focus is on the liquidity risk, we now discuss for which value of ϕ Condition (2.13) is satisfied. Define $Z(\phi)$ as the difference between the L-H-S and the R-H-S of Condition (2.13). For the sake of simplicity, let us assume that $c=1$ and $q=0$.

$$Z(\phi)=\frac{\phi^2 D}{2(1-\frac{\phi}{2})}-\left[1-\frac{\phi}{2}\right]\left[D-\gamma/2\right]\left[V-D\frac{\phi^2}{4}\frac{1+\frac{\phi}{2}}{(1-\frac{\phi}{2})^2}\right] \tag{2.16}$$

Note that $Z(\phi)$ is strictly increasing in ϕ. Furthermore, $Z(0)$ is negative. Hence, by continuity, it is sufficient that $Z(1)>0$ to have the existence of a threshold $\bar{\phi}$ such that: (i) for $\phi>\bar{\phi}$, $\alpha^E<\alpha^\star$ and (ii) for $\phi<\bar{\phi}$, $\alpha^E>\alpha^\star$.[6]
Therefore, if the bank faces sufficiently high liquidity risk, the equilibrium investment in the market portfolio will be lower than the social best.

2.4 Conclusion

Banks may eliminate the idiosyncratic risk embedded in their portfolios by investing in a joint mutual market portfolio. By doing so, individual default probabilities correlate with market soundness. The literature highlighted that banks' investments in the market portfolio would be above the social optimum if market crises induce costs beyond individual failure.
In this paper, we suggest that the opposite could also be true. That is, banks could invest a too low share of capital in the market portfolio. The critical assumption for our result is liquidity risk. During market crises, costs of raising liquidity rise. Therefore, banks subject to frequent liquidity crises find it convenient to reduce their correlation with the market conditions. Although stylised, our framework offers some interesting empirical predictions on the determinants of asset commonality in the banking system.

[6] Note that the condition $Z(1)>0$ is easily satisfied when R is not excessively high.

Chapter 3

The Economic Complexity Index and the Financial Fragility

Abstract

Complex economies produce and export sophisticated products only made by a handful of other countries. This paper relates the countries' Economic Complexity Index to the probability of experiencing financial crises. Results suggest that financial turmoils are less frequent in complex economies after controlling for the principal variables identified in the literature as crisis predictors. We conjecture that the negative correlation between the complexity of an economy and its financial fragility is due because market power on the global trade network. We contribute to the literature in two aspects. First, we suggest that rather than *how much* an economy is open, what matters for financial stability is *how* the economy is open. Second, up to our knowledge, no contributions explore the financial effects of the Economic Complexity Index. We start to fill this gap.

3.1 Introduction

Turmoils in the banking sector could have remarkable social and economic costs (Blinder and Zandi, 2010; Mukunda, 2018). Cross-country, we can observe significant heterogeneity in terms of the probability of experiencing systemic banking crises (Hoggarth et al., 2002; Aiginger et al., 2011). In explaining this heterogeneity, pre-existent literature focused on variables capturing the current state of the financial sector, the presence of macroeconomic imbalances, and economic growth.

The empirical literature identifies the economy's openness as a leading financial crisis predictor. In broad terms, the openness degree of an economy is the extent to which cross-border transactions take place. We can distinguish between financial openness (cross-border capital transactions) and trade openness (import/export of commodities). Several reasons justify the role of openness as a crisis predictor. At first, we can think about the exchange rate. Turmoils in the exchange rate leading to sharp currency depreciation could anticipate systemic banking crises (Kaminsky and Reinhart, 1999; Papi et al., 2015). Trade and financial openness play a role in either smoothing out or amplifying the impact of shocks on real exchange rates. For instance, increasing openness of the capital account leads to financial integration and increased episodes of contagious turmoil in the exchange rate and other financial markets (La Marca, 2007). Similarly, by reducing frictions or transaction costs in the international exchange of goods and services, trade openness would either limit or exacerbate the impact of nominal or real shocks on real exchange rates (Calderón and Kubota, 2018). A further reason linking openness and financial fragility is financial and economic development. There is a long tradition in the literature discussing the effects of openness on GDP and financial development (Yanikkaya, 2003; Kim et al., 2010) which are critical variables in predicting financial fragility.

In this paper, we enrich the debate on openness and financial fragility by suggesting a relationship between the characteristics of the bundle of products countries export and countries' financial fragility. In our idea, countries exporting products only produced by a handful of other countries should exhibit superior market power on the global trade market. The market power should reduce domestic firms' cash flow volatility, decrease the default probability, and increase the banks' domestic asset quality. Broadly, countries having market power on the global trade market should better absorb shocks originating from abroad and should face more stable foreign demand concerning countries that are less competitive. For instance, if two countries say A and B, sell the same product, say b, to country C, shocks changing the relative prices between the three countries should move the C' s demand towards country whose the good is cheaper. If A was monopolist on good b, the effect of such shocks on the quantity of b demanded from abroad to firms located in A should be much lower.

To measure the rarity of the bundle of products countries export, we use the Economic Complexity Index (Hidalgo and Hausmann, 2009). Essentially, the index summarizes the countries' economies into two dimensions: *diversity* and *ubiquity*. Diversity captures the number of products a country can export competitively. Ubiquity, instead, refers to the number of countries exporting such products in a competitive way. Loosely speaking, complex countries export a diversified bundle of products, and such products are exported only by a handful of other countries. In contrast, simple economies export a few products that many other countries export.

We describe the mathematical derivation of the Economic Complexity Index in Section 3.2. For the moment, the reader can refer to countries with a high

Complexity Index as countries exporting a bundle of products above the global mean both in terms of Ubiquity and Diversity. Ubiquity and Diversity provide two different pieces of information regarding market power in the global trade network. The Diversity of an economy informs about how many products a country has market power. Instead, the Ubiquity of a product informs about how strong this market power is. For instance, if a product b has Ubiquity equal to one, it means that there is only one country that can export such product in a competitive way. Ubiquity and Diversity could have an individual role in explaining the likelihood of financial crises. Countries with high Diversity could exploit diversification benefits. That is, economies with a high Diversity score could better cushion adverse shocks concerning one specific product. On the other hand, countries exporting products with low Ubiquity could act as a monopolist. That is, they could better manage adverse macro shocks like the one that we describe in the above example. Unfortunately, at the current stage of the research, we cannot distinguish between the two components of the Economic Complexity Index. Thus, we interpret our estimates as a correlation between market power on the global trade network and financial fragility, ignoring whether the market power comes from the high Diversity of the bundle of the export or from the low Ubiquity of the products.

The Economic Complexity Index captures economic aspects that the standard measure of the trade openness degree (the value sum of merchandise exports and imports divided by GDP) does not capture. For instance, the openness degree of a country cannot say too much about the country's competitiveness in the global trade market. Instead, a country with high Complexity Index is a country that exports products that only a handful of other countries can produce. In different terms, a complex economy (in the sense of the Economic Complexity Index) is necessarily an open economy. Nevertheless, an open economy could be not complex. Thus, the two measures capture different concepts.

Including the Economic Complexity Index in a test on financial fragility could also help obtain better estimates for variables that are crises predictors. The Economic Complexity Index seems to be very efficient in explaining heterogeneity cross-country in terms of GDP per capita, prosperity, and growth (Hidalgo and Hausmann, 2009; Abdon and Felipe, 2011; Hartmann et al., 2017). The intuition lies in unexploited potential. An emerging country whose complexity index is identical to the one of the riches is likely to exploit all its knowledge to jump-start economic development in the next future. Both growth and the real GDP are prominent variables in explaining banks' fragility. Moreover, one of the Economic Complexity Index components - Diversity - reflects the variety embedded in an economy. The financial sector can exploit a large variety in the real sector to allocate risk better. Loosely speaking, the banking system embedded in a sophisticated economy should be more diversified.

To shed light on the effects of the Economic Complexity Index on financial fragility, we run linear probability model in which the dependent dummy variable is equal to 1 for country-year observations in which a systemic banking crisis occurs. To identify country-year observations in which a systemic banking crisis occurs, we use the definition proposed by Laeven and Valencia (2013). That is, a systemic banking crisis is an event that meets two conditions:

(i) Significant signs of financial distress in the banking system (as indicated by significant bank runs, losses in the banking system or bank liquidations)

(ii) Significant banking policy intervention measures in response to the losses

Policy interventions are significant if at least three out of the following six measures have been used: (i) Deposit freezes or bank holidays, (ii) Significant bank nationalisations, (iii) Bank restructuring gross costs (at least 3% of GDP), (iv) Extensive liquidity support, (v) Significant guarantees put in place, (vi) Significant asset purchases. We source data from Laeven and Valencia (2020). Our dataset covers 41 years (1970-2010) and a significant number of countries.
The results of our empirical investigation suggest that the Economic Complexity Index is strongly associated with a reduction in the likelihood of experiencing a systemic banking crisis. Controls that we use reflect the economic theory, the data availability and the literature. Estimates for control variables are in line with those of the literature. In detail, we find that the quality of the political institutions and the financial institutions' efficiency are statistically significant in decreasing the likelihood of banking crises. We report that banking systems are fragile to macroeconomic imbalances. Moreover, we report that financial depth is strongly associated with an increase in the probability of crises. This evidence is in line with previous contributions highlighting that financial liberalization could threaten financial stability. Quite surprisingly, we report a strong positive relationship between economic growth (the growth rate in the real GDP) and the probability of banking crises. A theoretical explanation for this evidence could be as follows. During periods of growth, general euphoria and less risk aversion could lead agents - including banks - to take more risks. The realization of these risks or the cessation of the initial euphoria trigger the onset of the recession that affects the entire economic system, including the financial sector (Whalen, 2008; Cassidy, 2008).

We test the significance of the set of explanatory variables by estimating a linear probability model. Our finding suggests that the Economic Complexity Index has solid economic and statistical significance. In detail, we find that one unit increase in the Economic Complexity Index reduces the probability of experiencing a systemic banking crisis around 11%. To provide some evidence suggesting that the market-power on the global trade network is driving the result, we add to our main specification the interaction between the Economic Complexity Index and the standard measure of trade openness that the literature adopts: the sum of merchandise exports and imports divided by the value of GDP. We expect that the beneficial effects of the Economic Complexity Index should increase with the openness degree of the economy. The more an economy relies on global trade, the more a central position in the global trade network should be beneficial. Once we introduce the interaction term, the coefficient associated with the Economic Complexity Index becomes statistically insignificant. Instead, we report a negative and statistically significant coefficient for the interaction term. We interpret this result as follows. Having superior production capabilities that allow producing rare products - for its own sake - should not affect financial stability. Nevertheless, these products entail a dominant position on the global trade market. The beneficial effects of such market-power increase as the openness degree increases.

We are conscious that our estimates may not necessarily reflect casual relationships. Nevertheless, our paper contributes to the literature in several aspects. Scholars documented the real effects of the Economic Complexity Index. The sophistication gap between countries seems to be very efficient in explaining heterogeneity cross-country in terms of GDP per capita, prosperity, and growth (Hidalgo and Hausmann, 2009; Abdon and Felipe, 2011; Hartmann et al., 2017). Up to our knowledge, no contributions are exploring the financial effects of the Economic Complexity Index. This paper starts to fill this gap.
Our paper contributes to the literature assessing the determinants of financial fragility. Specifically, we suggest that beyond than *how much* an economy is open, it also matters for financial stability the composition of the bundle of products countries export. Broadly, we claim that the productive structure - through the export channel - could matter for the soundness of the financial sector. This claim could be an exciting starting point for future discussions since, up to now, the literature on financial fragility mainly focused on variables capturing the current state of the financial sector and the presence of macroeconomic imbalances.

3.1.1 Related Literature

This paper is related to extensive literature discussing the determinants of the systemic bank crisis. Several articles discussed the role of the main macroeconomic variables in explaining the banking crisis. Common evidence suggests that low growth rate, high inflation, high real interest rate, and credit growth correlate to the likelihood of banking crisis (Demirgüç-Kunt and Detragiache, 1998; Hardy and Pazarbaşioğlu, 1999). Kaminsky and Reinhart (1999) focused on twin crisis (episodes in which currency and banking crisis occur jointly). They showed that macroeconomic signals (decline in stock prices, increase in real interest rate, . . .) could predict financial turmoils. Following the contribution of Diaz-Alejandro (1985), several papers tested the effect of financial liberalization on the likelihood of crisis. The evidence seems mixed. Indeed, Noy (2004) found out that, by increasing competition and loosening supervision, financial liberalization leads to an increase in the probability of a banking crisis. On the other hand, Shehzad and De Haan (2009) showed that conditional on the excellent quality of bank supervision, financial liberalization could lead to a more resilient banking system.

A few contributions discussed how the country's degree of financial openness (Chinn and Ito, 2008) affects the likelihood of crisis. Joyce (2011) highlighted that foreign direct investment and financial openness significantly reduce the possibility of emergency. Still, Klomp (2010) provided evidence supporting the idea that globalisation increases financial fragility within countries. Furthermore, Papi et al. (2015) showed that countries participating in international support programs, like the IMF lending programs, are less likely to experience systemic banking crisis.

This paper is also related to a branch of the literature analysing the real financial crises' costs. Some authors focused on the costs of financial crises within individual countries. For the U.S., Bernanke et al. (1994) provide support for the credit crunch theory during the Great Depression. Other contributions focused on cross-country comparisons. Bordo et al. (2001) find that output losses during banking crises are, on average, in the range of 6–8% of annual GDP. Losses are even larger if currency crises accompany the banking distress. Later, Hoggarth et al. (2002) adjusted these estimates upwards. They highlighted that the cumulative output losses incurred during crisis periods are large, roughly 15–20%, on average, of annual GDP. They also suggest that output losses incurred during crises in developed countries are as high, or higher, on average, than those in emerging-market economies. Angkinand (2009) suggested that countries providing comprehensive deposit insurance coverage and enforcing strict bank capital adequacy requirements experience a smaller output cost of crises.

The paper is also related to the literature discussing the effects of the Economic Complexity Index. Most of the contributions focused on the real effects of the index and its positive correlation with income and growth (Hidalgo and Hausmann, 2009). The economic mechanism linking the Economic Complexity Index and growth lies in unexploited potential. An emerging country endowed with the same technology as advanced economies will soon exploit its potential to catch up. Abdon and Felipe (2011) suggested the existence of a poverty trap concerning the complexity. Emerging economies do not have the necessary resources to jump-start the structural transformation of their productive structures. Hence, they will remain not sophisticated with a low growth level. Hartmann et al. (2017) found evidence suggesting that the countries that are more sophisticated exhibit lower income inequality. Recent contributions relate the Economic Complexity Index with the extent to which an economy is green. They report a significant negative relationship between a country's Economic Complexity Index and carbon emissions (Vu, 2020; Romero and Gramkow, 2021).

3.2 Economic Complexity Index in a Nutshell

The Economic Complexity Index measures the sophistication of a country's productive structure by combining information on the number of products it exports and the number of countries that export those products. We start from exports data connecting countries to the products they have revealed comparative advantage (RCA):

$$RCA_{cp} = \frac{X_{cp}/\sum_{p'}^{P} X_{cp'}}{\sum_{c'}^{C} X_{c'p}/\sum_{c'}^{C}\sum_{p'}^{P} X_{c'p'}} \tag{3.1}$$

Where X_{cp} is the total export of country c in product p, C is the number of countries in the world and P is the number of products in the global trade market.
RCA is larger than one (denoting that a country has a comparative advantage in a product) if a country's export of a product is larger than the world average. It is now possible to construct a matrix $M \in \mathbb{R}^{C\times P}$ that allows quantifying the diversity of a country (the number of products its exports) and the *relevance* of the country in the global trade network (the number of countries that export the same products). Specifically:

$$M_{c,p} = 1 \text{ If } RCA_{cp} \geq 1$$

$$M_{c,p} = 0 \text{ If } RCA_{cp} < 1$$

Hence, the *diversity* of a country and the *ubiquity* of a product are computed as follows:

$$Diversity_c = k_{c0} = \sum_p M_{c,p}$$

$$Ubiquity_p = k_{p0} = \sum_c M_{c,p}$$

Intuitively, the Diversity of a country depends on the number of exported products in which it has a revealed comparative advantage. Instead, the Ubiquity of a product depends on the number of countries that have a revealed comparative advantage in exporting that product. Next, it is possible to define a matrix $\tilde{M} \in \mathbb{R}^{C\times C}$ whose entries are as follows:

$$\tilde{M}_{c,c'} = \sum_p^P \frac{M_{c,p}}{k_{c0}} \frac{M_{c'p}}{k_{p,0}}$$

The entry (c, c') in the matrix $\tilde{M}$ increases if countries c and c' have both relative comparative advantages in the same products. In fact, the term $\frac{M_{c,p}}{k_{c0}} M_{c'p}$ is positive if and only if RCA_{cp} and $RCA_{c'p}$ are both larger than one. The term $M_{c,p}M_{c'p}$ is divided for the ubiquity of the product p to weight more the products that are competitively exported only by a handful of other countries. The ECI of a country c is defined as:

$$ECI_c = \frac{K_c - \sum_c^C K_c/C}{\sigma_K}$$

Where K_c is the c entry of the eigenvector of $\tilde{M}$ associated to the second largest eigenvalue. Intuitively, a country has a positive Economic Complexity Index if the bundle it exports is above the world mean in terms of Diversity and Ubiquity. To clarify the role of the Ubiquity of a product and the Diversity of a country in defining the Economic Complexity Index, we use a numerical example.

Let us consider the case in which there are only three products (Iron, Wine, Chocolate) and three countries (Germany, Italy, France). Let us consider the matrix M whose rows' order is Germany, Italy, France and the columns' order is Iron, Wine, Chocolate:

$$M = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 1 \\ 0 & 1 & 0 \end{bmatrix} \tag{3.2}$$

Germany has a relative comparative advantage in exporting Iron, Italy has a comparative advantage in exporting Wine and Chocolate, and France has a comparative advantage in exporting Wine. Starting from (3.2), we have that:

$$Diversity_{Germany} = Diversity_{France} = 1$$

$$Diversity_{Italy} = 2$$

$$Ubiquity_{Iron} = 1 = Ubiquity_{Chocolate}$$

$$Ubiquity_{Wine} = 2$$

The matrix $\tilde{M}$ is as follows:

$$\tilde{M} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \frac{3}{4} & \frac{1}{4} \\ 0 & \frac{1}{2} & \frac{1}{2} \end{bmatrix} \tag{3.3}$$

Whose eigenvalues are equal to: $(1, 1, \frac{1}{4})$. The second largest eigenvalue is $\frac{1}{4}$ and the associated eigenvector is $(0, 0.4472, -0.8944)$. The average of this eigenvector is equal to -0.1491 while the standard deviation is 0.6831. Thus, we have:

$$ECI_{Germany} = \frac{0 - (-0.1491)}{0.6831} \simeq 0.22$$

$$ECI_{Italy} = \frac{1 - (-\frac{1}{3})}{1.247} \simeq 0.8875$$

$$ECI_{France} = \frac{-0.8944 - (-0.1491)}{0.6831} \simeq -1.09$$

Italy is more complex than Germany, which is more complex than France. This result is not surprising. In fact, Italy can export competitively two products. France and Germany can export competitively only one product. Germany is more complex than France because the product that France exports competitively (Wine) has higher Ubiquity than the product that Germany exports

competitively (Iron).
Let's discuss what happens if the matrix M changes as follows:

$$M = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 1 \\ 1 & 1 & 0 \end{bmatrix} \tag{3.4}$$

In this case, the diversity of France and the ubiquity of Iron increase. From (3.4), we have:

$$\tilde{M} = \begin{bmatrix} \frac{1}{2} & 0 & \frac{1}{2} \\ 0 & \frac{3}{4} & \frac{1}{4} \\ \frac{1}{4} & \frac{1}{4} & \frac{1}{2} \end{bmatrix} \tag{3.5}$$

The eigenvalues associated to matrix (3.5) are: $(1, 0.6545, 0.0955)$. The second largest eigenvalue is 0.6545 and the associated eigenvector is $(-0.7559, 0.6116, -0.2336)$. The average of this eigenvector is equal to -0.1260 while the standard deviation is 0.69. Thus, we have:

$$ECI_{Germany} = \frac{-0.7559 - (-0.1260)}{0.69} \simeq -0.91$$

$$ECI_{Italy} = \frac{0.6116 - (-0.1260)}{0.69} \simeq 1.068$$

$$ECI_{France} = \frac{-0.2336 - (-0.1260)}{0.69} \simeq -0.156$$

As expected, now France is more complex concerning the previous example since the Diversity of France is increasing. At the same time, the complexity of Germany is reducing since the Ubiquity of Iron is increasing. Finally, in this example also, the complexity of Italy is increasing. Now Italy is the unique country that can competitively export a product with the lowest possible Ubiquity (Chocolate). This feature makes the bundle of products Italy export *special* in terms of Ubiquity compared to the rest of the world.

3.3 Dataset Description and Empirical Specification

In the empirical analysis, we combine several datasets. We source data on the systemic banking crises from Laeven and Valencia (2020). The dependent dummy variable `Banking Crisis` is equal to 1 for country-year observations in which there was a systemic banking crisis according to the definition stated in Laeven and Valencia (2013).

Our main specification is stated as follows:

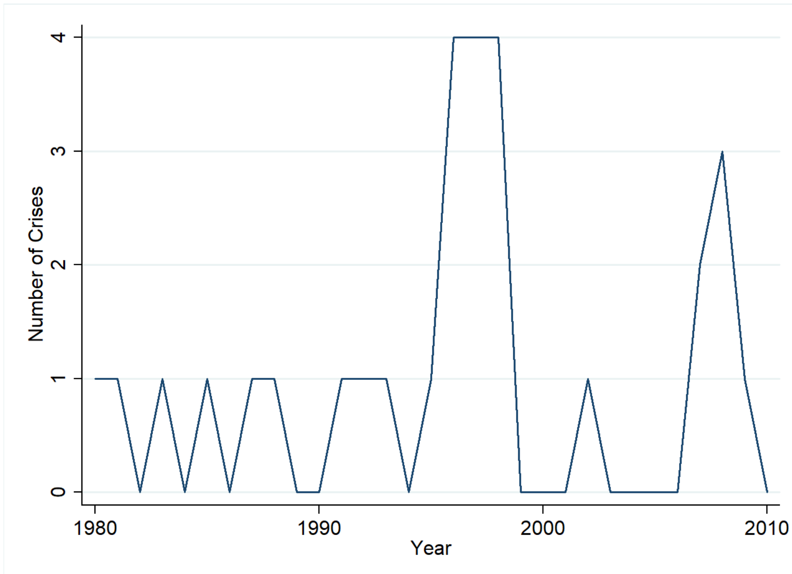
$$\texttt{Banking Crisis}_{i,t} = \vec{\beta}\mathbf{X}_{i,t-1} + a_i + \varepsilon_{i,t} \tag{3.6}$$

We estimate specification (3.6) through a linear probability model. In the related literature, some contributions consider contemporaneous explanatory variables. Contemporaneous regressors are likely to be endogenous in the cases

Table 3.1: Variables Description

Variable	Description	Source
Complexity Index	Section 3.2	https://ourworldindata.org/
Banking Crisis	Dummy variable equals to 1 for country-year observations in which there was a systemic banking crisis	Laeven and Valencia (2020)
Past Crises	Dummy variable equals to 1 for country-year observations in which either a systemic banking crisis or a currency crisis occurred in the past five years	Author's Computation
Real GDP	The log of the GDP expressed in 2015 USD	https://data.worldbank.org/
Growth	The growth rate of the Real GDP	https://data.worldbank.org/
Polity Index	Ranging from −10 (full autocracy) to +10 (full democracy), the variable measures the critical qualities of executive recruitment, constraints on executive authority, and political competition.	https://www.systemicpeace.org/
Deposit Insurance	The variable takes value one if an explicit scheme of bank deposit insurance is in place in the country.	Demirgüç-Kunt et al. (2014)
Financial Institution Efficiency	Ranging from 0 (low efficiency) to 1 (high efficiency), the variable captures the efficiency of the financial institutions (net interest margin, lending-deposit spread return on assets, return on equity, overhead costs to total asset)	Svirydzenka (2016)
Financial Institution Depth	Ranging from 0 to 1, the index adds to the standard banking sector depth measure used in the literature (bank credit to the private sector) indicators for other financial institutions the assets of the mutual fund and pension fund industries and the size of life and non-life insurance premiums	Svirydzenka (2016)
Trade Openness	The sum of merchandise exports and imports divided by the value of GDP, all in current U.S. dollars.	https://data.worldbank.org/
Real Interest Rate (annual growth rate)	The annual growth rate in the real interest rate	https://data.worldbank.org/
Inflation	Annual inflation rate	https://data.worldbank.org/
Currency Depreciation	Currency Depreciation concerning the USD dollar	https://data.worldbank.org/

Figure 3.1: Systemic Banking Crises in Our Sample



in which crisis effects propagate quickly.[1] That is, recessions, low economic growth, high inflation, high currency's depreciation rate, and high-interest rate may be the manifestation of an economic downturn caused by the banking crisis. Although it is challenging to address issues of causation, by considering lag controls, we try to reduce endogeneity issues.

We get rid of country time-unvarying unobservable characteristics by de-meaning model (3.6). The drawback is that we drop from the panel countries that have never experienced a systemic banking crisis. Thus, we end up with an unbalanced panel covering 24 countries from 1980 to 2010. Table 3.2 reports the list of countries, the period we observe them, the frequency of systemic banking crises experienced in that period, the average and the standard deviation from the Economic Complexity Index. We source data on the economic complexity index from the website https://ourworldindata.org/. We observe the minimum in the Economic Complexity Index at -2.76425 (Nigeria in 2009) and a maximum at 2.62482 (Japan in 1996). The descriptive statistic referring to the Economic Complexity Index highlights that - within countries - the index exhibits significant volatility (around 20% in Kenya, 15% in the Philippines). Therefore, our test exploits both cross and within variations. Our dataset shows some interesting patterns. As highlighted in previous contributions, the Economic Complexity Index is strongly correlated to the real aspects of the economy (Figure 3.2). Besides the real sector, the Economic Complexity Index is strongly correlated to some relevant financial variables. Figure 3.3 shows the

[1]Nevertheless, several factors suggest that cyclical downturns that accompany banking crises tend to be exogenous. See Kaminsky and Reinhart (1999)

Table 3.2: List of Countries

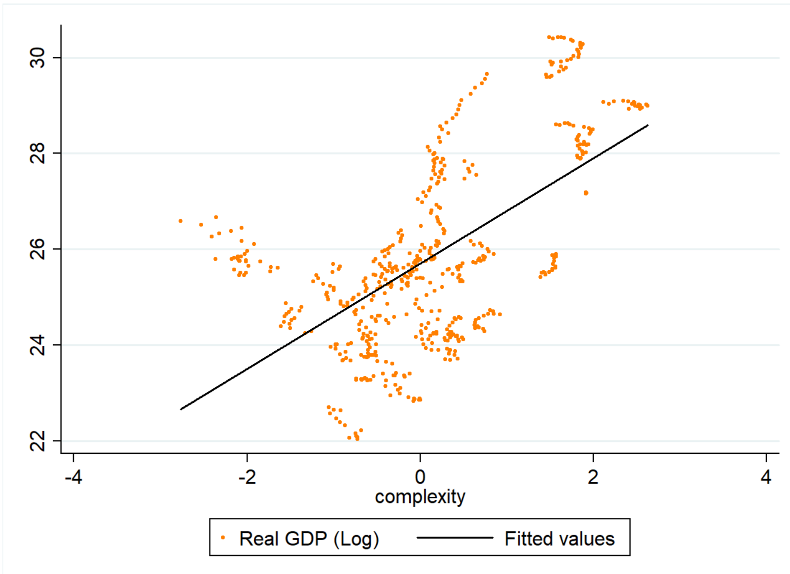
Country Name	Sample Period	Crisis' Frequency	Average Complexity	SD Complexity
Bangladesh	1987-2010	.0416667	-.9402773	.1964322
Bulgaria	1992-2010	.0555556	.3997969	.0556782
Switzerland	2008-2010	0.33	1.918123	.002299
China	1987-2010	.04166673	.3706059	.1965
Colombia	1991-2010	.0434783	0.5373	.11089
Czech Republic	1994-2010	.0555556	1.507	.0614
Egypt, Arab Rep.	1980-2010	.02852581	-.3979938	.1
United Kingdom	1980-2010	.02439	1.8443	.1
Croatia	1995-2010	0.066	0.733	.092
India	1980-2010	.0303	.1640	.079
Jamaica	1980-2010	.028571	-.346196	.2392
Japan	1993-2010	.055235	2.4462	.14266
Kenya	1980-2010	.05	-.7036	.1938197
Mongolia	1998-2010	0.07692	-.8615	.1311
Malaysia	1980-2010	.024392581	.30489	.37
Nigeria	1980-2010	.0487	-2.098	.2289
Philippines	1980-2010	.05714	-.1093	.1499
Paraguay	1994-2010	0.0588235	-.6	.0719
Romania	1997-2010	0.05555	.5141	.1290
Russian Federation	2002-2010	.1	.4515	.1830
Uruguay	1980-2010	.0571429	.1921	.1373
United States	1980-2010	.04878	1.6749	.1395
Vietnam	1996-2010	.066	-.6045	.098
Yemen	1996-2010	.066	-1.4764	.098

relation between the Economic Complexity Index and the resources (as the percentage of the GDP) provided to the private sector by financial corporations, such as through loans, purchases of non-equity securities, and trade credits and other accounts receivable, that establish a claim for repayment (the literature usually labels this variable as `Private Credit`). Since we conjecture that the effect of the Economic Complexity Index is towards the stability of the foreign demand, Figures 3.4 and 3.5 are of particular interest. In Figure 3.4, we plot the depreciation rate of the real exchange rate with respect to the USD dollar against the Economic Complexity Index. Complex Economy seems to exhibit lower volatility in the exchange rate.

3.3.1 Theory and Explanatory Variables

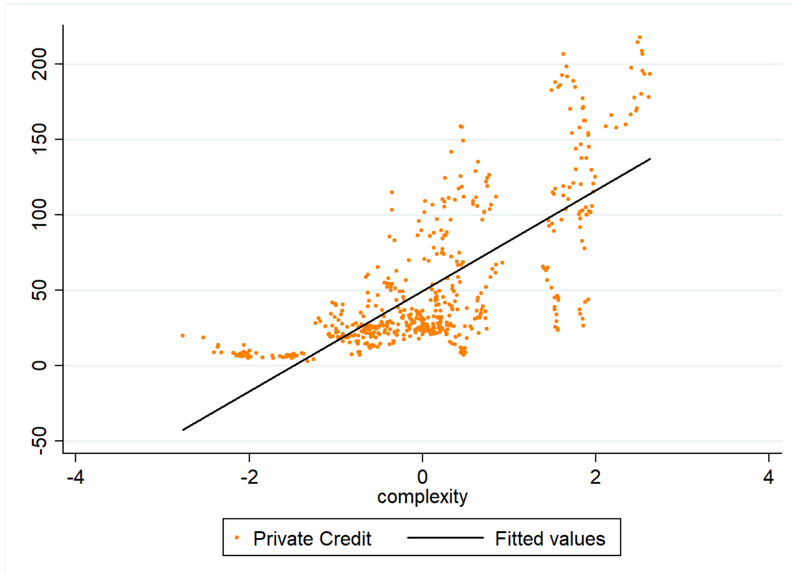
The choice of the covariates reflects the banking theory, the pre-existent literature, and data availability.
An essential function of banks is maturity transformation. Banks are financial intermediaries whose liabilities are mainly short-term deposits and whose assets are usually short and marketable long-term loans to businesses and consumers. Because of maturity transformation, banks face liquidity risk. Diamond and Dybvig (1983) highlighted that banks could be illiquid because depositors' self-fulfilling prophecies are not necessarily correlated to banks' fundamental value. The liquidity risk provides the rationale to implement an explicit deposit in-

Figure 3.2: The Economic Complexity Index and the Real GDP



surance scheme. Nevertheless, deposit guarantees could lead to moral hazard behaviours favouring banks' incentive to take a risk.
Banks also face interest rate risk. Assets are fixed-rate loans whose rate of return cannot be quickly adjusted. Bank balance sheets can deteriorate if the rate of return on bank assets falls short of the rate paid on liabilities. An obvious example is an increase in the short term interest rate forcing banks to increase returns on deposits.
Banks - and more generally any financial intermediary - get profits from the float on payments. Hence, inflation and depreciation in the domestic currency have evident effects on the profitability of banking activity.
In countries where the banking sector is liberalised, the fragility of the banking system could increase because of excessive risk-taking (Kaminsky and Reinhart, 1999). The combination between financial liberalisation and poor political institutions could lead to *looting* behaviours. That is, bank managers may invest in projects that are sure failures but from which they can divert money for personal use (Akerlof et al., 1993).
Like any lender, banks risk that borrowers cannot fill their repayments. The default risk should be negatively correlated with the business cycle. Nevertheless, during periods of growth, general euphoria and less risk aversion lead agents - including banks - to take more risks. The realisation of these risks or the cessation of the initial euphoria trigger the onset of the recession that affects the entire economic system, including the financial sector (Whalen, 2008; Cassidy, 2008).

Figure 3.3: The Economic Complexity Index and the Private Credit



To capture these aspects of the financial crises' theory, we combine several datasets. Table 3.1 presents our set of explanatory variables, the description and the source of the data. In Figure 3.5, we plot the Standard Deviation of the country's total export (as a percentage of the GDP) against the average Economic Complexity Index. It seems that the volatility of the exportation decreases as the economy's complexity increases.

3.4 Empirical Results

In Table 3.3, we show the results of our main specification. In the first column, we consider only country fixed effects. However, our sample encompasses thirty years. In such time frame, there could be odd years in which unobserved events hit several countries (for instance, Asian Crises (1997-1998) and the Global Financial Crises (2007-2009)). To control for this aspect, in the second column, we also consider year fixed effects.
The signs of the explanatory variables are in line with the theoretical prediction and the prior empirical contributions. Nevertheless, we report a positive and statistically significant correlation between the size of the economy (real GDP) and economic growth. Although prior empirical contributions usually report a negative sign for these variables, our findings are consistent with some theoretical predictions (see Section 3.3.1).

Our estimates report a strong and negative statistically significant relation-

Table 3.3: The Economic Complexity Index and Financial Fragility

	(1) Banking Crises	(2) Banking Crises
Complexity	-0.115**	-0.131***
	(-2.44)	(-2.97)
Polity Index	-0.00916***	-0.00587**
	(-3.91)	(-2.28)
Real GDP	0.0704**	0.164**
	(2.21)	(2.49)
Growth	0.747**	0.568*
	(2.72)	(1.98)
Insurance	-0.0448**	0.000696
	(-2.58)	(0.03)
Financial Institution Efficiency	-0.196*	-0.212*
	(-1.76)	(-1.95)
Financial Institution Depth	0.173*	0.256**
	(1.93)	(2.50)
Trade Openness	-0.102**	-0.108**
	(-2.37)	(-2.14)
Real Interest Rate (annual growth rate)	-0.0000732***	-0.0000160
	(-3.04)	(-0.24)
Inflation	0.000523*	0.000162
	(2.01)	(0.67)
Depreciation Rate	-0.0472	-0.0260
	(-1.28)	(-0.73)
Past Crises	0.0214	0.0236
	(0.95)	(0.76)
_cons	-1.274	-3.543**
	(-1.69)	(-2.20)
Country Fixed Effects	YES	YES
Year Fixed Effects	NO	YES
N	501	501

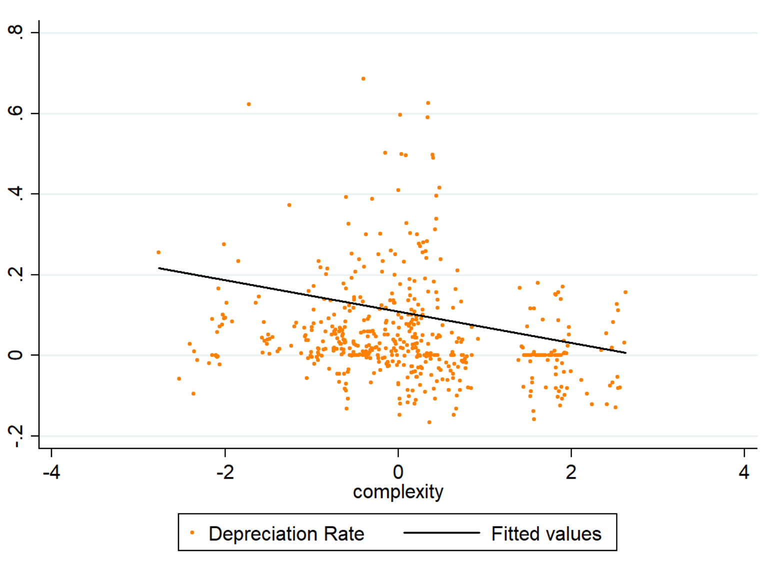
t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.4: The Economic Complexity Index and Financial Fragility (Interaction Term)

	(1) Banking Crises	(2) Banking Crises
Complexity	0.0864	0.0308
	(0.96)	(0.44)
Complexity × Trade Openness	-0.0502**	-0.0399**
	(-2.34)	(-2.29)
Polity Index	-0.00915***	-0.00588**
	(-3.75)	(-2.21)
Real GDP	0.0817**	0.167**
	(2.40)	(2.47)
Growth	0.715**	0.538*
	(2.68)	(1.86)
Insurance	-0.0484***	-0.00466
	(-2.99)	(-0.22)
Financial Institution Efficiency	-0.176	-0.203*
	(-1.56)	(-1.87)
Financial Institution Depth	0.176*	0.257**
	(1.88)	(2.48)
Trade Openness	-0.111**	-0.116**
	(-2.58)	(-2.24)
Real Interest Rate (annual variation)	-0.0000692***	-0.0000129
	(-2.82)	(-0.20)
Inflation	0.000471*	0.000122
	(1.78)	(0.50)
Depreciation Rate	-0.0425	-0.0222
	(-1.16)	(-0.62)
Past Crises	0.0245	0.0262
	(1.04)	(0.82)
_cons	-1.548*	-3.627**
	(-1.94)	(-2.18)
Country Fixed Effects	YES	YES
Year Fixed Effects	NO	YES
N	501	501

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

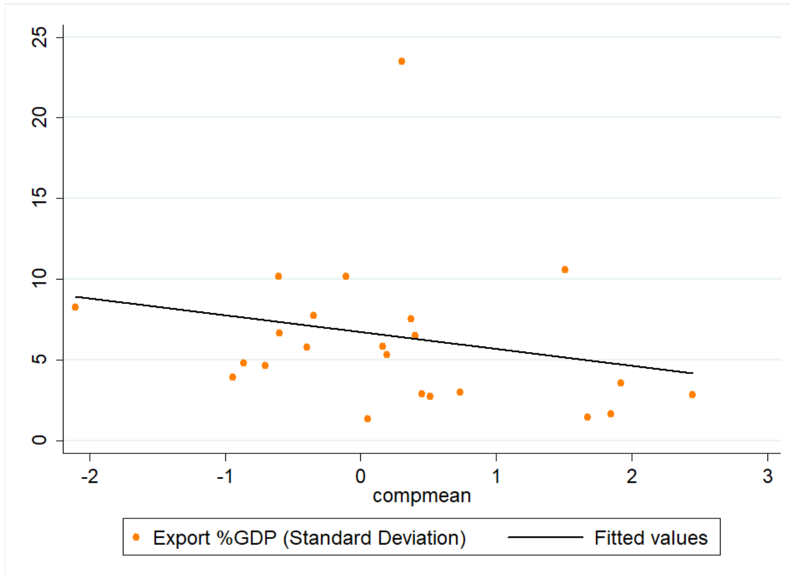
Figure 3.4: The Economic Complexity Index and the Currency Depreciation Rate



ship between the Economic Complexity Index and the likelihood of experiencing a systemic banking crisis. As stated in the introduction, we conjecture that the beneficial effects of the economic complexity index on the likelihood of experiencing systemic banking crises come from the market power on the global trade network. If our conjecture is correct, we should expect that the effects of the Economic Complexity Index are more pronounced as the relevance of international trade for the economy increases. To test our conjecture, we introduce an interaction term between the Economic Complexity Index and trade openness. In Table 3.4, we report results.

To introduce the interaction term does not change the qualitative results of Table 3.3 except for the coefficient of the Economic Complexity Index. Table 3.4 shows that - once we introduce the interaction term - the Economic Complexity Index is no longer statistically significant. However, the coefficient of the interaction is negative and statistically significant. We interpret this evidence as follows. Having superior production capabilities that allow producing rare products - for its own sake - should not affect financial stability. Nevertheless, these products entail a dominant position on the global trade market. The beneficial effects of such market-power increase as the relevance of international trade for the economy increases.

Figure 3.5: The Economic Complexity Index and the Export% GDP (Standard Deviation)



3.5 Conclusion

This paper investigates the financial effects of the Economic Complexity Index. We report evidence suggesting that more sophisticated countries - countries that export many products exported only by a handful of other countries - are less likely to experience systemic banking crises. We conjecture that the effect is driven by the fact that complex economies exploit market power on the global trade market, allowing them to better cushion shocks originating from abroad. We are conscious that our estimates do not necessarily reflect causal links. Still, as an early warning, we suggest that the characteristics of the bundle of products countries export could have remarkable effects on financial fragility.

Bibliography

Abdon, Arnelyn and Jesus Felipe, "The product space: What does it say about the opportunities for growth and structural transformation of Sub-Saharan Africa?," 2011.

Acemoglu, Daron, Asuman Ozdaglar, and Alireza Tahbaz-Salehi, "Systemic risk and stability in financial networks," *American Economic Review*, 2015, *105* (2), 564–608.

Acharya, Viral V and Tanju Yorulmazer, "Too many to fail—An analysis of time-inconsistency in bank closure policies," *Journal of financial intermediation*, 2007, *16* (1), 1–31.

Aiginger, Karl et al., "Why growth performance differed across countries in the recent crisis: the impact of pre-crisis conditions," *Review of Economics and Finance*, 2011, *1* (4), 35–52.

Akerlof, George A, Paul M Romer, Robert E Hall, and N Gregory Mankiw, "Looting: The economic underworld of bankruptcy for profit," *Brookings papers on economic activity*, 1993, *1993* (2), 1–73.

Allen, Franklin, Ana Babus, and Elena Carletti, "Asset commonality, debt maturity and systemic risk," *Journal of Financial Economics*, 2012, *104* (3), 519–534.

_ and Douglas Gale, "Financial contagion," *Journal of political economy*, 2000, *108* (1), 1–33.

_ and _ , "Financial fragility, liquidity, and asset prices," *Journal of the European Economic Association*, 2004, *2* (6), 1015–1048.

_ and _ , *Understanding financial crises*, Oxford University Press, 2009.

Angkinand, Apanard P, "Banking regulation and the output cost of banking crises," *Journal of International Financial Markets, Institutions and Money*, 2009, *19* (2), 240–257.

Bernanke, Ben S, "Non-monetary effects of the financial crisis in the propagation of the Great Depression," Technical Report, National Bureau of Economic Research 1983.

— , **Mark Gertler, and Simon Gilchrist**, "The financial accelerator and the flight to quality," 1994.

Blei, Sharon K and Bakhodir Ergashev, "Asset commonality and systemic risk among large banks in the United States," *Available at SSRN 2503046*, 2014.

Blinder, Alan S and Mark M Zandi, "How the great recession was brought to an end," 2010.

Blume, Lawrence, David Easley, Jon Kleinberg, Robert Kleinberg, and Éva Tardos, "Which networks are least susceptible to cascading failures?," in "2011 IEEE 52nd Annual Symposium on Foundations of Computer Science" IEEE 2011, pp. 393–402.

Bordo, Michael, Barry Eichengreen, Daniela Klingebiel, and Maria Soledad Martinez-Peria, "Is the crisis problem growing more severe?," *Economic policy*, 2001, *16* (32), 52–82.

Brown, Craig O and I Serdar Dinç, "Too many to fail? Evidence of regulatory forbearance when the banking sector is weak," *The Review of Financial Studies*, 2011, *24* (4), 1378–1405.

Caccioli, Fabio, J Doyne Farmer, Nick Foti, and Daniel Rockmore, "How interbank lending amplifies overlapping portfolio contagion: a case study of the Austrian banking network," *arXiv preprint arXiv:1306.3704*, 2013.

— , **Munik Shrestha, Cristopher Moore, and J Doyne Farmer**, "Stability analysis of financial contagion due to overlapping portfolios," *Journal of Banking & Finance*, 2014, *46*, 233–245.

Calderón, César and Megumi Kubota, "Does higher openness cause more real exchange rate volatility?," *Journal of International Economics*, 2018, *110*, 176–204.

Cassidy, John, "The Minsky Moment," *The New Yorker*, 2008, *4*, 19.

Chinn, Menzie D and Hiro Ito, "A new measure of financial openness," *Journal of comparative policy analysis*, 2008, *10* (3), 309–322.

Cifuentes, Rodrigo, Gianluigi Ferrucci, and Hyun Song Shin, "Liquidity risk and contagion," *Journal of the European Economic association*, 2005, *3* (2-3), 556–566.

Cont, Rama and Eric Schaanning, "Monitoring indirect contagion," *Journal of Banking & Finance*, 2019, *104*, 85–102.

Dasgupta, Amil, "Financial contagion through capital connections: A model of the origin and spread of bank panics," *Journal of the European Economic Association*, 2004, *2* (6), 1049–1084.

Demirgüç-Kunt, Asli and Enrica Detragiache, "The determinants of banking crises in developing and developed countries," *Staff Papers*, 1998, *45* (1), 81–109.

_ , Edward J Kane, and Luc Laeven, "Deposit insurance database," Technical Report, National Bureau of Economic Research 2014.

Diamond, Douglas W and Philip H Dybvig, "Bank runs, deposit insurance, and liquidity," *Journal of political economy*, 1983, *91* (3), 401–419.

Diaz-Alejandro, Carlos, "Good-bye financial repression, hello financial crash," *Journal of development Economics*, 1985, *19* (1-2), 1–24.

Ellul, Andrew, Chotibhak Jotikasthira, and Christian T Lundblad, "Regulatory pressure and fire sales in the corporate bond market," *Journal of Financial Economics*, 2011, *101* (3), 596–620.

Freixas, Xavier, Bruno M Parigi, and Jean-Charles Rochet, "Systemic risk, interbank relations, and liquidity provision by the central bank," *Journal of money, credit and banking*, 2000, pp. 611–638.

Gai, Prasanna and Sujit Kapadia, "Contagion in financial networks," *Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 2010, *466* (2120), 2401–2423.

Glasserman, Paul and H Peyton Young, "How likely is contagion in financial networks?," *Journal of Banking & Finance*, 2015, *50*, 383–399.

Gorton, Gary and Lixin Huang, "Liquidity, efficiency, and bank bailouts," *American Economic Review*, 2004, *94* (3), 455–483.

Greenwood, Robin, Augustin Landier, and David Thesmar, "Vulnerable banks," *Journal of Financial Economics*, 2015, *115* (3), 471–485.

Haldane, Andrew G, "Rethinking the financial network," in "Fragile stabilität–stabile fragilität," Springer, 2013, pp. 243–278.

Hardy, Daniel C and Ceyla Pazarbaşioğlu, "Determinants and leading indicators of banking crises: further evidence," *IMF staff papers*, 1999, *46* (3), 247–258.

Hartmann, Dominik, Miguel R Guevara, Cristian Jara-Figueroa, Manuel Aristarán, and César A Hidalgo, "Linking economic complexity, institutions, and income inequality," *World development*, 2017, *93*, 75–93.

Hidalgo, César A and Ricardo Hausmann, "The building blocks of economic complexity," *Proceedings of the national academy of sciences*, 2009, *106* (26), 10570–10575.

Hoggarth, Glenn, Ricardo Reis, and Victoria Saporta, "Costs of banking system instability: some empirical evidence," *Journal of Banking & Finance*, 2002, *26* (5), 825–855.

Ibragimov, Rustam, Dwight Jaffee, and Johan Walden, "Diversification disasters," *Journal of financial economics*, 2011, *99* (2), 333–348.

Jackson, Matthew O, *Social and economic networks*, Princeton university press, 2010.

Joyce, Joseph P, "Financial globalization and banking crises in emerging markets," *Open Economies Review*, 2011, *22* (5), 875–895.

Kaminsky, Graciela L and Carmen M Reinhart, "The twin crises: the causes of banking and balance-of-payments problems," *American economic review*, 1999, *89* (3), 473–500.

Kaufman, George G and Kenneth E Scott, "What is systemic risk, and do bank regulators retard or contribute to it?," *The independent review*, 2003, *7* (3), 371–391.

Kim, Dong-Hyeon, Shu-Chin Lin, and Yu-Bo Suen, "Dynamic effects of trade openness on financial development," *Economic Modelling*, 2010, *27* (1), 254–261.

Kindleberger, Charles P, Panics Manias, and A Crashes, "History of Financial Crises," 1996.

Klomp, Jeroen, "Causes of banking crises revisited," *The North American Journal of Economics and Finance*, 2010, *21* (1), 72–87.

Laeven, Luc and Fabian Valencia, "Systemic banking crises database," *IMF Economic Review*, 2013, *61* (2), 225–270.

_ **and** _ , "Systemic banking crises database II," *IMF Economic Review*, 2020, *68* (2), 307–361.

Marca, Massimiliano La, "Carry trade and financial fragility," *Coping with globalized finance: recent challenges and long term perspectives. UNCTAD/GDS/2007/2, United Nations, Geneva and New York*, 2007.

Mayshar, Joram, "Transaction costs in a model of capital market equilibrium," *Journal of Political Economy*, 1979, *87* (4), 673–700.

Mistrulli, Paolo Emilio, "Assessing financial contagion in the interbank market: Maximum entropy versus observed interbank lending patterns," *Journal of Banking & Finance*, 2011, *35* (5), 1114–1127.

Morgan, Donald P, "Rating banks: Risk and uncertainty in an opaque industry," *American Economic Review*, 2002, *92* (4), 874–888.

Morris, Stephen and Hyun Song Shin, "Illiquidity component of credit risk," Technical Report, working paper, Princeton University 2009.

Mukunda, Gautam, "The social and political costs of the financial crisis, 10 years later," *Harvard Business Review*, 2018, *25.*

Næs, Randi, Johannes A Skjeltorp, and Bernt Arne Ødegaard, "Stock market liquidity and the business cycle," *The Journal of Finance*, 2011, *66* (1), 139–176.

Nier, Erlend, Jing Yang, Tanju Yorulmazer, and Amadeo Alentorn, "Network models and financial stability," *Journal of Economic Dynamics and Control*, 2007, *31* (6), 2033–2060.

Noy, Ilan, "Financial liberalization, prudential supervision, and the onset of banking crises," *Emerging Markets Review*, 2004, *5* (3), 341–359.

Papi, Luca, Andrea F Presbitero, and Alberto Zazzaro, "IMF lending and banking crises," *IMF Economic Review*, 2015, *63* (3), 644–691.

Poledna, Sebastian, Serafín Martínez-Jaramillo, Fabio Caccioli, and Stefan Thurner, "Quantification of systemic risk from overlapping portfolios in the financial system," *Journal of Financial Stability*, 2021, *52*, 100808.

Romero, João P and Camila Gramkow, "Economic complexity and greenhouse gas emissions," *World Development*, 2021, *139*, 105317.

Samuelson, Paul A, "General proof that diversification pays," *Journal of Financial and Quantitative Analysis*, 1967, *2* (1), 1–13.

Shehzad, C Tanveer and Jakob De Haan, "Financial liberalization and banking crises," in "Conference of the Royal Economic Society, University of Surrey (April 20–22, 2009)" Citeseer 2009.

Shen, Peilong and Zhinan Li, "Financial contagion in inter-bank networks with overlapping portfolios," *Journal of Economic Interaction and Coordination*, 2020, *15* (4), 845–865.

Shleifer, Andrei and Robert Vishny, "Fire sales in finance and macroeconomics," *Journal of economic perspectives*, 2011, *25* (1), 29–48.

_ **and Robert W Vishny**, "Liquidation values and debt capacity: A market equilibrium approach," *The journal of finance*, 1992, *47* (4), 1343–1366.

Smaga, Pawel, "The concept of systemic risk," 2014.

Svirydzenka, Katsiaryna, *Introducing a new broad-based index of financial development*, International Monetary Fund, 2016.

Tasca, Paolo and Stefano Battiston, "Market procyclicality and systemic risk," *Quantitative Finance*, 2016, *16* (8), 1219–1235.

Vu, Trung V, "Economic complexity and health outcomes: A global perspective," *Social Science & Medicine*, 2020, *265*, 113480.

Wagner, Wolf, "Diversification at financial institutions and systemic crises," *Journal of Financial Intermediation*, 2010, *19* (3), 373–386.

Whalen, Charles, "Understanding the credit crunch as a Minsky moment," *Challenge*, 2008, *51* (1), 91–109.

Yanikkaya, Halit, "Trade openness and economic growth: a cross-country empirical investigation," *Journal of Development economics*, 2003, *72* (1), 57–89.