An Essay on Common and Private Value Actions

and

Essays on the Effect of Non-Performing Loans on Lending, Sectoral Credit Composition and Banking Sector Market Concentration

by

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Koç University

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This is to certify that I have examined this copy of a doctoral dissertation by

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ÖZETÇE

Ortak ve Özel Değer İhalelerine Dair Bir Makale
ve
Bankacılık Sektörü Tahsili Gecikmiş Alacaklarının Kredi Verme Davranışlarına, Sektörel Kredi Kompozisyonuna ve Bankacılık Sektör Yoğunlaşmasına Dair Makaleler

Mehmet Emre Şamcı
Ekonomi, Doktora
9 Eylül 2022

Tezin ilk bölümünde, her ihale katılımcısının belirli olasılıkla ya ortak değer türünden ya da özel değer türünden katılımcı olduğu, $k + 1$'inci en yüksek teklifin fiyat olarak belirlendiği bir ihale modelini inceliyoruz. Saf ortak değer ihalelerinin aksine, mal sayısına, sinyal dağılımına ve katılımcının değer türü olasılığına bağlı olarak bazı parametrik kısıtlamalar altında herhangi bir dengede havuzlama olması gerektiğini gösteriyoruz. Ayrıca ortak değer türünden katılımcıların sinyal uzayının alt bölümünde aynı teklif değerinde birleştiği büyük ihale dengesi buluyoruz. Dengede oluşan fiyat, ihaleye konan nesnenin gerçek değerine yakınsamamakla birlikte nesnenin düşük ya da yüksek değerde olma durumu hakkında bilgi vermektedir. Ayrıca ortak ve özel değerli katılımcıların bulunduğu büyük ve küçük ihalelerde dengenin varlığına dair bazı önkoşullar verilmektedir.

İkinci bölümde, tahsili gecikmiş alacaklar (TGA) ile kredi büyümesi arasındaki etkileşimi inceliyoruz. COVID-19 pandemi döneminin ardından dünya genelinde parasal ve finansal koşullarda yaşanan sıkılaşma, tüm ülkelerin bankacılık aktif kalitesini tehdit etmektedir. Bu bağlamda, sorunlu krediler ile kredi büyümesi arasındaki geri besleme etkilerinin analizi, ekonomik büyüme projeksiyonları ve finansal istikrar için önemlidir. Bu çalışma, aktif kalitesindeki değişimlerin Türkiye'de banka kredileri, bankacılık sektörü piyasa yoğunlaşması ve ekonomik sektör kredi dağılımı üzerindeki etkisini, banka bazında ve ekonomik sektör düzeyinde verilere panel VAR uygulayarak analiz etmektedir. Birinci bölümde bankaların TGA oranında artışın banka kredilerini azalttığını gösteriyor, kamu bankaları ve özel bankaların

TGA artışına tepkisini 2016 öncesi ve sonrasını ayırt ederek inceliyoruz. Bankaların büyüklük, sermaye ve likidite yapısı gibi özelliklere göre TGA şoklarına nasıl farklı tepki verdiğini göstermek için bu özelliklerinin banka davranışındaki rolünü de inceliyoruz. Ayrıca, banka kredisi dağılımının farklı kantillerinde TGA'nın etkisinin panel kantil tahmini elde edilerek TGA şokları nedeniyle banka kredilerinde oluşan sıkılaşmanın kredi dağılımının yüksek kantillerinde daha belirgin olduğu gösterilmektedir. İkinci olarak, bir sektörün TGA oranı arttığında, sektörün toplam banka kredilerinden aldığı payın azaldığını gösteren analiz, ekonomik sektörler bazında, panel verilerle yapılmıştır. Kredilerin TGA şokuna tepkisinin yönü, büyüklüğü ve süresinin banka düzeyindeki analizle tutarlı olduğu ve orta-uzun vadeli kredilerin tepkinin esas sürükleyicisi olduğu görülmektedir. Üçüncüsü, klasik VAR kullanarak, tahsili gecikmiş alacak oranındaki dışsal bir artışın, bankacılık sektöründeki piyasa yoğunlaşmasını artırdığı, bunun sürükleyicisinin de kamu bankaları olduğu gözlemlenmektedir. Takipteki alacakların geri bildirim mekanizmasının sektörel düzeyde analizi, TGA'nın kredi kullandırma davranışı ile etkileşimine ilişkin panel VAR niceliksel yaklaşımlar ve TGA'nın bankacılık sektörü yoğunlaşma endeksleri ile etkileşimi, potansiyel politika çıkarımlarını üretebilecek türden, daha önceki çalışmalarda yer almayan yeni sonuçlardır.

ABSTRACT

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In the first part, we study a $k + 1^{st}$ price auction model where each bidder is either a common value bidder or a private value bidder with a given probability. We show that as opposed to pure common value auctions, there has to be pooling in any equilibrium under some parametric restrictions depending on the number of goods, distribution of signals and probability of a bidder belonging to either type. We find a large auction equilibrium in which common value bidders pool at the bottom of the signal space. The price in equilibrium does not converge the true value of the object; however, it does reflect the state of the world. We also provide some conditions for a pooling equilibrium in large and small auctions with common and private value bidders.

In the second part, we study the interaction of non-performing loans (NPL) and credit growth. The period of tightening in monetary and financial conditions around the globe following the COVID-19 pandemic threatens the asset quality of banks worldwide. An analysis of the feedback effects between non-performing loans and credit growth is therefore important for economic growth projections and for the financial stability of banking system. This study analyzes the impact of changes in bank asset quality on lending, market concentration and economic sector loan distribution in Turkey by implementing panel VAR on bank level and economic sector level data. In the first part, we show that rise in the NPL ratio of banks decreases the bank loans. We distinguish the response of public and private banks to NPL rise before and after 2016. We also examine the role of bank characteristics, such as size, capital and liquidity structure to demonstrate how banks react differently to NPL

shocks with respect to these characteristics. Moreover, we provide a panel quantile estimation of the effect of NPL in different quantiles of bank loan distribution and show that tightening in bank lending due to NPL shocks is more pronounced at the higher quantiles of loan distribution. Second, we work on panel data of economic sectors to show that when NPL ratio of a sector increases, share of outstanding loans of the sector in total bank loans shrinks. We find that the direction, magnitude and duration of the response of loans to NPL shock is consistent with bank-level analysis, with medium to long-term loans the main driver of the response. Third, we demonstrate using classical VAR that an exogenous rise in the NPL ratio increases the market concentration in the banking sector, with concentration being driven by public banks. Sectoral level analysis of NPL feedback mechanism, quantile regression approach to interaction of NPL with lending and interaction of NPL with banking sector concentration indices are novel results with possible policy implications.

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ABBREVIATIONS

CBRT	Central Bank of Republic of Turkey
IP	Industrial Production
CPI	Consumer Price Index
CDS	Credit Default Swap
GDP	Gross Dometic Product
NPL	Non Performing Loans
VAR	Vector Auto Regression
US	United States of America
IID	Independently and Identically Distributed
CDF	Cumulative Distribution Function
MLRP	Monotone Likelihood Property
CESEE	Central, Eastern and South-Eastern Europe
OLS	Ordinary Least Squares
GMM	Generalized Method of Moments
AIC	Akaike Information Criterion
Turkstat	Turkish Statistical Institute
BRSA	Banking Sector Regulation and Supervision Agency
IRF	Impulse Response Function
FEVD	Forecast Error Variance Decomposition
HHI	Herfindahl-Hirschman Index
CD	Coefficient of Determination
JP Morgan	John Pierpont Morgan
BIST	Borsa Istanbul
LIBOR	London Inter-Bank Offered Rate
MCMC	Markov chain Monte Carlo

Chapter 1

AUCTIONS WITH COMMON AND PRIVATE VALUE BIDDERS

1.1 Introduction

Auctions are studied typically in two categories: "private value" and "common value" auctions. In private value auctions, bidders know their own valuations of the object and know only the distribution of the values of other bidders. The classical example for the private value auctions is the sale of paintings in a gallery auction. In common value auctions on the other extreme, bidders have a common value for the object and each receive a partially informative signal about the value of the object. Oil drilling rights being auctioned out by the state to the oil-drilling companies is a classical example of a pure common value auction. Both of these auction types are extensively studied in the literature.

We consider a generalization of these models where both common and private value bidder types participate in the auction. In our model, from the perspective of a given bidder, each of the other bidders is a common value bidder or a private value bidder with a given probability. In order to visualize this kind of a scenario, consider a gallery auction in Paris where not all the bidders are art collectors or connoisseurs who want to keep the paintings for themselves, instead, some of the bidders participating in the auction want to acquire a painting and sell it in US for profit. So those who want to resell the item have a common monetary value for the paintings, and bidders only know the probability with which each bidder is a private value bidder. Real estate market is also another good example of this. Some people look for a house where they will will live with their family, so they have private considerations as opposed to people who want to use real estate as a way of investment, to resell at a later time. These two types of people coexisting and competing for a house is similar to the scenario in our model. Actually, in any Vickery auction, if bidders comprises of both consumers and investors, we have the model that we are studying. In such scenarios two distinct types of bidders will mix together and pure common and pure private value auction models will not be realistic. Neither a model where bidder's valuations have common and private value components will cover this kind of a scenario.

This looks like a straightforward generalization of pure common and private values case. However the generalized model we produce has fundamentally different features of informational efficiency and allocative efficiency. Let's say that information is aggregated if the auction price converges the true value of the object as n grows large. First of all, in symmetric equilibrium, on a certain range of parameters, we find that common value bidders pool at the bottom of the signal space. The intuition for this is as follows. Pooling equilibrium in the pure common values case is eliminated by using "winner's curse" affecting the pool bidders; depending on the state, there will be more or less people tying at the pooling bid, therefore tying bidders should deviate. In our model, when the pooling bidder is winning more, this could be due to the accumulation of private value bidders below the pooling bid, as a result pooling cannot be eliminated. In previous models of single type bidders, symmetric equilibrium bidding strategies are typically monotone. Moreover, we have the random presence of private value bidders in the market, posing a risk for common value bidders and potentially raising the prices. We find that auction price does not converge the true value of the object.

This brings us to the other distinctive feature of our model concerning the allocative efficiency. In a $k+1$'st price auction, pure bidder type auction allocations are ex-post efficient. That is because in a $k+1$'st price auction, if there are only private value bidders, those with the highest valuations get the items and in common value bidders case, since everybody has the same value for the object, allocations are trivially efficient. It is known that there will be inefficiency in other mechanisms like first price or all-pay auctions, here we have an allocatively inefficient scenario for the $k + 1'$st price auction. In our model, prices do not aggregate information for common value bidders due to pooling. But after the auction is over, there will be more information that common value bidders can use. This in turn means that even when the number of bidders grow without bound, those common value bidders who won an object will sometimes realize that they have underbid or overbid after the auction is over and allocations are made, or price is announced. If they overbid, they will want to sell the item to those private value bidders who value the object more then they do. In other times, when they could not get an object although the state is more likely to be high, they will want to pay those private value bidders the difference between their common value and the private value. In other words, there will be allocative inefficiencies in $k + 1$'st price auction and there will be incentives for the common value bidders to engage in ex-post trade.

1.2 Background and Literature Review

One of the reasons why auction models are such a popular focus of research is because they seem to simulate well a competitive market economy with rational expectations. Past researchers studied common value auctions to prove information aggregation results, because common value auctions are a tractable non-cooperative model of price setting with dispersed information and rational expectations equilibrium. $k + 1$'st price common value auctions are particularly attractive because in such auctions bidders are price takers who cannot affect the market price. Also the information about the state of the world, held by the many bidders, may be accumulated to the price, and although none of the individual bidders know the true state of the world, price can converge to the true value as number of bidders goes to infinity and dispersed information gets aggregated.

Earliest remarkable effort towards modeling perfect competition as a common value auction goes back to [Wilson, 1977]. A single object auction with unknown value is considered. Participants in the auction receive a signal about the value, and then submit a bid. The highest bidder wins the object and pays his bid. Wilson proves that under certain parametric conditions relating value to signals, price converges in probability to the true value of the object as the number of participants goes to infinity.[Milgrom, 1979] proved that in a $k+1$'st price common value auction, prices converge to the true value as the number of bidders go to infinity, under somewhat stringent informational assumptions. [Pesendorfer and Swinkels, 1997] showed that if both the number of identical objects and number of bidders that are not allocated an object go to infinity, then without those restrictive informational assumptions, it is possible to derive information aggregation results in the symmetric monotone equilibrium.

There are studies pointing out that information aggregation may not be such a natural feature of auction environments even with mildest modifications to the model. For example rather recently, Atakan and Ekmekci [Atakan and Ekmekci, 2014] show that adding ex-post actions to the auction, which is the principal use of the prices in the first place, changes the whole story. They considered an auction environment with only common value bidders. In their model, bidder's valuation for the object is determined not only by the state of the world, but jointly by the state of the world and an action that he chooses after winning the object but before he observes the state. So winner of an object uses the price of the auction to decide which action to take. In the previous models of auction without ex-post action, after the object is allocated, the information that price of the object reveals to the bidder is of no value. As a result, the "winner's curse" prohibits any pooling in monotone strategies. But in [Atakan and Ekmekci, 2014], as opposed to the previous literature, auction price will not aggragate information, in the sense that it will not reflect the state of the world, since information content of it is used to make later decisions. They prove that pooling is possible, because effect of "winner's curse" could be counterbalanced by the positive value of information coming from learning about the price. As a result, information will not be aggregated even for arbitrarily large markets. Their second contribution is the strong result that in any symmetric monotone equilibrium under certain conditions price fails to reflect the true state.

[Jackson and Peck, 1993] analyses common value uniform price auction mechanisms with costly information aquisition and a large number of bidders. He shows that informational efficiency fails even with a slightly positive cost to information, and allocative efficiency breaks down when the information costs are not too high. These results suggests that free informative signals is a crucial assumption for the information aggregation and allocative efficiency. In another information aggregation failure paper, [Ronald M. Harstad, 2008] considers a uniform price common value auction where the participants are uncertain about the number of rivals they are facing. They find that even with informative signals, information fails to aggregates unless uncertainty about the fraction of winning bidders vanishes.

All of the above models are pure common value auctions. [Jackson, 2003] consider a $k+1$'st price auction where bidder's preferences have common and private value components. They show that the tension between the allocative efficieny and information aggregation of prices disappear, hence equilibrium becomes efficient in both senses as the number of bidders go to infinity. However they can not show the existence of equilibrium for finite number of bidders due to the two dimensional preferences. This turns out to be a serious problem, as shown by [Jackson, 2009] who proves that even with a slight perturbation to the Vickery type and English auction models with pure common and private values, classical equilibrium results may fail. In our study, we do prove the existence of equilibrium for finite and large bidders case.

The paper with the most similar model at the first sight, but which has some significant differences is the one by [Tan and Xing, 2011]. They consider a second price auction with M common value, N private value bidders. They prove the existence of a monotone equilibrium in second price auctions. An analysis of the bidding behaviour as the proportion of common and private value bidders change is given. Their model is differ from ours in two important aspects: in our model a bidder does not know the exact number of common and private value bidders in the market, only the probability of a given bidder belonging to each type is known, as opposed to given number of common and private bidders in their paper. Secondly we have two state model whereas they have continuum of states, which is not expected to make a crucial difference. On the other hand, first point of departure seems to have significant consequences: in Tan and Xing's model, since bidders only know about M and N, it might seem like the only thing that matters is the ratios $\frac{M}{M+N}$ and $\frac{N}{M+N}$ which corresponds to c and $1-c$ in our model. However in our model each bidder has an independent probability of being one of the types and total number of neither type is known, whereas in Xu Tan and Yiqing Xing's model probability of each bidder being one of the types is interdependent. This structure turns out to be quite important and gives rise to an equilibrium with fundamentally different qualities. One can find different scenarios where either assumption is realistic.

In our model with common and private value bidder types we give a natural generalization to the previous auction models of information aggregation. Surprisingly we find that as opposed to the classical models, symmetric equilibrium bidding strategies exhibit pooling, without relying on ex-post actions. We also prove that price do not converge the true value of the object. Since private value bidders bid their own valuations in the spirit of Vickery auctions, allocations of objects will also be inefficient as a result. Our model differs from the models where bidders have preferences with both common and private value components, because in our scenario the group of bidders have private and common value types, and it is expected that this is a fundamentally different story.

1.3 The Model

There are $n+1$ bidders competing for k goods in a $k+1^{st}$ price auction. A bidder is a private value bidder with probability $1-c$ with values distributed IID (independently and identically distributed) and CDF (cumulative distribution function) $G(.)$. A bidder is a common value bidder with probability c. A typical common value bidder knows that there are two possible values of the good; $v \in \{0, 1\}$ and receives signals about the value of the good with conditionally IID signal distribution $F(s|v)$, which admits a density function $f(s|v)$, where $s \in [0, 1]$. Let $l(s) = \frac{f(s|1)}{f(s|0)}$ denote the likelihood ratio function.

Definition 1. *The signals for the value of the good for common value bidders is said to satisfy MLRP (Monotone Likelihood Ratio Property) if $l(s)$ is increasing in s.*

Lemma 1. *If signal space $s \in [0,1]$ of common value bidders satisfy MLRP, the equilibrium bidding function $b(s)$ of common value bidders is non-decreasing in signals s.*

Proof. The proof is standard and follows from Lemmata 2-6 in [Pesendorfer and Swinkels, 1997]. □

Since the equilibrium bidding function $b(s)$ is non-decreasing, this means that symmetric equilibrium bidding function $b(s)$ is going to be differentiable outside a countable subset of the signal space.

Let for the moment the symmetric equilibrium bid $\beta(.) = b(s)$ of common value bidders to be strictly increasing in signals. Let $\frac{k}{n} = \kappa$ for large n. Let $Y_n^k(b)$ be the event that bid b is the k^{th} highest bid among n remaining bids and there is at least one other bid equal to b. Note that the other bid equal to b could come from a common value bidder or a private value bidder. Then the probability of being pivotal conditional on state $w \in \{0,1\}$ for a common value bidder bidding $b(s)$ is:

$$P\big(Y_n^k(b(s))|w\big) = n\binom{n-1}{k-1}\big[cF(s|w)+(1-c)G(b(s))\big]^{n-k}\big[1-cF(s|w)-(1-c)G(b(s))\big]^{k-1}$$

$$\times\frac{cf(s|w)+(1-c)g(b(s))b'(s)}{b'(s)}f(s|w)$$

To see how we get this, let $\beta(.)$ be a symmetric equilibrium bidding strategy of the game and assume that it is strictly increasing. Denote by $H(b|w)$ the cumulative distribution function of a given bidder's bid, conditional on state w. Then,

$$H(b|w) = cF(\beta^{-1}(b)|w) + (1-c)G(b)$$

and probability density function is

$$h(b|w) = c(\beta^{-1})'(b)f(\beta^{-1}(b)|w) + (1-c)g(b)$$

Remembering that $(\beta^{-1})'(b) = \frac{1}{\beta'(\beta^{-1}(b))}$ and $\beta(.) = b(s)$ in equilibrium, we find that;

$$h(b|w) = \frac{cf(s|w) + (1-c)g(b(s))b'(s)}{b'(s)}$$

where $b'(s) > 0$ by the hypothesis of strictly monotone bidding.

Then, from the perspective of a common value bidder with signal s, the probability of being pivotal, in other words, the probability that from among other n bidders, there are $n-k$ bidders below $b(s)$ and $k-1$ bidders above it and there is one bid of exactly $b(s)$ is:

$$n\binom{n-1}{k-1}H(b(s)|w)^{n-k}[1-H(b(s)|w)]^{k-1}h(b(s)|w)f(s|w)$$

which gives the above expression.

Then the likelihood ratio of the pivotal common value bidder who received signal $s > 0$ is:

$$L(s) = \left(\frac{c(1-F(s|1)) + (1-c)(1-G(b(s)))}{c(1-F(s|0)) + (1-c)(1-G(b(s)))}\right)^{k-1}\left[\frac{cF(s|1) + (1-c)G(b(s))}{cF(s|0) + (1-c)G(b(s))}\right]^{n-k}$$

$$\times\left(\frac{cf(s|1) + (1-c)g(b(s))b'(s)}{cf(s|0) + (1-c)g(b(s))b'(s)}\right)\frac{f(s|1)}{f(s|0)} \tag{1.1}$$

1.4 Existence of Pooling

1.4.1 Zero Private Values

We consider as a motivation the special case where each private value bidder has value zero, i.e $G(t) \equiv 1$. In this case, all of the private value bidders will bid their value zero, as a result a common value bidder will anticipate bulk of private value bidders below his/her positive bid. We show this will force pooling at zero in equilibrium for large n if equilibrium exists.

Proposition 0. *In a large auction with common and private value bidders, if the private values are all zero and signals of common value bidders satisfy strict MLRP; then there has to be pooling around $s = 0$ in equilibrium if $c > \kappa$ and $f(0|0) > f(0|1)$, if equilibrium exists.*

Proof. Assume the contrary that $b(s)$ is strictly increasing in s for all $s \in [0, 1]$. Plug $G(.) \equiv 1$ in above formula for likelihood:

$$L(s) = \left(\frac{1 - F(s|1)}{1 - F(s|0)}\right)^{k-1} \left[\frac{cF(s|1) + 1 - c}{cF(s|0) + 1 - c}\right]^{n-k} \left(\frac{f(s|1)}{f(s|0)}\right)^2$$

Let $l(s) = \log L(s)$ and take the derivative:

$$\frac{L'(s)}{nL(s)} = \frac{k-1}{n}\left[\frac{f(s|0)}{1 - F(s|0)} - \frac{f(s|1)}{1 - F(s|1)}\right] + \frac{n-k}{n}\left[\frac{cf(s|1)}{cF(s|1) + 1 - c} - \frac{cf(s|0)}{cF(s|0) + 1 - c}\right]$$

$$+\frac{1}{n}\frac{d}{ds}\left(\frac{f(s|1)}{f(s|0)}\right)^2$$

Then for large n we will have,

$$\frac{1}{n}l'(0) = \frac{L'(0)}{n} = \frac{\kappa - c}{1 - c}[f(0|0) - f(0|1)]$$

Therefore if $c > \kappa$ and $f(0|0) > f(0|1)$, $L'(0) < 0$; likelihood is decreasing around zero, which contradicts the assumption of strictly increasing signals. This, together with the non-decreasing bidding strategies result implies that there has to be pooling in equilibrium around zero, if equilibrium exists. $\square$

Both $c > \kappa$ and $f(s|0) > f(s|1)$ assumptions are plausible, because the first one requires the existence of enough common value bidders in the market, which is necessary to avoid a trivial result. Second one is satisfied for example when we have only two signals, high and low.

1.4.2 Uniformly Distributed Private Values

Assume private value bidders are distributed uniformly on $[0,1]$. In order to prove that in this case also there will be pooling, we calculate the likelihood ratio and prove that it is decreasing around $s=0$.

Proposition 1. *In a large auction with common and private value bidders, if the private values are distributed uniformly on* $[0,1]$*, then there has to be pooling around* $s=0$ *in equilibrium under the following restriction:*

$$\frac{f(0|0)}{f(0|1)+f(0|0)} > \kappa$$

if equilibrium exists.

Proof. Assume for a contradiction that symmetric bidding strategies $b(s)$ of common value bidders are strictly increasing $\forall s \in [0,1]$. Let $Y_n^k(b(s))$ be the event that $b(s)$ is pivotal in the presence of n bidders and k goods. Then a la Pesendorfer and Swinkels;

$$b(s) = E\big[v|Y_n^k(b(s), s_1 = s)\big] = \frac{P\big(Y_n^k(b(s))|1\big)}{P\big(Y_n^k(b(s))|1\big) + P\big(Y_n^k(b(s))|0\big)} = \frac{1}{1+L(s)^{-1}} \tag{1.2}$$

where we have already calculated that:

$$L(s) = \frac{\big[cF(s|1)+(1-c)b(s)\big]^{n-k}\big[1-cF(s|1)-(1-c)b(s)\big]^{k-1}}{\big[cF(s|0)+(1-c)b(s)\big]^{n-k}\big[1-cF(s|0)-(1-c)b(s)\big]^{k-1}}$$

$$\times\frac{cf(s|1)+(1-c)b'(s)}{cf(s|0)+(1-c)b'(s)} \times \frac{f(s|1)}{f(s|0)}$$

Claim. $b(0) \neq 0$

Proof. Assume that in equilibrium $b(0)=0$. Divide both the numerator and denominator in (2) by s^{n-k} and let $s \to 0$. Then since $b(0) = 0$,

$$b(0) = 0 = \frac{[cf(0|1) + (1-c)b'(0)]^{n-k+1} f(0|1)}{[cf(0|1) + (1-c)b'(0)]^{n-k+1} f(0|1) + [cf(0|0) + (1-c)b'(0)]^{n-k+1} f(0|0)}$$

$$\Rightarrow b'(0) = -\frac{c}{1-c} f(0|1)$$

which implies that $b'(0) < 0$, contradiciting the hypothesis that $b(.)$ is strictly increasing. □

So we now know that $b(0) \neq 0$. Then (2) will give $b(0)$ to be equal to

$$b(0) = \frac{[cf(0|1) + (1-c)b'(0)] f(0|1)}{[cf(0|1) + (1-c)b'(0)] f(0|1) + [cf(0|0) + (1-c)b'(0)] f(0|0)} \tag{1.3}$$

Note the independence of $b(0)$ from n and k. To get the desired contradiction, calculate the derivative of the log-likelihood,

$$\frac{L'(s)}{nL(s)} = \left[\frac{cf(s|1) + (1-c)b'(s)}{cF(s|1) + (1-c)b(s)} - \frac{cf(s|0) + (1-c)b'(s)}{cF(s|0) + (1-c)b(s)}\right] \frac{n-k}{n}$$

$$+\left[\frac{cf(s|0) + (1-c)b'(s)}{c(1-F(s|0)) + (1-c)(1-b(s))} - \frac{cf(s|1) + (1-c)b'(s)}{c(1-F(s|1)) + (1-c)(1-b(s))}\right] \frac{k}{n}$$

$$+\frac{1}{n}\frac{d}{ds}\left[\left(\frac{cf(s|1) + (1-c)g(b(s))}{cf(s|0) + (1-c)g(b(s))}\right) \frac{f(s|1)}{f(s|0)}\right]$$

Again, for large n and under appropiate conditions, the last term could be ignored. At $s = 0$ and for large n, this expression will boil down to:

$$\frac{L'(0)}{nL(0)} = \frac{c}{1-c}\left(\frac{1-\kappa}{b(0)} - \frac{\kappa}{1-b(0)}\right)[f(0|1) - f(0|0)]$$

which is negative if $1 - b(0) - \kappa > 0$ and $f(0|1) - f(0|0) < 0$ giving the desired contradiction. However $b(0)$ is an equilibrium notion and we need to pin down $b(0)$ in terms of the parameters of the model.

Equation (3) gives $b(0)$ in terms of parameters and $b'(0)$ which is determined again in equilibrium. So we still need to know what $b'(0)$ is. To find another equation relating $b(0)$ and $b'(0)$, take the derivative of both sides in (2) and put $s = 0$:

$$b'(0) = \frac{L'(0)}{[1 + L(0)]^2}$$

By above calculation,

$$L'(0) = nL(0)\frac{c}{1-c}\left(\frac{1-\kappa-b(0)}{b(0)[1-b(0)]}\right)[f(0|1) - f(0|0)]$$

where

$$L(0) = \frac{[cf(0|1) + (1-c)b'(0)]f(0|1)}{[cf(0|0) + (1-c)b'(0)]f(0|0)} = \frac{b(0)}{1-b(0)}$$

Writing everything in terms of $b(0)$, we have two equations relating $b(0)$ and $b'(0)$;

$$b'(0) = [1-b(0)]^2 L'(0) = n\frac{c}{1-c}[1-b(0)-\kappa][f(0|1) - f(0|0)]$$

$$b(0) = \frac{[cf(0|1) + (1-c)b'(0)]f(0|1)}{[cf(0|1) + (1-c)b'(0)]f(0|1) + [cf(0|0) + (1-c)b'(0)]f(0|0)}$$

Plugging the first equation in the second one and using large n assumption we find:

$$b(0) \approx \frac{f(0|1)}{f(0|1) + f(0|0)}$$

As a result, pooling condition $b(0) < 1 - \kappa$ becomes;

$$\frac{f(0|0)}{f(0|1) + f(0|0)} > \kappa$$

□

1.5 Conditions for A Pooling Equilibrium

Here we give some conditions for an equilibrium where the common value bidders bid in the following way: $b(s) = b^p > 0, \forall s \in [0, s^p]$ and $b(s)$ is strictly increasing on

$(s^p, 1]$, whereas private value bidders are distributed uniformly on $[0, 1]$ and bid their own valuation. If auction price $p > b_p$, pooling bidder loses and gets 0, if $p \leq b_p$, we care about the price only when $p = b_p$. Then the expected utility of a common value bidder with signal $s \in [0, s^p]$ bidding the pooling bid is:

$$\begin{aligned} u(b = b^p|s) \quad &= P(1|s)P(p = b^p|1)P(\text{win}|1, s, p = b^p, b = b^p)(1 - b^p) \\ &- P(0|s)P(p = b^p|0)P(\text{win}|0, s, p = b^p, b = b^p)b^p \end{aligned}$$

with a slight increase in the bid bidder wins for sure if price is b^p

$$u(b = b^p + \epsilon|s) = P(1|s)P(p = b^p|1)(1 - b^p) - P(0|s)P(b = b^p|0)b^p$$

Then conditions for b^p to be the equilibrium pooling bid are

$$\begin{aligned} u(b = b^p|s) - u(b = b^p - \epsilon|s) &\geq 0 \\ u(b = b^p|s) - u(b = b^p + \epsilon|s) &\geq 0 \end{aligned}$$

which translates into the pair of inequalities:

$$\begin{aligned} &P(1|s)P(p = b^p|1)P(\text{win}|p = b^p, b = b^p, 1)(1 - b^p) - P(0|s)P(p = b^p|0)P(\text{win}|p = b^p, b = b^p, 0)b^p \geq 0 \\ &P(1|s)P(p = b^p|1)P(\text{win}|p = b^p, b = b^p, 1)(1 - b^p) - P(0|s)P(p = b^p|0)P(\text{win}|p = b^p, b = b^p, 0)b^p \\ &- P(1|s)P(p = b^p|1)(1 - b^p) + P(0|s)P(p = b^p|0)b^p \geq 0 \end{aligned}$$

We have the following necessary condition for pooling:

Lemma 2. *If we have a pooling equilibrium of above type, then*

$$P(win|p = b^p, b = b^p, 1) \geq P(win|p = b^p, b = b^p, 0)$$

Proof. Assume $P(\text{win}|p = b^p, b = b^p, 1) < P(\text{win}|p = b^p, b = b^p, 0)$. There are two cases to consider:

1. $P(1|s)P(p = b^p|1)(1 - b^p) - P(0|s)P(p = b^p|0)b^p \leq 0$. Then

$$\begin{aligned} 0 &\leq P(1|s)P(p = b^p|1)P(\text{win}|p = b^p, b = b^p, 1)(1 - b^p) - P(0|s)P(p = b^p|0)P(\text{win}|p = b^p, b = b^p, 0)b^p \\ &< P(\text{win}|p = b^p, b = b^p, 1)\big[P(1|s)P(p = b^p|1)(1 - b^p) - P(0|s)P(p = b^p|0)b^p\big] \leq 0 \end{aligned}$$

contradiction.

2. $P(1|s)P(p = b^p|1)(1 - b^p) - P(0|s)P(p = b^p|0)b^p \geq 0$. Then,

$$\begin{aligned} &\big[P(\text{win}|p = b^p, b = b^p, 0) - P(\text{win}|p = b^p, b = b^p, 1)\big]\big[P(1|s)P(p = b^p|1)(1 - b^p)\big] \\ &+ \big[1 - P(\text{win}|0)\big]\big[P(1|s)P(p = b^p|1)(1 - b^p) - P(0|s)P(p = b^p|0)b^p\big] > 0 \end{aligned}$$

After opening the paranthesis, we see that this translates back to

$$u(b = b^p + \epsilon|s) - u(b = b^p|s) > 0$$

which contradicts the equilibrium condition. □

Lets get a sense of $P(\text{win}|p = b^p, b = b^p, w), w \in \{0, 1\}$. It is clear that :

$$P(\text{win}|p = b^p, w) = E\big[\frac{X}{Y}|p = b^p, w\big]$$

where X is the number of goods left and Y is the number of people that are tying. Assume $nF(s^p|w) \to \infty$.

Lemma 3.

$$E\big[\frac{X}{Y}|p = b^p, w\big] = \frac{E\big[X|p = b^p, w\big]}{E\big[Y|p = b^p, w\big]}$$

Proof. We use the following form of the Chernoff bounds:

Theorem 1. *Let $X_1, X_2, ...X_N$ be random variables such that $X_i \in \{0, 1\}$ for each i. Let $X = \sum_{i=1}^{N} X_i$ and set $\mu = E[X]$. Then for all $\delta > 0$,*

- *(Upper tail): $P(X > (1 + \delta)\mu) \leq e^{\frac{-2\delta^2\mu^2}{N}}$;*

- *(Lower tail):* $P(X < (1-\delta)\mu) \leq e^{\frac{-\delta^2\mu^2}{N}}$;

$$P(win|p = b^p) = E\big[\frac{X}{Y}|p = b^p\big] = E\big[\frac{X}{Y}|p = b^p, Y \geq (1+\delta)\bar{Y}\big]P(Y \geq (1+\delta)\bar{Y}) + E\big[\frac{X}{Y}|p = b^p, Y < (1+\delta)\bar{Y}\big]P(Y < (1+\delta)\bar{Y})$$

By Theorem 1,

$$P(Y \geq (1+\delta)\bar{Y}) \leq e^{\frac{-2\delta^2\bar{Y}^2}{n^2}}$$

which goes to 0 as n grows large. So the first term in the above equation disappears and we are left with:

$$P(win|p = b^p) \geq \frac{1}{(1+\delta)\bar{Y}}E\big[X|p = b^p, Y < (1+\delta)\bar{Y}\big] = \frac{\bar{X}}{(1+\delta)\bar{Y}}$$

for all $\delta > 0$. Similarly,

$$P(win|p = b^p) = E\big[\frac{X}{Y}|p = b^p\big] = E\big[\frac{X}{Y}|p = b^p, Y \leq (1-\delta)\bar{Y}\big]P(Y \leq (1-\delta)\bar{Y}) + E\big[\frac{X}{Y}|p = b^p, Y > (1+\delta)\bar{Y}\big]P(Y > (1-\delta)\bar{Y})$$

By Theorem 1,

$$P(Y \leq (1-\delta)\bar{Y}) \leq e^{\frac{-\delta^2\bar{Y}^2}{n^2}}$$

which goes to 0 as n grows large. So the first term in the above equation disappears and we are left with:

$$P(win|p = b^p) \leq \frac{1}{(1-\delta)\bar{Y}}E\big[X|p = b^p, Y > (1-\delta)\bar{Y}\big] = \frac{\bar{X}}{(1-\delta)\bar{Y}}$$

for all $\delta > 0$. Letting $\delta \to 0$ and combining the two inequality, we get the desired lemma. $\square$

Lemma 4.

$$\frac{P(win|p=b^p, b=b^p, 1)}{P(win|p=b^p, b=b^p, 0)} > 1$$

Proof. Expected number of people tying on the pooling bid b^p is $(1-\kappa)\frac{ncF(s^p|w)}{1-cF(s^p|w)-(1-c)b^p}$. Following quantity is the expected number of goods that are left:

$$E\left[\text{Number of goods left}|b=b^p, s=s^p, w\right] = \frac{\sum_{i=0}^{k} i\binom{n}{k-i}q^{n-k+i}(1-q)^{k-i}}{\sum_{i=0}^{k}\binom{n}{k-i}q^{n-k+i}(1-q)^{k-i}} \tag{1.4}$$

where $q = cF(s^p|w) + (1-c)b^p$ and $P(p = b^p|w) = \sum_{i=0}^{k}\binom{n}{k-i}q^{n-k+i}(1-q)^{k-i}$.

Here is the reasoning for $P(p = b^p|w) = \sum_{i=0}^{k}\binom{n}{k-i}q^{n-k+i}(1-q)^{k-i}$. : If there are $k-i$ people above the pooling bid b^p and i goods are left, it means we have $n-k+i$ people with bids less than or equal to b^p. Portion of common value bidders among those would be $c(n-k+i) = n(1-\kappa)c + ci \to \infty$, then, in expectation there will be infinite number of common value bidders, each of which is bidding b^p. As a result, the price will be equal to b^p with probability 1.

Under the assumption that $\lim_{n\to\infty}\frac{k}{n} = \kappa$, we will give an asymptotic estimate of the above quantity using [Arratia, 1989]. The binomial probability can be estimated by putting $k = n\kappa$:

$$\binom{n}{n\kappa - i}q^{n(1-\kappa)+i}(1-q)^{n\kappa - i} \sim \frac{1}{\sqrt{2\pi\kappa(1-\kappa)}}\left[\frac{q\kappa}{(1-q)(1-\kappa)}\right]^i\left[\left(\frac{q}{1-\kappa}\right)^{1-\kappa}\left(\frac{1-q}{\kappa}\right)^{\kappa}\right]^n$$

in the sense that their ratios go to 1 as $n \to \infty$. Using this and plugging in the binomial term to see that Equation (1.4) is equivalent to

$$E\left[\text{Number of goods left}|b=b^p, s=s^p, w\right] = \frac{\sum_{i=0}^{\infty} i\left(\frac{q\kappa}{(1-q)(1-\kappa)}\right)^i}{\sum_{i=0}^{\infty}\left(\frac{q\kappa}{(1-q)(1-\kappa)}\right)^i} = \frac{\frac{q\kappa}{(1-q)(1-\kappa)}}{1-\left(\frac{q\kappa}{(1-q)(1-\kappa)}\right)} = \frac{q\kappa}{1-\kappa-q}$$

for large n. So,

$$P(\text{win}|p = b^p, b = b^p, w) = \frac{\kappa}{n(1-\kappa)} \frac{1 - cF(s^p|w) - (1-c)b^p}{cF(s^p|w)} \frac{cF(s^p|w) + (1-c)b^p}{1 - \kappa - (cF(s^p|w) + (1-c)b^p)}$$

Observe that because of MLRP$(F(s^p|1) < F(s^p|0))$, $P(\text{win}|p = b^p, b = b^p, 1) \geq P(\text{win}|p = b^p, b = b^p, 0)$ is going to be proved if the function

$$f(x) = \frac{x + (1-c)b^p}{1 - \kappa - (x + (1-c)b^p)} \frac{1 - (x + (1-c)b^p)}{x}$$

is decreasing in x around 0, where $x = cF(s^p|w)$. Taking the logarithm and derivative, we find:

$$\begin{aligned} \frac{f'(x)}{f(x)} &= \frac{1}{x + (1-c)b^p} + \frac{1}{1 - \kappa - (x + (1-c)b^p} \\ &- \frac{1}{1 - (x + (1-c)b^p)} - \frac{1}{x} \end{aligned}$$

$\Rightarrow \lim_{x \to 0} f'(x) = -\infty$, which means that by continuity of $F(s|w)$, there is an interval around $s = 0$ for which statement in the lemma is true. □

Lemma 5. *If $f(0|0) > f(0|1)$ and $f(1|0) < f(1|1)$, there is a unique type $s^p \in (0,1)$ such that*

$$l(p = b^p | s_i = s^p) = \lim_{s \to s^p+} l(p = \beta(s) | s_i = s^p)$$

$l(.|s_i = s^p)$ is the likelihood ratio and p is the auction price. Moreover, as $n \to \infty$, the interval $[0, s^p]$ stays as a nontrivial interval.

Proof. The bidding function after the pooling may have a jump or may continue continuously. In either case calculations below holds true. We can directly calculate $l(p = b^p|s_i = s^p)$ using the same calculation in the proof of Lemma 4 and assuming that n is large:

$$\begin{aligned} l(p=b^p|s_i=s^p) &= \frac{\sum_{i=0}^{k}\binom{n}{k-i}q_1^{n-k+i}(1-q_1)^{k-i}}{\sum_{i=0}^{k}\binom{n}{k-i}q_0^{n-k+i}(1-q_0)^{k-i}}\frac{f(s^p|1)}{f(s^p|0)} \\ &= \frac{q_1-\kappa}{q_1(1-\kappa)}\Big/\frac{q_0-\kappa}{q_0(1-\kappa)}\frac{f(s^p|1)}{f(s^p|0)} = \frac{q_1-\kappa}{q_0-\kappa}\frac{q_0}{q_1}\frac{f(s^p|1)}{f(s^p|0)} \end{aligned}$$

where $q_w = 1 - cF(s^p|w) - (1-c)b^p$.

$$\begin{aligned} \lim_{s\to s^{p+}} l(p=\beta(s)) &= \left(\frac{c(1-F(s^p|1))+(1-c)(1-b(s^p))}{c(1-F(s^p|0))+(1-c)(1-b(s^p))}\right)^{k-1}\left[\frac{cF(s^p|1)+(1-c)b(s^p)}{cF(s^p|0)+(1-c)b(s^p)}\right]^{n-k} \\ &\times\frac{f(s^p|1)}{f(s^p|0)}\frac{cf(s^p|1)+(1-c)}{cf(s^p|0)+(1-c)} \end{aligned}$$

After cancellation we see that these two functions are to be compared ;

$$\begin{aligned} g(s^p) &= \frac{q_1(s^p)-\kappa}{q_0(s^p)-\kappa} \\ f(s^p) &= \left(\frac{q_1(s^p)}{q_0(s^p)}\right)^k\left(\frac{1-q_1(s^p)}{1-q_0(s^p)}\right)^{n-k}\frac{cf(s^p|1)+(1-c)}{cf(s^p|0)+(1-c)} \end{aligned}$$

Calculate at $s^p = 0$;

$$g(0) = 1 > f(0) = \frac{cf(0|1)+(1-c)}{cf(0|0)+(1-c)}$$

because $f(0|1) < f(0|0))$ and,

$$g(1) = 1 < f(1) = \frac{cf(1|1)+(1-c)}{cf(1|0)+(1-c)}$$

because $f(1|1) > f(1|0)$. So there exists $s^p \in (0,1)$ such that $f(s^p) - g(s^p) = 0$. If we have binary signals, s^p will be unique.

For the last item, note that as $n \to \infty$, beliefs around $s^p = 0$ will tend to 0, as a result $\lim_{n\to\infty} f(s^p) = 0$, and we will have the condition $1-\kappa = cF(s^p|1)+(1-c)b^p$, which leaves a nontrivial interval for s^p. □

Pooling bid b^p makes the pooling bidder indifferent between bidding the pooling bid and a slightly higher bid . In other words, following equation implicitly gives b^p, if there exists one.

$$\begin{aligned}u(b = b^p|s) \quad &= P(1|s)P(p = b^p|1)P(\text{win}|1, s, p = b^p, b = b^p)(1 - b^p)\\ &-P(0|s)P(p = b^p|0)P(\text{win}|0, s, p = b^p, b = b^p)b^p\\ &= P(1|s)P(p = b^p|1)(1 - b^p) - P(0|s)P(b = b^p|0)b^p\\ &= u(b = b^p + \epsilon|s)\end{aligned}$$

When $b^p = 0$,

$$\begin{aligned}u(b = 0|s) \quad &= P(1|s)P(p = b^p = 0|1)P(\text{win}|1, s, p = b^p = 0, b = 0)\\ &< P(1|s)P(p = b^p|1) = u(b = \epsilon|s)\end{aligned}$$

While $b^p = 1 - \epsilon$(close to 1),

$$\begin{aligned}u(b = 1|s) \quad &= -P(0|s)P(p = b^p = 1 - \epsilon|0)P(\text{win}|0, s, p = b^p = 1 - \epsilon, b = 1)\\ &> -P(0|s)P(b = 1|0) = u(b = 1|s)\end{aligned}$$

if winning probabilities in both states are in open interval $(0, 1)$. As a result, it seems there always exists a pooling bid b^p that makes pooling bidders indifferent between bidding b^p and a slight overbid.

1.6 Equilibrium for Large n

Assume that private value bidders are distributed uniformly on $[0, 1]$. For common value bidders assume the following signal structure:

$$f(s|1) = \begin{cases} 2(1 - f_h) & \text{if } s \leq \frac{1}{2} \\ 2f_h & \text{if } s > \frac{1}{2} \end{cases}$$

$$f(s|0) = \begin{cases} 2(1-f_l) & \text{if } s \leq \frac{1}{2} \\ 2f_l & \text{if } s > \frac{1}{2} \end{cases}$$

For $f_h > f_l$ MLRP is satisfied.

$$F(s|1) = \begin{cases} 2(1-f_h)s & \text{if } s \leq \frac{1}{2} \\ 2f_h(s-1)+1 & \text{if } s \geq \frac{1}{2} \end{cases}$$

$$F(s|0) = \begin{cases} 2(1-f_l)s & \text{if } s \leq \frac{1}{2} \\ 2f_l(s-1)+1 & \text{if } s \geq \frac{1}{2} \end{cases}$$

Imagine for large n an equilibrium with a cutoff signal s^*, where common value bidders with signals $s > s^*$ bid $b(s) = 1$ and those below the cutoff bid $b(s) = 0$.

1.6.1 Existence of the cutoff

Assume that $cf_h > \kappa$...(R1). Let x_h and s satisfy

$$\kappa - c(1 - F(s|1)) = x_h$$

where $x_h \in [0, \kappa]$ and s is the candidate signal for the cutoff. So from among those who win an object, x_h of them is private value bidder and $\kappa - x_h$ of them is common value bidder in the high state. Then,

$$s = 1 - \frac{\kappa - x_h}{2cf_h} > 1 - \frac{\kappa - x_h}{2\kappa} = \frac{\kappa + x_h}{2\kappa} = \frac{1}{2} + \frac{x_h}{2\kappa} > \frac{1}{2}$$

from (R1), which means that s is a high signal. Use this to find,

$$x_l = \kappa - c[1 - F(s|0)] = \kappa - \frac{f_l}{f_h}(\kappa - x_h) \geq x_h$$

Let

$$(1-c)(1-v_h) = x_h$$

$$(1-c)(1-v_l) = x_l$$

So v_l and v_h are the values above which a private value bid wins an object depending on the state. As a result, they are actually the prices in the corresponding state. Then,

$$v_h = 1 - \frac{x_h}{1-c}$$

$$v_l = 1 - \frac{\kappa}{1-c} + \frac{f_l}{f_h}\frac{\kappa - x_h}{1-c}$$

For v_l and v_h to stay in $[0, 1]$ while x_h is changing in $[0, \kappa]$, we will need the parameter restriction $\kappa \leq 1 - c$...(R2). Consider now,

$$Q(x_h) = (1 - v_h)\frac{f_h}{f_h + f_l} - v_l\frac{f_l}{f_l + f_h}$$

$$= \frac{x_h}{1-c}\frac{f_h}{f_h + f_l} - \left(1 - \frac{\kappa}{1-c} + \frac{f_l}{f_h}\frac{\kappa - x_h}{1-c}\right)\frac{f_l}{f_l + f_h}$$

So $Q(x_h)$ is the expected payoff of the type s common value bidder(candidate cutoff). We need to find an x_h^* such that $Q(x_h^*) = 0$, which will give us the desired cutoff s^* through $\kappa - c(1 - F(s^*|1)) = x_h^*$. This is a necessary condition ensuring that there is no surplus left to those below s^* and those above it have a nonnegative expected payoff. Plug in $x_h = \kappa$ and $x_h = 0$,

$$Q(\kappa) = \frac{\kappa}{1-c} - \frac{f_l}{f_h + f_l}$$

$$Q(0) = -\left(1 - \frac{\kappa}{1-c} + \frac{f_l}{f_h}\frac{\kappa}{1-c}\right)\frac{f_l}{f_l + f_h}$$

(R2) gives $Q(0) \leq 0$. For $Q(\kappa) \geq 0$ we will need the additional restriction that $\frac{\kappa}{1-c} \geq \frac{f_l}{f_h + f_l}$...(R3). Therefore there is $x_h^* \in (0, \kappa)$ such that $Q(x_h^*) = 0$.

Note that (R2) and (R3) are satisfied if $\kappa\frac{f_h}{f_l} < 1 - c$...(R*). Since (R1) and R* are compatible, we can summarize the parametric restrictions with the following condition for the existence of above equilibrium:

$$\kappa < \min\{cf_h, \frac{f_l}{f_h}(1-c)\} \tag{1.5}$$

1.6.2 Checking Beliefs of Bidders

Remember that there are $\kappa - x_w^*(w \in \{h, l\})$ common value bidders winning an object, which is the same as the number of people above the cutoff s^*. Since they bid 1, there are no private value bidders above them. As a result the likelihood ratio of every bidder above the cutoff type is going to look like:

$$\left[\frac{(1-x_h^*)^{1-\kappa}(\kappa - x_h^*)^\kappa}{(1-(x_l^*)^{1-\kappa}(\kappa - x_l^*)^\kappa}\right]^n$$

The function $g(t) = t^\kappa(1-t)^{1-\kappa}$ is increasing for $t \in [0, \kappa)$ $x_l \geq x_h$, as a result this ratio is going to go to infinity as $n \to \infty$ as consistent with the behaviour of bidders above the cutoff bidder.

A similar calculation could be done for the bidders at 0, There are $1 - c + c(1 - F(s^*|1)) = 1 - cF(s^*|1)$ bidders above the cutoff bidder(and above every bidder below the cutoff bidder) in the high state, where s^* again is the same cutoff signal. As a result likelihood ratio will look like:

$$\left[\frac{(1-cF(s^*|1))^\kappa F(s^*|1)^{1-\kappa}}{(1-cF(s^*|0))^\kappa F(s^*|0)^{1-\kappa}}\right]^n$$

The function $h(t) = t^{1-\kappa}(1-t)^\kappa$ is increasing for $t \in [0, 1-\kappa)$ this time. We have $t^* = F(s^*|w) = x_w + c - \kappa \leq c \leq 1 - \kappa$ for $w \in \{h, l\}$ by the previos restriction made. MLRP gives $F(s^*|1) < F(s^*|0)$. As a result likelihood ratio will go to zero, as consistent with the behavior of bidders below the cutoff.

This exploration of a possible equilibrium paves a way for the construction of a similar equilibrium for finite n. Next we try that.

1.7 Equilibrium Conditions with Small n

We have seen that atoms are unavoidable in bidding strategies for the case of zero and uniformly distributed private values. However, what would an equilibrium look like if there is any?

Assume that $f_h = 1$, i.e, low signals are perfectly informative. Then for $0 \leq s \leq \frac{1}{2}$, $b(s) = 0$. We want to construct an equilibrium where bidding function strictly increases for $\frac{1}{2} \leq s \leq 1$. In the range where bidding function is strictly increasing, it will take the form implicitly determined by the functional equation in (1). We need to prove that it has a solution for an open neighbourhood of type space. This can be done using implicit function theorem for two variables.

However first lets first see that likelihood is strictly increasing after $s = \frac{1}{2}$. Taking the derivative of the likelihood in (1) and rearranging we get:

$$\frac{L'(s)}{nL(s)} = (1-\kappa)\frac{c^2[F(s|0)f(s|1) - F(s|1)f(s|0)]}{[cF(s|0) + (1-c)b(s)][cF(s|1) + (1-c)b(s)]}$$

$$+(1-\kappa)\frac{c(1-c)b'(s)[F(s|0) - F(s|1)] + c(1-c)b(s)[f(s|1) - f(s|0)]}{[cF(s|0) + (1-c)b(s)][cF(s|1) + (1-c)b(s)]}$$

$$+\kappa\frac{c^2[F(s|0)f(s|1) - F(s|1)f(s|0)]}{[c(1-F(s|0)) + (1-c)(1-b(s))][c(1-F(s|1)) + (1-c)(1-b(s))]}$$

$$+\kappa\frac{c(1-c)b'(s)[F(s|0) - F(s|1)] + c[(1-c)b(s) - 1][f(s|1) - f(s|0)]}{[c(1-F(s|0)) + (1-c)(1-b(s))][c(1-F(s|1)) + (1-c)(1-b(s))]}$$

MLRP gives $F(s|0) - F(s|1) > 0$. For the above signal structure we have $f(s|1) - f(s|0) = 2(f_h - f_l) > 0$ and

$$F(s|0)f(s|1) - F(s|1)f(s|0) = 2(f_h - f_l) > 0$$

for $s > \frac{1}{2}$. These inequalities make all above terms positive except for the second term in the numerator of last fraction. If we also have $b(s) \geq \frac{1-2cf_l}{1-c}$ for $s > \frac{1}{2}$, we are done, i.e the likelihood is strictly increasing after $\frac{1}{2}$. This is a strange condition though, especially when c is close to 1.

1.7.1 Existence of a Bidding Function

We need to prove that the functional equation

$$b = E\big[v|Y_b\big] = \frac{P\big(Y_b|1\big)}{P\big(Y_b|1\big) + P\big(Y_b|0\big)} = \frac{1}{1 + L(b,s)^{-1}}$$

where

$$L(s,b) = \frac{\big[cF(s|1) + (1-c)b\big]^{n-k}\big[1 - cF(s|1) - (1-c)b\big]^{k}[cf(s|1) + 1 - c]f(s|1)}{\big[cF(s|0) + (1-c)b\big]^{n-k}\big[1 - cF(s|0) - (1-c)b\big]^{k}[cf(s|0) + 1 - c]f(s|0)}$$

has a solution $b(.)$.

I will use the following form of Implicit Function Theorem:

Theorem 2 (*Simple Implicit Function Theorem*)**.** *Suppose that $\phi(x_1, x_2)$ is a real valued function defined on a domain D and continuously differeniable on the real domain $D^1 \subset D \subset \mathcal{R}^2$, $(x_1^0, x_2^0) \in D^1$ and*

$$\phi(x_1^0, x_2^0) = 0$$

Further suppose that

$$\frac{\partial\phi(x_1^0, x_2^0)}{\partial x_1} \neq 0$$

Then there exists a neighbourhood $V_\delta(x_2^0) \subset D^1$, an open set $W \subset \mathcal{R}^1$ containing x_1^0 such that

$$x_1^0 = \psi(x_2^0)$$

$$\phi(\psi(x_2^0), x_2^0) = 0$$

Furthermore,

$$\frac{\partial\psi(x_2^0)}{\partial x_2} = -\frac{\frac{\partial\phi(x_1^0,x_2^0)}{\partial x_2}}{\frac{\partial\phi(x_1^0,x_2^0)}{\partial x_1}}$$

In our case we have

$$\phi(b,s) = b - \frac{1}{1 + L(b,s)^{-1}}$$

The derivative is:

$$\phi_b(b,s) = 1 - \frac{L_b(b,s)}{\left(1 + L(b,s)^{-1}\right)^2}$$

where the partial derivative $L_b(b,s)$ can be calculated to be:

$$\frac{L_b(b,s)}{L(b,s)} = (n-k)(1-c)\left[\frac{1}{cF(s|1) + (1-c)b} - \frac{1}{cF(s|0) + (1-c)b}\right]$$

$$+k(1-c)\left[\frac{1}{1 - cF(s|0) - (1-c)b} - \frac{1}{1 - cF(s|1) - (1-c)b}\right] > 0$$

simply because $F(s|0) > F(s|1)$. We again ignored the term independent from n and k.

Chapter 2

EFFECT OF NON-PERFORMING LOANS ON LENDING, SECTORAL CREDIT COMPOSITION AND BANKING SECTOR MARKET CONCENTRATION

2.1 Introduction

Managing the performance of the asset portfolio is one of the main tasks a bank has to conduct carefully in order to have a strong profitability outlook and for resilience against potential stress in the financial markets and the economy. A certain amount of bad debt in the portfolio of a bank is an inevitable result of its business model. Disruptions in the payment capacity of economic agents frequently arise in a stochastically evolving economic and financial environment.

A non-performing loan (NPL) is defined as a loan in which the borrower is in default and has not paid the monthly principal and interest repayments for a specified period. NPLs are considered to be bad debt with a small probability of recovery; as a result, bank needs to take actions to relieve the effects on its balance sheet. The lender can take over the assets pledged as collateral to compensate part of the debt, sell the debt to asset management companies, -usually at a significant discount, or keep NPL on its balance sheet and follow the processes to deal with the debt internally.

Banks build profits essentially from the interest they charge on loans. However, this is not the only channel through which NPL have negative effects on bank's operations. NPLs may limit bank lending in several ways.

Profit and capital: The loss of income from the interest and/or principal amount leaves bank less resource and bad debt provisions paid from the existing profits or capital inhibit bank's lending capacity.

Funding costs: High NPLs increase the uncertainty regarding the capital position of the bank and therefore limit its access to financing. This in turn drives the lending rates up and slows down the credit growth.

Signal: High NPLs may serve as a signal to banks, revealing the deteriorating conditions in real economy. Banks as a result may be less willing to supply credit due to concerns about the future payment capacity of agents in the economy.

The management of a bank could have following considerations on its lending policy after registering an increase in its bad debt portfolio:

- They could simply have less resources to issue further loans due to the costs borne out of NPLs, resulting in a tendency to decrease the loan portfolio,

- They could choose to take a stricter stance on the supply of loans, due to worsening expectations on the future of the economy, despite the relative abundance of resources.

- They could decide to decelerate loan growth to take a more cautious stance, by considering the past bad management of credit risk,

- They could accelerate the loan growth to make up for the realized losses (gambling out effect),

- They could just continue the business as usual, with no effect on the loans.

If banks choose to focus on strengthening their balance sheets and decrease their lending in the face of an increase in NPL, slowdown in economic growth is bound to follow. During periods when a chain of firms defaults and the amount of bad loans in the economy starts to increase, a feedback mechanism takes hold and deepens the business cycle: associated credit contraction leads to further worsening in asset quality outlook, putting even more pressure on the economy. Therefore, it is important to understand the response of bank lending to a negative shock to NPLs. The policies aimed at reducing the negative effects of NPL on the economy could be designed and implemented once the nature of the linkages are better understood.

From the perspective of a particular economic sector, like construction, manufacturing, agriculture, etc. sector specific NPL shocks could deepen the business cycle through similar feedback mechanisms. For example, an exogenous rise in the NPLs of construction sector may lead to a sharp increase in risk perception towards the sector. Construction firms in turn may face an indiscriminate credit shortage regardless of their risk profile, resulting in further deterioration in financial outlook of the sector. In this sense, a negative irrational bias on behalf of banks could lead to inefficiencies and harm the healthy parts of the sector. Understanding the nature of these links is important for designing a policy aimed at ameliorating negative effects of NPLs.

The main purpose of this study is to consider the effect of an increase in NPL of banks on the level and distribution of loans extended in the following period. Our first set of results reveals that rise in the NPLs have a persistent negative effect on the bank loans in the five-year period that follows the NPL shock. We show that response of public banks to NPL shocks is similar to that of the private banks before 2016, however, the nature of the link between lending and NPL changed for public banks after 2016. Second, we use data on economic sector level to analyze impact of a sector-specific NPL shock on the loans provided to the given sector. We show that the share of outstanding cash loans contracts in response to the rise in a particular sector's NPL ratio. The five-year duration of the negative effect is in line with the bank-level results. We observe that short-term loans are relatively unaffected while negative effect on the medium to long-term loans lasts almost for seven years after the NPL shock. Decrease in competition in any sector is undesirable as it leads to dampened innovation, unhealthy price formations, inefficiencies and productivity slowdown. In the third part of the study, we analyze the impact of a shock to the total NPL ratio on the market concentration of the banking sector and on the distribution of sectoral cash loans. We find that market concentration in the banking sector increases with the rise in the NPL ratio. This is a novel channel through which NPLs could potentially have an impact on the structure of the economy. Rapid resolution of NPLs and a well-measured push supporting the smaller banks in their struggle to deal with bad debt could save the economy from the long-lasting consequences of decreased competition in banking sector.

Our study contributes the empirical literature on the interaction between credit growth and non-performing loans. We exploit bank level data using panel VAR methodology to analyze the response of bank lending to NPL and show in detail how the size, ownership and capital structure of banks characterize their behavior. Then we use sectoral level loan data to understand how the share of loans received by economic sectors evolve in response to exogenous NPL shocks. We also analyze how the bank response to NPL changes at different quantiles of the bank credit distribution, using panel quantile regression. Results show that when the credit is already at a higher level, bank tightening in the face of NPL shock is more severe. Lastly, we examine how NPL interacts with concentration indices for bank level loans and loans to economic sectors. One way our paper differs from other related work is that we use bank level panel VAR analysis to understand how the banks with different characteristics respond differently to NPL shocks. Moreover, there is no other work we know of that uses sectoral level loans to demonstrate how supply of loans to each sector is affected by sectoral NPL shocks. Linkages between NPL and concentration of banks/sectors are also novel contributions to the literature.

Policy Implications

- The main result that NPL shocks lead to credit tightening driven by long term loans has implications for policies whose purpose is to reduce macroeconomic fluctuations. In stressful periods when a sector or the economy as a whole experience a payment capacity problem, policy makers could provide well-measured support to the problematic part of a sector if it can be resuscitated in the future, thereby sustaining the natural functioning of the system as a whole.

- The discrepancy of public vs. private bank behavior in the face of NPL shocks is already the result of a policy choice, and is understood as a method that a government uses to intervene the real economy.

- More subdued and quicker response of small size banks to NPL shocks may imply that in periods of asset quality stress, it could be the larger banks that needs support if the purpose is to rebalance the credit market and smooth out the business cycle. Also, smaller banks seem to have a range of different reactions to NPL, making them a more difficult group to implement a single supportive policy.

- Interaction of bank response to NPL with the liquidity and capital ratios imply that these variables do explain part of the mechanism that leads banks to tighten credit. As a result, policies that support the capital and liquidity could provide some relief to banks and indirectly to the problematic sectors of the economy.

- More pronounced response of banks to NPL shock when the credit level is already high means that macroeconomic down-cycles due to NPL feedback effects could be more severe if the down-cycle succeeds a high credit growth period. As a result, NPL resolution mechanisms clearly have more significant role in such recessionary periods.

- Lastly, increase in the banking sector concentration of Turkey in recent years seems to be due to public banks' market share gains. We see that the market share gains of public banks did not increase the concentration in private banks, on the opposite, it decreased the concentration. Moreover, the NPL is a driver of banking sector concentration when the public banks are included.

2.2 Literature Review

There has been a surge in the number of studies analyzing the determinants and effects of non-performing loans (NPL) after the great financial crisis of 2008. Studies that focus on the determinants of NPL obtain similar results: ([Bofondi and Ropele, 2011]; [Louzis et al., 2012]; [Vogiazas and Nikolaidou, 2011]; [Farhan et al., 2012]; [Klein, 2013]; [Messai and Jouini, 2013]; [Bruno et al., 2015]). Research reveals that there are two different categories of determinants: bank specific determinants (size, capitalization, funding level and efficiency) and macroeconomic determinants (GDP, inflation rate, unemployment and investment rates).

There are also older discussions of the issue: [Keeton et al., 1987] studied non-performing loan determinants in the USA during the period 1979 - 1985, and found that the crises in the agriculture and energy sectors were the main determinants of the worsening in NPL. [Sinkey and Greenawalt, 1991] and [Gambera et al., 2000] also studied the determinants of NPL in the USA and showed the important effects of macroeconomic variables on the trend of NPL.

[Us et al., 2016] analyzes the determinants of non-performing loans in the Turkish banking sector before and after the global crisis. Estimation results suggest that the determinants of non-performing loans have changed after the crisis. Non-performing loans are mostly shaped by bank-specific factors before the crisis, whereas bank-specific factors have a reduced effect after the global crisis.

Determinants of lending behavior in the Turkish banking system has also been studied: [Tomak, 2013] finds a significant relationship between NPL and bank lending behavior in State owned banks and NPL show a negative impact on the growth of total loans. Paper employs macroeconomic determinants like gross domestic product and lending rate as the explanatory variable to examine the determinants of bank lending in Turkey from year 2003 to year 2012 using a sample of 18 banks (3 state and 15 privately owned). In the paper, the negative effect of NPL on lending behavior is explained by the unfavorable macroeconomic conditions constraining the banks' lending capacity. However, there has been no effort to disentangle the effect of capital decisions and loan loss provisions from macro-variables and signaling effect of existing NPL stock in this paper or any other paper, to the knowledge of the author.

The studies on the relationship between credit growth and bank risk-taking has a long history ([Furlong and Keeley, 1989]; [Calem and Rob, 1999]; [Gonzalez, 2005]). These studies find that incentives to increase asset risk decline as capital increases. Before the financial crisis, banks had a higher risk appetite and were willing to lend at more risk. With the financial crisis, NPL started to grow rapidly, which led banks to reduce their risk taking and their lending behavior. [Bouvatier and Lepetit, 2012] analyze the effects of loan loss provisions on growth of bank lending and do international comparisons. They find that backward-looking provisioning systems exacerbate banks' lending fluctuations in both developed and emerging countries, but with a stronger impact for emerging countries. [Michelangeli and Sette, 2016] study the effect of bank capital on the supply of mortgages. They find that higher bank capital is associated with a higher likelihood of application acceptance and lower offered interest rates; banks with lower capital reject applications by riskier borrowers and offer lower rates to safer ones. They also show that the effect of bank capital is stronger when capital is low. [Cucinelli, 2015] asks whether the deterioration of banking loans during recent years has any effect on bank lending behavior of the Italian banks. They also investigate whether commercial and cooperative banks have a different behavior during financial crisis. They pose the following hypotheses:

- An increase in bank credit risk in period $t-1$ leads banks to supply less credit;
- This behavior differs for commercial and cooperative banks.

Paper's findings show a negative impact of credit risk on bank lending behavior, with regard to both credit risk measures: the non-performing loans and the loan loss provision ratio.

[Matteo Accornero, 2017] employs an extensive loan-level dataset to analyze the impact of NPLs on the supply of bank credit to real sector firms in Italy between 2008 and 2015. They use the 2014 Asset Quality Review on NPLs in Italy to identify an exogenous shock to the NPL ratios. Their findings imply that NPLs do not have a meaningful effect on bank lending when adjusted for the worsening of demand by firms. They postulate that only the exogenous shocks to NPL induces a dampening in lending.

[Huljak, 2020] estimates a panel Bayesian VAR model with ten variables and for twelve euro area countries for the period between the first quarter of 2006 and the third quarter of 2017 to understand the effect of NPL on banking sector variables and the macroeconomy. Because of the sample size, they assume a hierarchical prior that allows for country-specific coefficients and use Choleski decomposition to identify the model. Their impulse response analysis shows that exogenous shock to the change in NPL ratios decrease lending, dampens real GDP growth and leads to a fall in residential real estate prices. FEVD analysis to shows that change in NPL ratio explain a large share of the variance of the bank and macro variables, especially for countries with high NPL ratios.

[Bredl, 2022] investigates channels through which the stock of NPL of euro area banks affects lending rates on new loans. More precisely, it looks for an effect that extends beyond losses caused by that stock which have already been incorporated into the banks' capital positions. The results of the paper indicate that a higher stock of net NPLs is associated with higher lending rates, whereby there are indications that this relation tends to be offset by loan loss reserves. Paper also questions whether NPL affects funding costs and interest rate pass through of banks. Results suggest that there is no strong link between NPL stock and funding costs or interest rate pass through.

[Özbekler, 2019] studies the credit portfolio diversification of Turkish banks and their asset quality. The effects of sectoral loan concentration on profitability and credit risk indicators are examined using Arellano-Bond Dynamic Panel Generalized Method of Moments. The results show that sectoral credit concentration index has a positive and significant effect on credit risk.

[Bertay et al., 2015] studies how public banks react to business cycle fluctuations using a sample of 1633 banks from 111 countries over the 1999–2010 period. Methodology in the paper is to use Arellano-Bond dynamic equations and employ system GMM; taking lagged first differences as instruments. The use of system GMM to deal with endogeneity is similar to our approach, however, we also include impulse response functions for variables of interest. They demonstrate that public bank lending is less pro-cyclical than private banks, especially in countries with higher index of government effectiveness. Further, they show that public banks in high-income countries extend credit in a counter-cyclical fashion. They find that on the liabilities side of the balance sheet, public banks increase their non-deposit liabilities less than the private banks during economic upswings. Their results suggest a stabilizing influence of public banks for the macroeconomy and financial stability. The results in this paper aligns with our finding that public banks behave differently from private banks depending on the nature of the period, and act as a stabilizer during stressful times.

[Klein, 2013] analyzes the determinants and macroeconomic effects of non-performing loans (NPLs) in Central, Eastern and South-Eastern Europe (CESEE) in the period of 1998–2011 using dynamic panel methodology. Examination of the feedback effects from NPL to macro-variables reveal strong macro-financial linkages in the region. [Vuslat, 2020] analyzes the interaction of NPL and other major bank level variables using panel VAR for Turkish banking sector data. She documents the changing dynamics of the feedback effects between NPL and other variables after the global financial crisis. Although her methodology is similar to ours, our focus is on the impact of NPL on loans, sectoral credit distribution and bank concentration.

2.3 Methodology and Data

In the first two parts of this study, we use panel VAR to explore feedback effects between endogenous panel variables, while for the last part, we employ traditional VAR framework to understand the relationship between macro-variables we are interested in.

Panel VAR allows us to exploit the bank level data and sectoral level data and combine results from two separate panels to get a wider range of insights on the relationship between NPLs and loans. In order to implement panel VAR using STATA, we refer to Abrigo and Love, 2015, which relies on techniques developed by [Holtz-Eakin et al., 1988]. STATA package, which is publicly available, includes Granger causality tests [Granger, 1969] and conducts optimal moment and model selection following [Andrews and Lu, 2001] see Appendix C.

We consider a k-variate panel VAR of order p with panel-specific fixed effects represented by the following system of linear equations:

$$\begin{aligned} \mathbf{Y}_{it} &= \mathbf{Y}_{it-1}\mathbf{A}_1 + \mathbf{Y}_{it-2}\mathbf{A}_2 + ... + \mathbf{Y}_{it-p+1}\mathbf{A}_{p-1} + \mathbf{Y}_{it-p}\mathbf{A}_p + \mathbf{u}_{it} + \mathbf{e}_{it} \\ & i \in \{1,2,3,...,N\}, t \in \{1,2,3,...,T\} \end{aligned} \tag{2.1}$$

where $\mathbf{Y}_{it}$ is a vector of endogenous variables, $\mathbf{u}_{it}$ and $\mathbf{e}_{it}$ vectors of fixed effects and idiosyncratic errors, respectively.

Estimating Eq. (1) using ordinary least squares (OLS) would lead to inconsistent and biased results because of panel fixed effects and time effects. Taking the first difference of the above equation does not solve the inconsistency problem either, since the panel fixed effects are correlated with the lag of the independent variable ([Arellano and Bond, 1991]). As a solution, [Holtz-Eakin et al., 1988] creates instruments using observed realizations, with missing observations substituted with zero. Then the model is estimated as a system of equations (system GMM). GMM is a commonly used method when there are no strictly exogenous variables or instruments ([Doytch and Uctum, 2011]). Panel fixed effects are removed using forward orthogonal deviation or "Helmert transformation", instead of ordinary mean differencing (i.e. expressing all variables as deviations from their full sample period means). This way, the bias coming from the correlation of fixed effects and regressors due to the existence of lagged dependent variables is eliminated. Helmert transformation removes the forward mean, i.e. the mean of all future observations available in the sample and preserves the orthogonality between transformed variables and lagged regressors. Since the data we use have a relatively large time dimension, use of lagged variables as instruments does not create small sample problems.

In the first section, panel variable is the banks and the period covers December 2002-December 2020. We have 33 banks for which loan and NPL data on the given period is reported (N= 33, T= 73). These banks cover 91 percent of the sector assets as of December 2020. We have Consumer Price Index (CPI) and Industrial Production Index (IP) and five year Credit Default Swap Spread (CDS) of Turkey as macro-variables. Bank-level data is from Central Bank of Republic of Turkey (CBRT), CPI and IP are retrieved from Turkish Statistical Institute (TUIK) and

CDS is from Bloomberg Terminal.

In the second section, economic sectors according to the classification of Banking Sector Regulation and Supervision Agency (BRSA) sectoral loan composition are used as a panel variable. Sectoral distribution for short-term loans, medium to long-term loans, performing loans, non-performing loans, total loans and non-cash loans are publicly available on Monthly Banking Sector Data section of BRSA website. The list of the sectors in the classification is given in Appendix A. There are 22 main sectors and 47 subsectors. Total number of distinct sectors is 60. Out of these sectors, we take 27 sectors with loan share of 1 percent or more as of December 2020, to get a result that represents the whole sector with respect to loan volume. The subsample we take covers more than 95% of the sector for each loan type. We repeat the analysis for 60 subsectors for completeness. Quarterly sectoral loan data covers December 2004-December 2020 ($N = 27, T = 65$).

All the panel variables are trimmed using `winsor2` command to smooth out extreme values in first percentile. We run panel VAR, calculate impulse response functions (IRF) using Choleski decomposition and evaluate the results in the sections below. Panel cointegration tests, lag selection tests, Granger causality analysis and Forecast Error Variance Decomposition (FEVD) are given in Appendix D.

In the third section, banking sector asset concentration is calculated using Herfindahl-Hirschman Index (HHI) with panel data from first and second parts. Then classical VAR techniques are implemented to document endogenous interrelations between non-performing loans, concentration index and CDS.

2.4 Empirical Results and Discussions

In this section, we describe the model variables in detail and discuss the empirical results.

2.4.1 Response of Bank Loans to NPL

In the first part of the analysis, we investigate the relationship between NPL in bank balance sheets and the loan stock. For this purpose, we take first the NPL rate[1] ($NPLr$) and total loans/total assets ratio ($LoansAsset$) for each bank and time period with CPI (CPI) and IP (IP) as macro-variables. Impact of NPL on lending shows up with a delay, however, when credit increase, there is an instantaneous negative mechanical effect on NPL. We use 6 lags of the variables as instruments in system GMM estimation. In order to check for robustness and to get a quantitative measure of the link, we repeat the analysis using the CPI adjusted outstanding loans and NPL ($realLoan$ and $realNPL$). In order to be able to interpret the coefficients of panel VAR estimations, relevant variable combinations should be cointegrated. Variable combinations described above are indeed cointegrated according to three alternative tests [2]. Model selection tests determine optimal lag length to be $p = 1$.

Table 2.1: Panel VAR Estimation Results

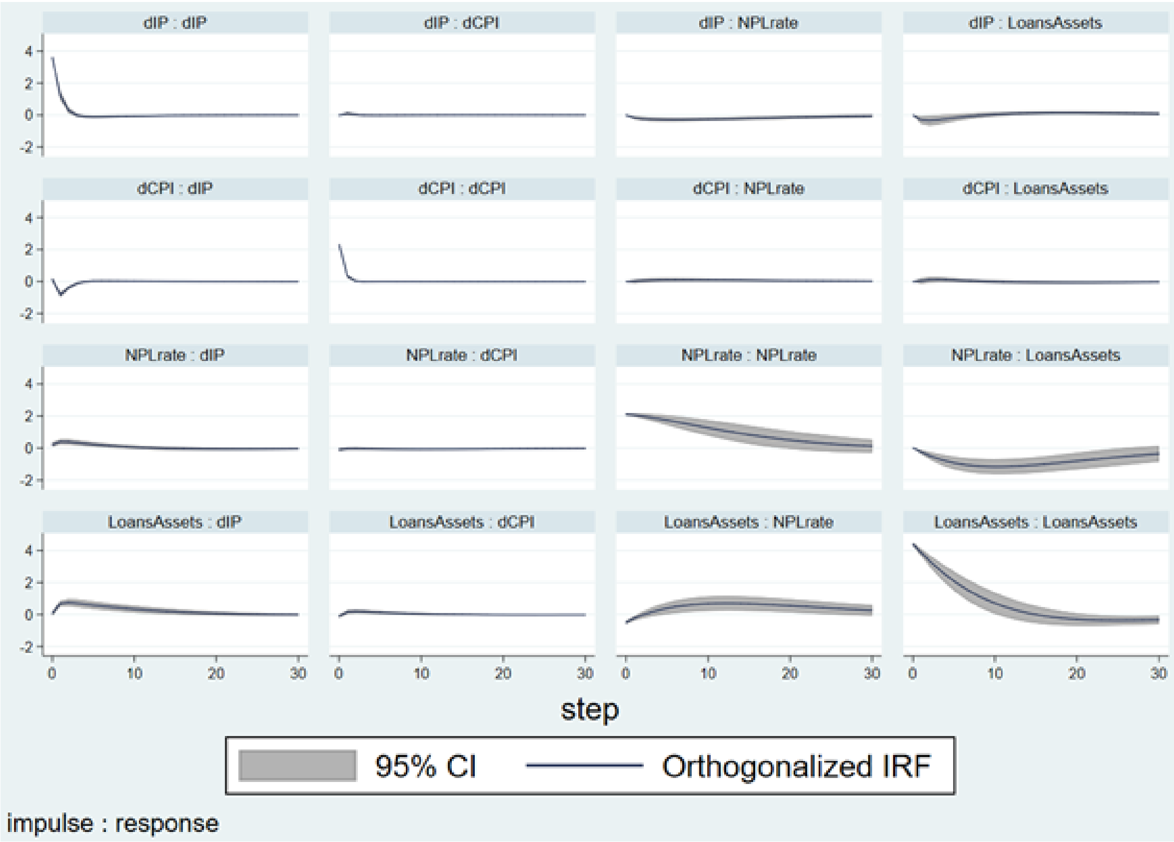
	Dependent Variables			
Independent Variables	$LoansAssets$	$NPLr$	ΔIP	ΔCPI
$LoansAssets_{t-1}$	0.877	0.059*** (0.011)	0.158*** (0.024)	0.039*** (0.014)
$NPLr_{t-1}$	-0.106*** (0.030)	0.984	0.135*** (0.028)	-0.016 (0.018)
ΔIP_{t-1}	-0.083** (0.033)	-0.045*** (0.013)	0.332***	0.028* (0.015)
ΔCPI_{t-1}	0.022 (0.041)	0.009 (0.022)	-0.368*** (0.034)	0.143

Note: $*p < 0.1$ $**p < 0.05$ $***p < 0.01$

[1]NPL rate is defined as the ratio of nonperforming loans to total loans.

[2]`xtcointtest` embedded in STATA implements `kao, pedroni, westerlund` tests, each of which work differently, but allows us to come to the same conclusion: the panels are cointegrated.

Figure 2.1: Impulse Response Functions for NPL Rate and Loans/Assets Ratio



Estimation results suggest that an exogenous increase in $NPLr$ leads to a decline in the level of *LoansAssets* of banks for approximately 7 years, with peak impact being reached in 3 years (Figure 2.1). 1 percent shock to the bank's $NPLr$ have a 0.1% negative effect on *LoansAssets* ratio in the immediate next quarter. On the other side of the feedback effect, 1 percent increase in *LoansAssets* ratio increases the $NPLr$ by 0.05 percent in the next quarter, with peak response reached in 3 years (Figure 2.1). FEVD analysis shows that $NPLr$ explains approximately 6% of the variation in *LoansAssets* and vice versa in a 10 quarter horizon (Table D.1). The duration of the response shows that our model captures an element beyond the mechanical denominator effect of loans on $NPLr$. We observe that CPI does not respond to $NPLr$, however, *LoansAssets* ratio has a positive and significant effect on CPI and IP, in line with the intuition. Granger-causality test results are consistent with these findings (Table E.1).

2.4.1.1 Response of Bank Loans to NPL: CPI Deflated NPL and Loans

In order to test for robustness and get the magnitude of the effect of NPLs on the level of loans, we run panel VAR with **real level of loans** and **real NPL level**. For this, we take the initial amounts (as of December 2002) for loans and NPL and increase them by real growth rate; calculated as nominal TL-equivalent growth adjusted for CPI (using Fisher formula) each quarter. As a result, we get real amounts of loans and NPLs for each bank and each time period.

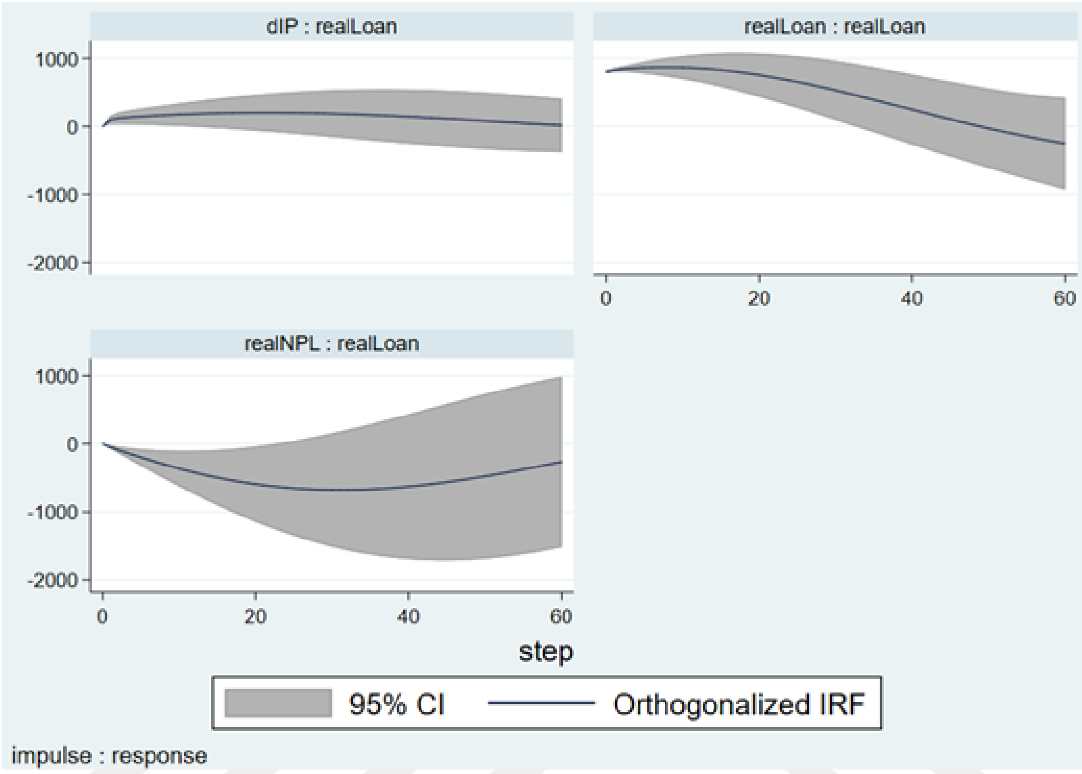
Table 2.2: Panel VAR Estimation Results for Real Loan and Real NPLs

	Dependent Variables		
Independent Variables	$RealLoan$	$RealNPL$	ΔIP
RealLoan t-1	1,000	0.003*** 0.001	0.000*** 0.000
$RealNPL_{t-1}$	-0.690*** 0.178	0.976	0.000** 0.000
ΔIP_{t-1}	32*** 8	-3.9*** 0.858	0.526

Note: $*p < 0.1 \quad **p < 0.05 \quad ***p < 0.01$

Panel VAR estimation results reveal that a 1 unit shock to real NPL level results in 0.5-0.6 unit of decrease in the next quarter's real loans outstanding. The coefficient is significant and the duration of the effect is longer than in the impulse response analysis with $LoansAssets$ ratio and $NPLr$ (Table 2.2 and Figure 2.2). FEVD analysis for real variables shows that $RealNPL$ explains 2,2% of the variation in $realLoan$ for 10 quarter horizon, while on the other side of the feedback effect, $realLoan$ explains approximately 2,6% of the variation in $realNPL$. Granger-causality test results confirm the strong links between $realLoan$ and $realNPL$ (Table E.2).

Figure 2.2: Response of Real Level of Loans to Real NPL Level



2.4.1.2 Response of Bank Loans to NPL: Public Banks vs. Private Bank

There was a coup attempt that took place in Turkey in July of 2016. Policies stimulating the growth of the economy were implemented following this date, changing the lending dynamics of public banks significantly. In this section, we compare the response of public and private banks to an increase in NPL, taking into account the phase shift that took place in 2016. We consider five public banks and run panel VAR separately for both periods and for the whole period. The coefficient of NPL rate for different regressions are given in the table below for comparison. Endogenous variables used in the estimations are $NPLr$, $LoansAssets$, CPI and IP as before. Panel cointegration tests and other statistics are presented in Appendix B.

Note that the sign of the response of public bank lending to NPL rate shock is positive for 2016-2020, although it has negative sign before 2016 and for the whole period. This reflects the fact that public bank lending became more of a policy instrument and NPL shocks did not deter public banks from lending after 2016. For

Table 2.3: Panel VAR Estimation Results of the Coefficient of NPL Rate

	Dec.2002-Dec.2015	Jan.2016-Dec.2020	Dec.2002-Dec.2020
Public Banks	-0.065 0.020	3,629 0.302	-0.142 0.025
Private Banks	-0.104 0.030	-2,222 0.389	-0.100 0.033
Sector	-0.089 0.027	-2,151 0.376	-0.106 0.030

Note: All the coefficient estimates are significant.

the private banks on the other hand, loans decreased following an NPL shock before and after 2016.

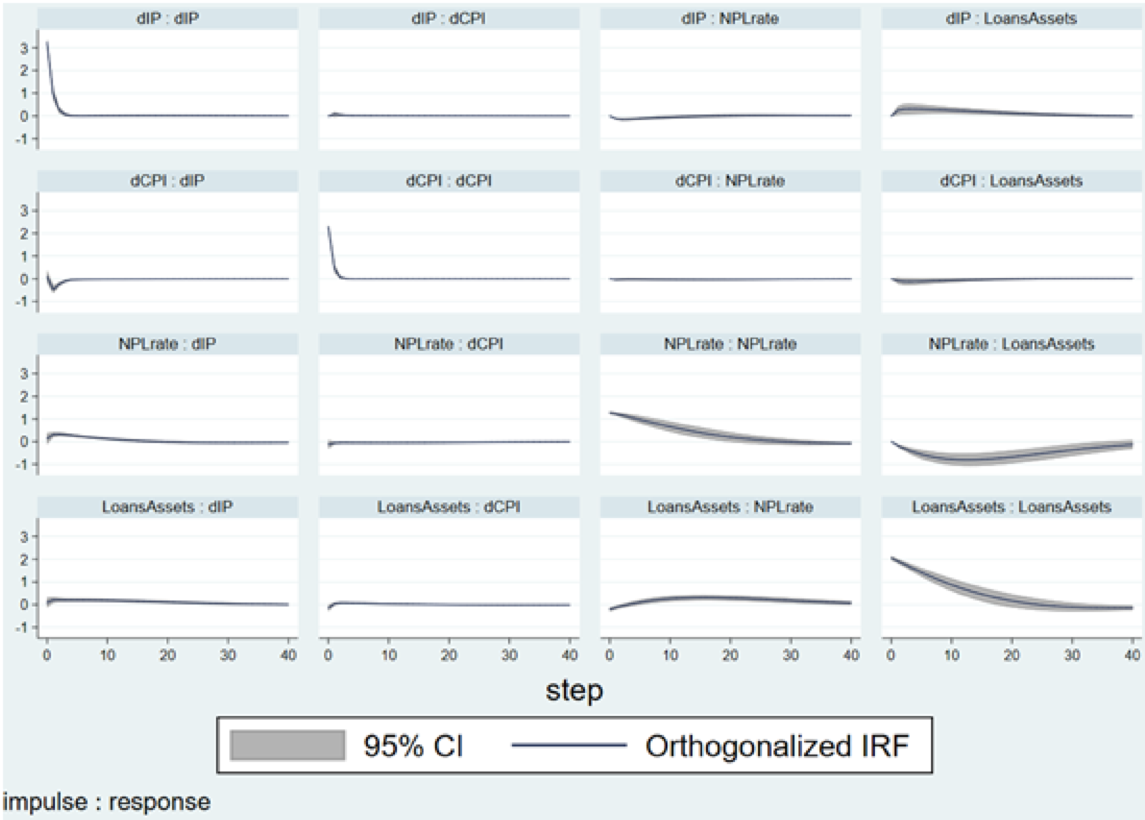
2.4.1.3 Response of Bank Loans to NPL: Big Banks vs. Small Banks

Size of a bank is determines the outline of how the main banking operations are conducted. Smaller banks tend to have a less diversified portfolio of customers and more constraints on their capital and funding structure. Bigger banks in general have more market power and more capacity to manage risk. As a result, shocks to the asset quality of smaller banks could lead to different implications for credit outlook than larger banks.

In the next step of the analysis, panel of banks is divided into two groups with respect to their asset size. At each time period, the banks with asset share of more than 2 percent in the sector are considered as big banks, with remaining banks categorized as small banks. There are 13 banks categorized as big versus 33 banks categorized as small at at least one time period. A bank may switch category from time to time.

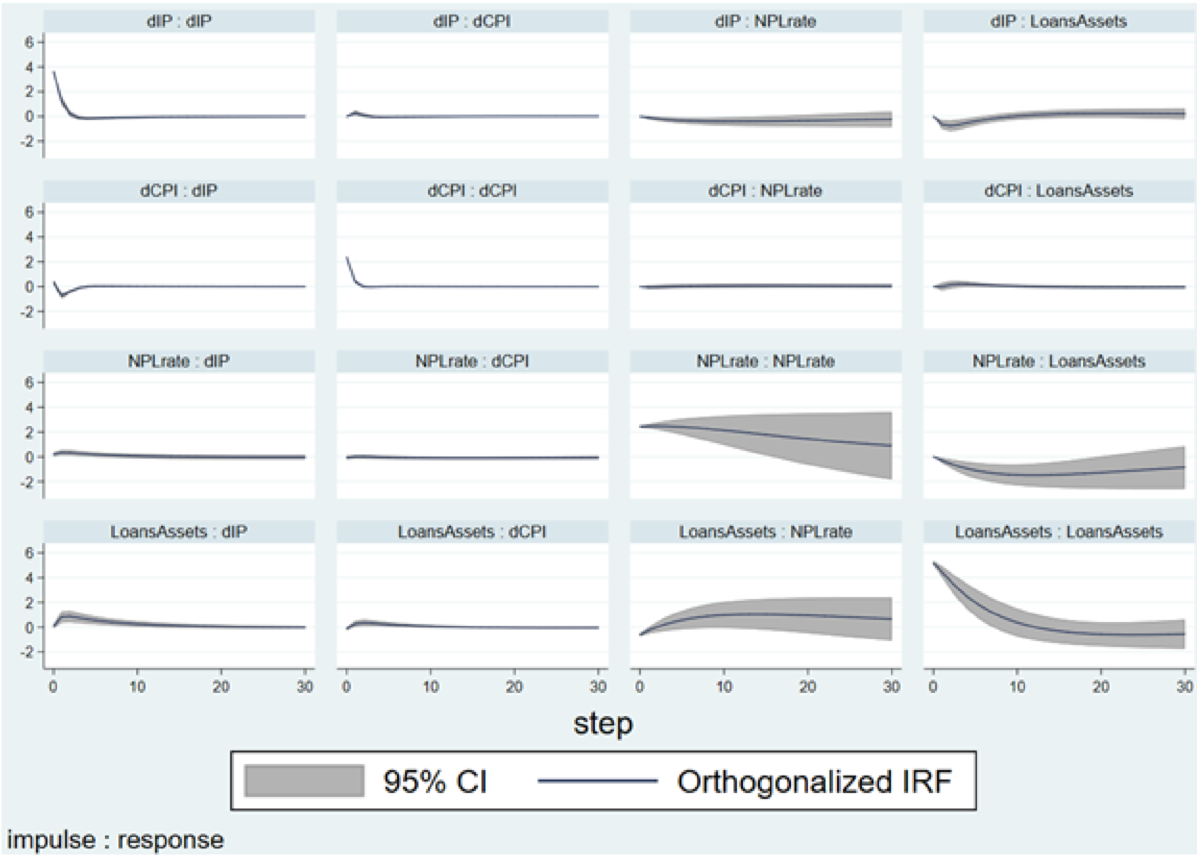
Figure 2.3 below shows the impulse responses for big banks. For big banks, the negative effect of NPL on credit lasts longer than the baseline model (compare with Figure 2.1).

Figure 2.3: Impulse Response Functions of Big Banks



For smaller banks, the recovery from the effects of NPL is quicker and the magnitude is smaller. Since there is more variation in behavior among smaller banks, the confidence bands for their impulse response function estimations are wider.

Figure 2.4: Impulse Response Functions of Small Banks



Coefficient estimates for panel VAR estimations are provided below.

Table 2.4: Panel VAR Estimation Results for Big Banks

	Dependent Variables			
Independent Variables	$LoansAssets$	$NPLr$	ΔIP	ΔCPI
$LoansAssets_{t-1}$	0.9180	0.038*** (0.005)	0.094*** (0.024)	0.032*** (0.011)
$NPLr_{t-1}$	-0.133*** (0.020)	0.964	0.197*** (0.028)	-0.029 (0.020)
ΔIP_{t-1}	-0.0710*** (0.024)	-0.038*** (0.007)	0.293***	0.021*** (0.019)
ΔCPI_{t-1}	0.036 (0.029)	0.010 (0.010)	-0.217*** (0.034)	0.143

Note: $*p < 0.1 \quad **p < 0.05 \quad ***p < 0.01$

Table 2.5: Panel VAR Estimation Results for Small Banks

	Dependent Variables			
Independent Variables	$LoansAssets$	$NPLr$	ΔIP	ΔCPI
$LoansAssets_{t-1}$	0.859	0.068*** (0.002)	0.158*** (0.041)	0.055** (0.025)
$NPLr_{t-1}$	-0.097*** (0.039)	1,014	0.103*** (0.038)	-0.038 (0.025)
ΔIP_{t-1}	-0.180*** (0.049)	-0.029 (0.021)	0.336***	0.075*** (0.024)
ΔCPI_{t-1}	0.025 (0.063)	-0.012 (0.032)	-0.365*** (0.054)	0.150

Note: $*p < 0.1$ $**p < 0.05$ $***p < 0.01$

2.4.1.4 Response of Bank Loans to NPL: Liquidity and Capital

Banks shape their lending strategies in conjunction with their liquidity and capital structure. It is natural to expect that a liquidity-tight bank tends to react more to negative developments in the system. Also, the capital structure could determine how much room the bank has to extend more credit. A pre-requisite for comfortable lending by bank is adequate capital buffers. We analyze in this section how the liquidity and capital ratios of banks interact with lending variables. We use liquidity-asset[3] and equity-asset ratios as proxies for liquidity coverage and capital adequacy ratios respectively.

[3]We take the sum of cash, free correspondent placements and free securities for bank liquidity.

Table 2.6: Panel VAR Estimation Results with Liquidity-NPL Interaction Term

	Dependent Variables				
Independent Variables	$LoansAssets$	$NPLr$	$NPLr * Liquidity$	ΔCPI	ΔIP
$LoansAssets_{t-1}$	0.794	0.050**	0.881	0.270*	0.119**
		(0.023)	(1.25)	(0.015)	(0.017)
$NPLr_{t-1}$	-0.269***	1,084	0.9726***	0.114***	0.128***
	(0.030)		(3.04)	(0.035)	(0.028)
$NPLr * Liquidity$	0.005***	-0.032**	0.619	0.0017	-0.001**
	(0.052)	(0.050)		(0.0008)	(0.0005)
ΔCPI_{t-1}	0.486***	0.142***	0.3905*	0.044	-0.289***
	(0.011)	(0.036)	(2.00)		(0.0269)
ΔIP_{t-1}	0.187***	-0.421***	-24.41***	0.449***	0.393
	(0.037)	(0.027)	(1.68)	(0.244)	

Note: $*p < 0.1$ $**p < 0.05$ $***p < 0.01$

The positive and significant coefficient estimation of $NPL * Liquidity$ suggests that banks with higher liquidity to assets ratio could afford to react less to a rise in NPL. Similarly, interaction of equity with NPL indicates that higher equity eliminates some of the NPL induced credit tightening.

Table 2.7: Panel VAR Estimation Results with Equity-NPL Interaction Term

	Dependent Variables				
Independent Variables	$LoansAssets$	$NPLr$	$NPLr * Equity$	ΔCPI	ΔIP
$LoansAssets_{t-1}$	0.906	0.0172 (0.0121)	-2.38*** (0.86)	0.068*** (0.014)	0.119*** (0.017)
$NPLr_{t-1}$	-0.194*** (0.0465)	1,112	Oca.43 (1.85)	0.062** (0.031)	0.252*** (0.035)
$NPLr * Equity$	0.003** (0.0009)	-0.030*** (0.0007)	0.851	-0.0017*** (0.0005)	-0.003** (0.0006)
ΔCPI_{t-1}	0.06 (0.045)	0.554** (0.022)	19.35*** (1.70)	-0.218	-0.36*** (0.024)
ΔIP_{t-1}	-0.236*** (0.0359)	0.119*** (0.016)	9.92*** (1.05)	0.063*** (0.015)	0.366

Note: $*p < 0.1$ $**p < 0.05$ $***p < 0.01$

2.4.2 Response of Sectoral Credit to NPL

We change the perspective in this section and analyze the effect of an economic sector's NPL rise on its share in performing loans. In section 2.4.1 we have seen that when the asset quality of a bank worsens, the decrease in the loans follows. In this section, we will see that when the NPL rate of a sector rises, the share of that sector in the total credit of banking sector decreases. The contraction in the credit share of the sector could stem from the bank's perception regarding the riskiness and profitability of the distraught sector, but it could also stem from the fall in demand. Unfortunately, we don't have the sectoral level loan spread to match the banks' lending appetite on specific sectors, so here we cannot disentangle the demand and supply factors. However, analysis of the effect of sector specific NPL on sector credit is useful because not only the results here enhance and verify the conclusions of section 2.4.1, but also it tells us about the relationship between the credit risk and credit distribution on sectoral level.

Variables of interest: NPL rates and loan share ($secNPL$, $LoanShare$) are panel cointegrated. Optimal lag length is determined to be $p = 1$.

We first run a panel VAR for sectoral level NPL rate and loan share:

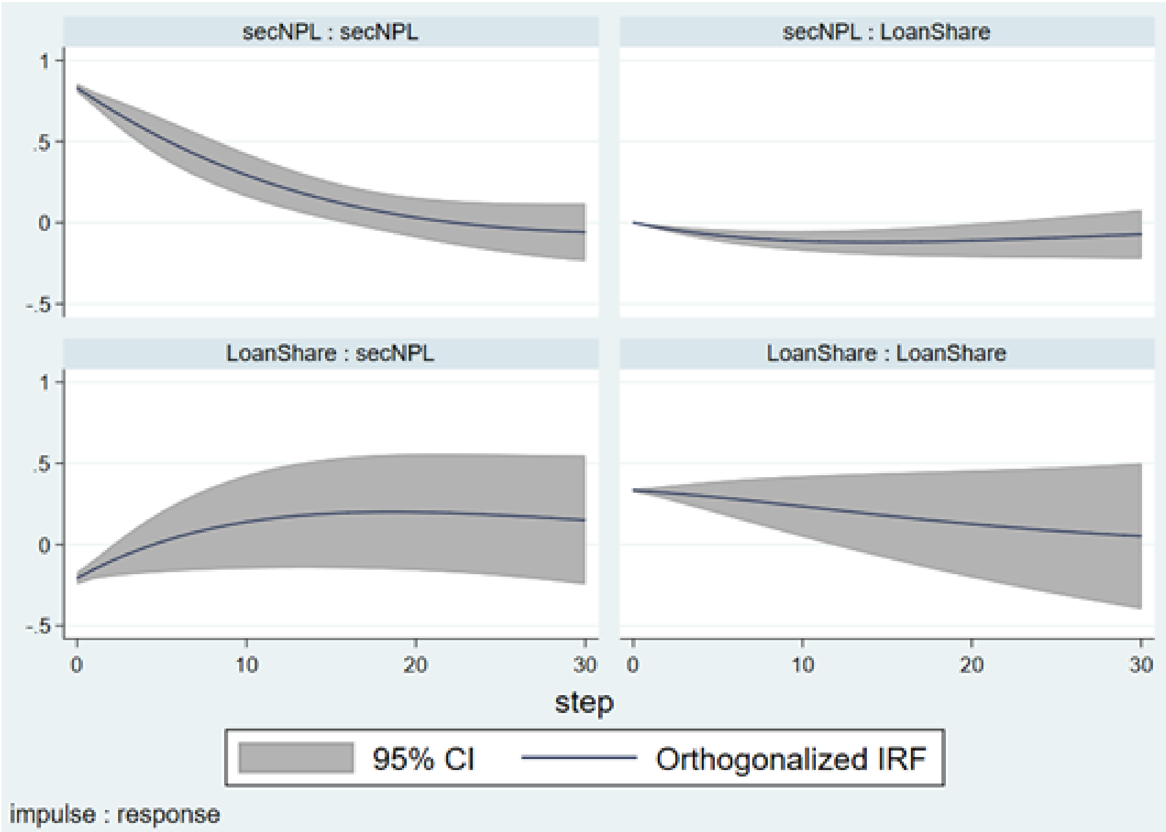
Table 2.8: Panel VAR Estimation with Sector NPL and Loan Share

	Dependent Variables	
Independent Variables	$secNPL$	$LoanShare$
$secNPLr_{t-1}$	0.917	-0.241***
		(0.005)
$LoanShare_{t-1}$	0.113*	0.964
	(0.066)	

Note: $*p < 0.1$ $**p < 0.05$ $***p < 0.01$

A one percent increase in the NPL rate of a sector decreases its share of loans in total loans by 0.24 percent (Table 2.8). The sector NPL increases by 0.11 percent in response to a one percent loan share increase. On the other hand, the response of loans to NPL is persistent; it takes 7 years for the sector to recover from the effects of an NPL shock (Figure 2.5).

Figure 2.5: Response of Sector's Loan Share to NPL Shock



We see that our result is in line with 2.4.1. NPL decreases the loans, the initial effect is small and it takes time for the loans to recover from the effects of the shock. Next, we show that NPL shock impacts medium to long term loans, with little effect on short term loans.

Table 2.9: Panel VAR Estimation with Sector NPL and Medium to Long Term-Loan Share

	Dependent Variables	
Independent Variables	$secNPL$	$MLTLoanShare$
$secNPLr_{t-1}$	0.954	-0.036***
		(0.009)
$MLTLoanShare_{t-1}$	0.525*	0.972
	(0.032)	

Note: $*p < 0.1 \quad **p < 0.05 \quad ***p < 0.01$

Estimation results suggest that a one percent increase in NPL rate of a sector decreases the share of medium to long-term loans allocated to the sector by 0.04 percent for the immediate next quarter. This time the duration of the effect is longer at almost 9 years, although the magnitude of the effect is smaller. Further delay in the response of credit to NPL is consistent with its maturity profile.

Figure 2.6: Response of a Sector's Medium to Long-Term Loan Share to NPL Rate

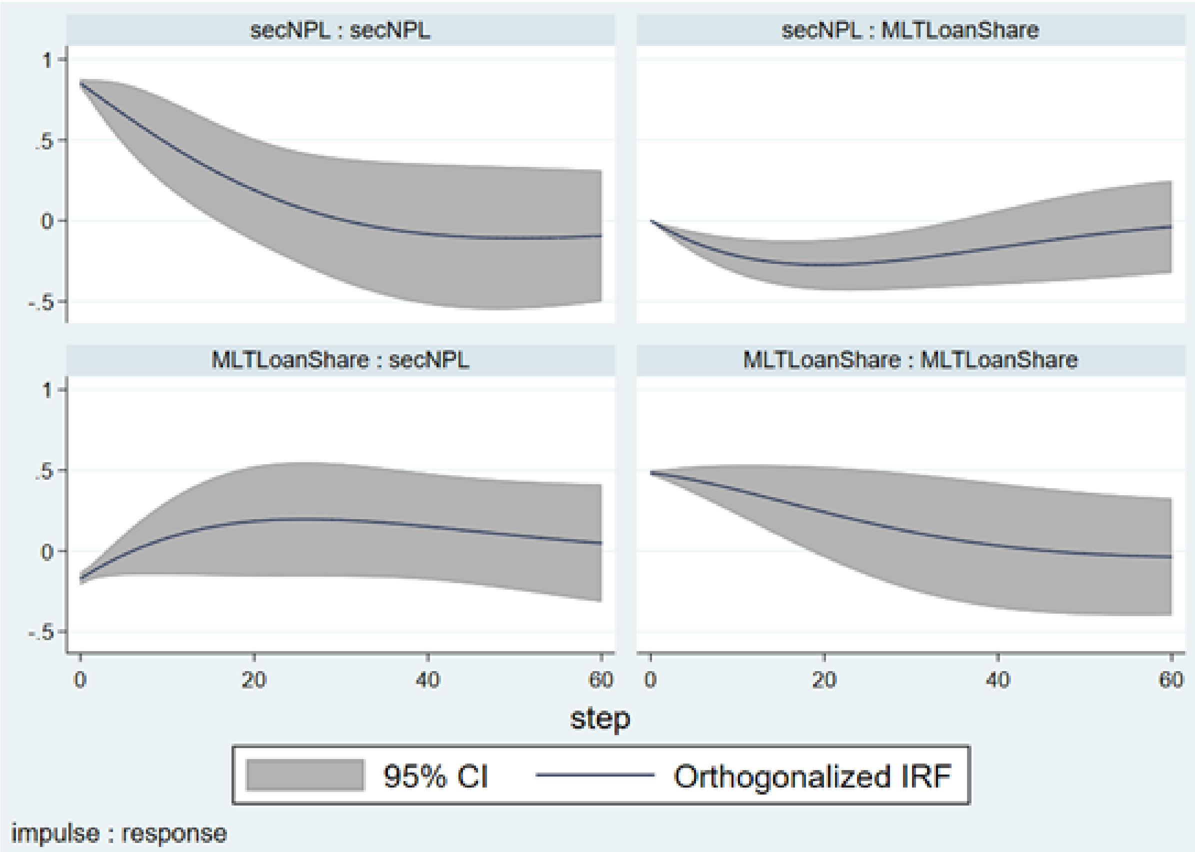


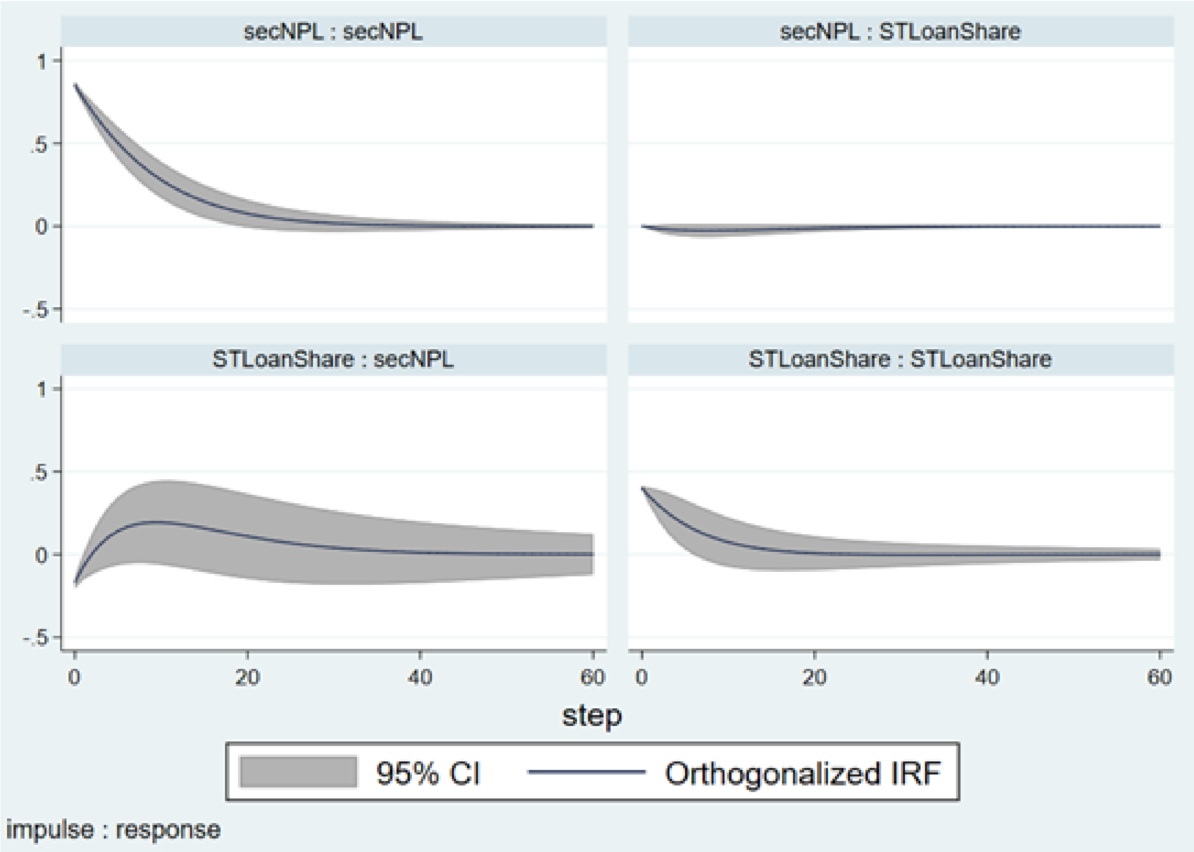
Table 2.10: Panel VAR Estimation with Sector NPL and Short-Term Loan Share

	Dependent Variables	
Independent Variables	$secNPL$	$STLoanSharee$
$secNPLr_{t-1}$	0.904	-0.01 (0.009)
$STLoanShare_{t-1}$	0.204* (0.032)	0.852

Note: $*p < 0.1$ $**p < 0.05$ $***p < 0.01$

For the short-term loans, the NPL increase does have a small effect, but the effect is short-lived and statistically insignificant. This shows that deterioration in payment profile of a sector does not decrease its access to short-term loans.

Figure 2.7: Response of a Sector's Short Term Loan Share to NPL Rate



2.4.3 Response of Loans to NPL: Panel Quantile Regression

In this section, we examine the transmission of NPL shock at different quantiles of conditional credit/assets ratio. Previous sections focused exclusively on the NPL shock's impact on conditional mean of credit distribution. Conventional estimations of the effects of NPL cannot distinguish between the high credit growth periods from low credit growth periods. Quantile regressions offers a method to empirically assess the importance of these different regimes [Koenker, 2004]. In particular, quantile regressions allow us to analyze whether the NPL shock induces similar response on lending in high credit growth periods and low credit growth periods.

We use the STATA package created by [Machado and Silva, 2019] to implement a panel quantile regression with fixed effects. The STATA package "`xtqreg`" uses a "quantiles via moments" estimator. Estimation is performed basically using two fixed effects regressions and computing a univariate quantile.

Figure 2.8: Coefficient Estimates of NPL Rate at Different Quantiles of Loans to Assets Ratio

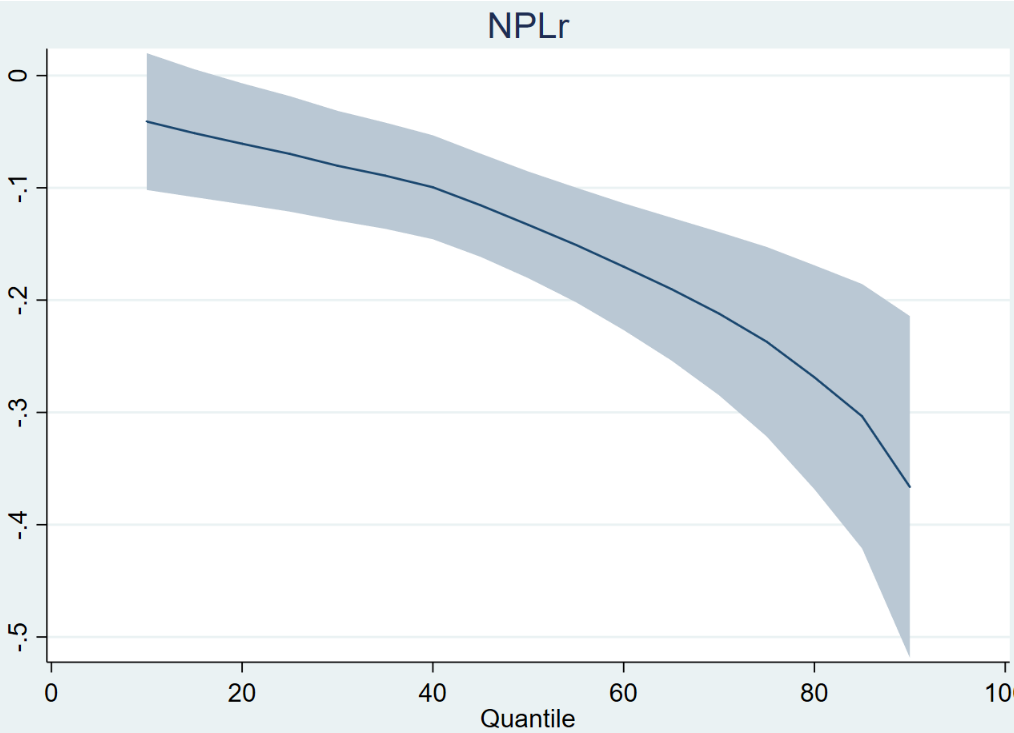


Figure 2.8 below shows the coefficient estimate of NPL rate at quantiles of *LoansAssets* ratio with quantile size of 0.1 considered, when *LoansAssets* ratio is taken as the dependent variable. We see that response of *LoansAssets* ratio to NPL is less severe in the lower quantiles of *LoansAssets* ratio. This shows that if the lending of the bank is already at a low level, NPL shock hinders credit growth less severely. In the higher quantiles of *LoansAssets* ratio, we see a more pronounced negative impact of NPL.

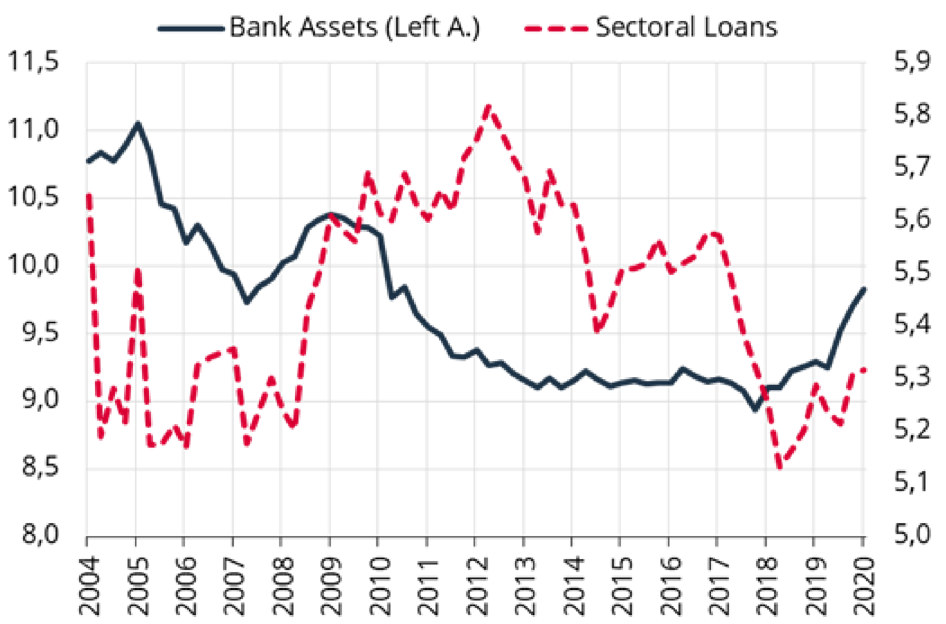
When there is a recession following the high credit growth period, we typically see the quick deterioration in firms' payment capacity. Part of this deterioration comes from banks' tendency to tighten credit to firms somewhat indiscriminately. The results in this section reveal the importance of strong NPL resolution mechanisms in recessionary periods following high credit growth, and imply that liquidity, capital and know-how support to banks in such periods could provide some relief to rising systemic risks and resulting macroeconomic imbalances.

2.4.4 Response of Bank Concentration And Sectoral Loan Distribution to NPL

In this section, we investigate the impact of an NPL shock on the distribution of loans rather than the level or growth. In the panel VAR setting used in previous sections, the estimation results are based on panel-specific fixed effects. Hence, it is not possible to capture the structural impact of an increase in the NPL on the distribution of credit/assets. Our methodology employs Herfindahl-Hirschman Index to summarize the concentration by a single number, and then analyze the endogenous relationship between NPL and banking sector market concentration.

Herfindahl-Hirschman Index (HHI) is calculated by summing the square of the market share of each participant. Since the number of banks and number of sectors in our setup is fixed, there is no need for the use of adjusting factor. We calculate HHI for the 33 banks, and 60 economic sectors using their share of total loans for 65 periods between December 2004 and December 2020. HHIBank is HHI for bank assets, NPL is NPL ratio of the banking sector, CDS is 5 year Credit Default Swap Cost for Turkey.

Figure 2.9: HHI Measure of Concentration for Bank Assets and Sectoral Loans



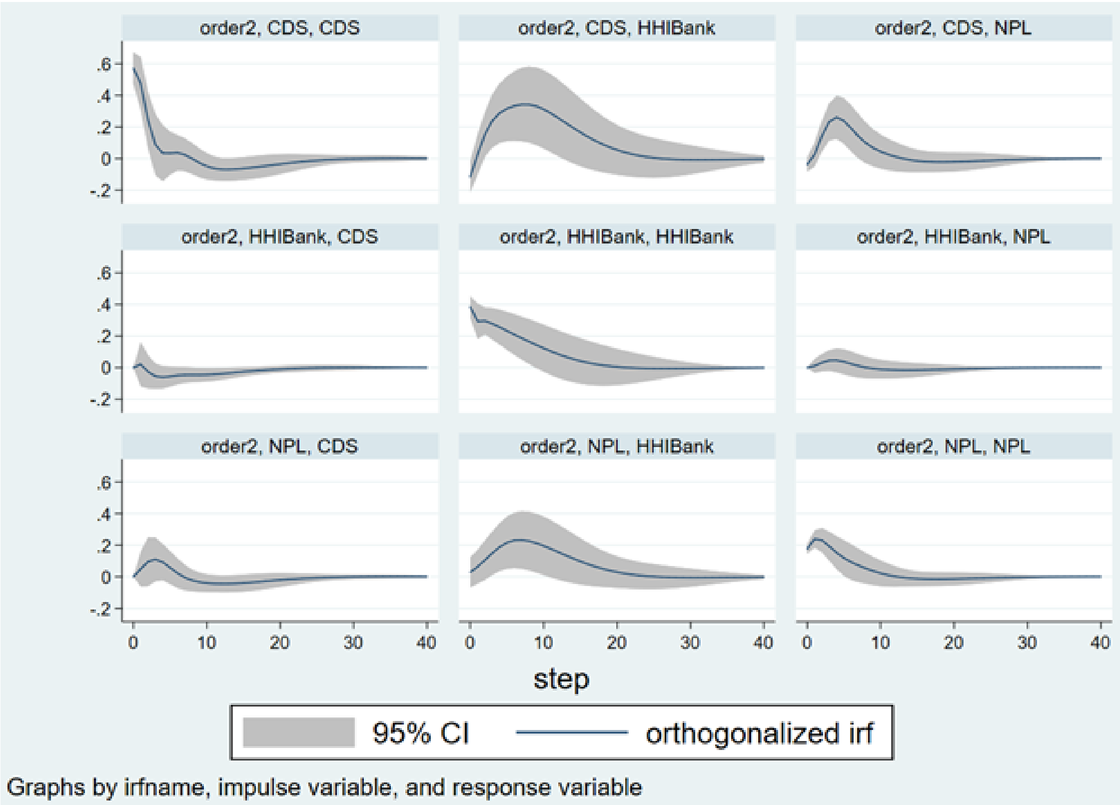
Our VAR model orders the variables as follows: CDS, NPL, HHIBank. The results for impulse response function estimates are given below (Figure 2.10).

Results show that a shock to CDS increases the concentration in the banking sector. This is in line with the general notion that, when stressful conditions arrive, bigger companies perform better and increase their market share. With this idea in mind, it is natural to expect that when CDS increases, an indicator for the local risk perception of financial markets, banking sector market concentration increases. The positive response of NPL to CDS is indicative of the fact that an increase in financial market stress harms the debt rollover capacity of the borrowers.

We observe that an NPL shock increases the banking concentration, adjusted for CDS; our proxy for macro-financial stress. Our results in section 2.4.1 pointed to a contraction in the loans of banks in response to an NPL shock. The estimation result here goes one step further and proves that this contraction is not the same for every bank; smaller banks lose market share, while bigger banks preserve or even increase their share in the sector, when the asset quality outlook worsens.

The rise in the concentration of sectoral loans is a bad signal for the banking sector asset quality profile. When the analysis is repeated for the sectoral loan distribution, we find that there is no effect of NPL shock on sectoral loan concentration index. Although we saw in previous sections that credit share of a sector decreases with the rise in its NPL rate, NPL rate does not seem to matter for the concentration of sectoral loans, which is a positive finding on behalf of banks.

Figure 2.10: Impulse Response Functions for Market Concentration, NPL and CDS



When we exclude public banks and focus on the relationship between concentration among private banks and their NPL's, we have a different picture (Figure 2.11 and Figure 2.12). We see that HHI index of private banks' response to an increase in NPL is not statistically significant. This suggests that the increase in concentration following NPL shocks is driven by public banks.

Figure 2.11: HHI Measure of Concentration for All Banks vs. Private Banks

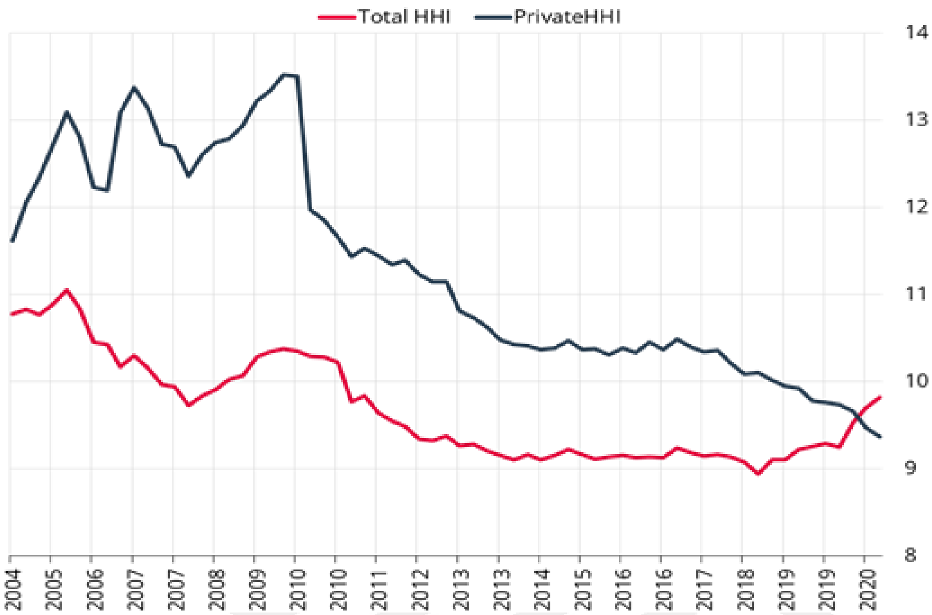
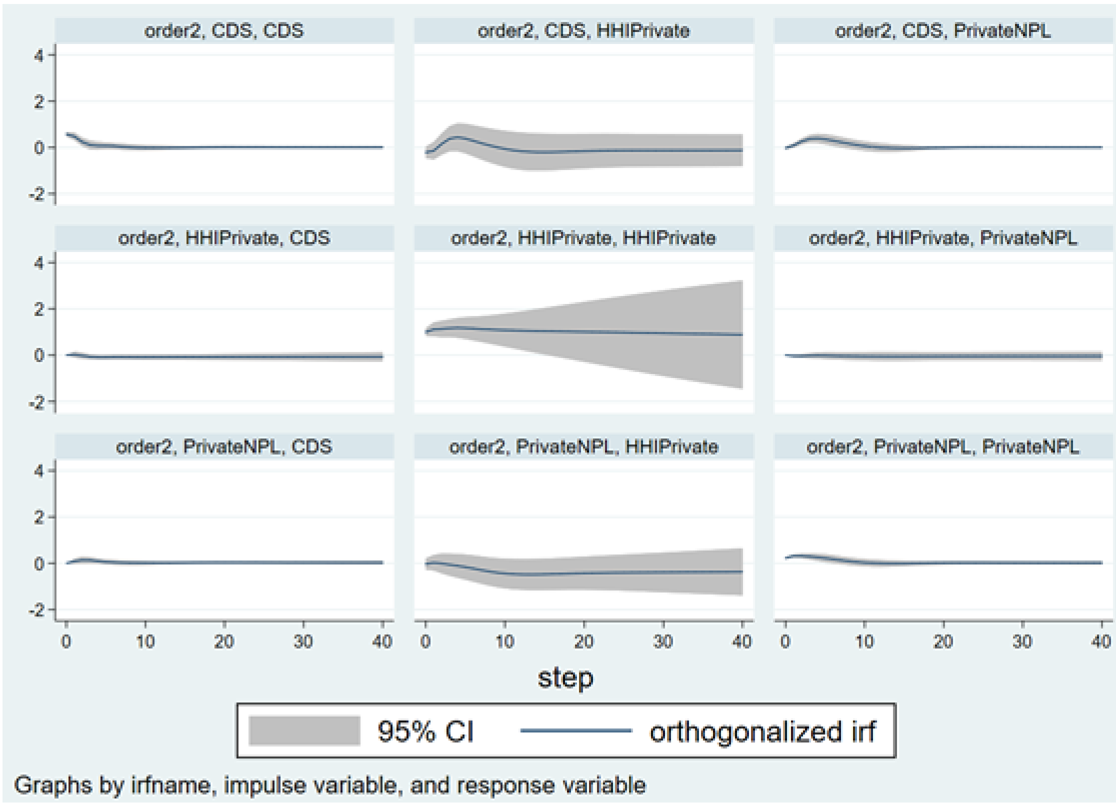


Figure 2.12: Impulse Response Functions for Market Concentration, NPL and CDS for Private Banks



Appendix A

SECTORAL LOAN DISTRIBUTION

Table A.1: Sectoral Loan Distribution (Million TL), Period:2020/12

	Short-Term Loans	Medium-Long Loans	Loans	Non-Performing Loans	Total Loans	Non-Cash Loans
Agriculture, Hunting and Forestry	**35,034**	**90,333**	**125,367**	**5,014**	**130,381**	**6,129**
Agriculture	34,492	89,248	123,740	4,978	128,719	5,343
Hunting	26	30	56	1	57	8
Lumber and Forest Products	516	1,055	1,571	34	1,605	777
Fishing	761	2,261	3,022	178	3,200	1,135
Mining and Quarrying	**8,549**	**36,236**	**44,784**	**1,319**	**46,104**	**10,056**
Extracting of Mines Producing Energy	3,258	20,838	24,096	216	24,312	5,842
Extracting of Mines not Producing Energy	5,291	15,397	20,688	1,104	21,792	4,213
Manufacturing	294,227	434,069	728,296	27,150	755,446	325,828
Food, Beverage and Tobacco Ind.	**49,245**	**61,448**	**110,694**	**4,184**	**114,878**	**25,043**
Textile and Textile Products Industry	48,454	73,259	121,713	5,198	126,911	42,370
Leather and Leather Products Industry	1,420	3,503	4,923	562	5,485	954
Wood and Wood Products Industry	3,209	9,161	12,370	339	12,709	6,482
Paper Raw Materials and Paper Products Indusrty	8,652	18,799	27,452	363	27,814	5,120
Nuclear Fuel and Refined Petroleum and Coke Coal Ind.	7,518	22,205	29,723	265	29,988	15,608
Chemical Products Industry	26,211	27,220	53,431	689	54,120	27,343
Rubber and Plastic Products Industry	17,165	24,010	41,175	2,632	43,807	13,678
Other Mines Excluding Metal Industry	15,108	39,983	55,092	2,030	57,122	14,161
Main Metal Industry	53,422	65,818	119,240	3,861	123,101	80,393
Machine and Equipment Industry	15,597	23,220	38,816	1,416	40,232	22,262
Electrical and Optical Devices Indusrty	15,706	18,845	34,551	2,791	37,341	24,059
Transportation Vehicles Industry	24,417	30,214	54,631	1,605	56,236	41,715
a) Building and Repairing Ships and Boats	3,665	5,125	8,791	790	9,581	12,111
b) Manufacture and Repair of Motor and Other Vehicles	20,752	25,089	45,840	815	46,656	29,604
Manufacturing Industry Not Classified In Another Places	8,104	16,383	24,487	1,213	25,700	6,639
Electric, Gas and Water Resources	**18,544**	**224,667**	**243,211**	**14,427**	**257,638**	**57,333**
Construction	**53,040**	**220,701**	**273,742**	**28,415**	**302,157**	**199,567**
Wholesale and Retail Trade, Sale and Repair of Motor Vehicles and Personel Products	**152,520**	**283,370**	**435,890**	**24,213**	**460,103**	**148,683**
Retail Sell of Motor Vehicles and Its Fuel Oil	20,104	43,434	63,537	2,993	66,531	22,122
Wholesale Trade and Brokerage	92,791	145,226	238,017	14,453	252,469	99,747
Retail Trade and Personnel Products	39,625	94,710	134,335	6,767	141,103	26,814
Hotels and Restaurants	**22,724**	**106,343**	**129,067**	**7,341**	**136,408**	**16,193**
Hotels	16,329	84,139	100,468	5,192	105,659	11,709
Restaurants	2,372	14,035	16,408	593	17,001	1,859
Other Tourism	4,023	8,169	12,192	1,556	13,748	2,626
Transportation, Storage and Communication	**40,606**	**179,869**	**220,475**	**5,880**	**226,355**	**54,793**
Railroad Transportation	122	1,707	1,828	29	1,858	726
Road Transportation	2,058	20,507	22,565	430	22,995	1,758
Road Haulage	5,725	19,906	25,631	1,062	26,692	5,547
Maritime Transportation	2,112	19,994	22,106	2,823	24,928	2,574
Air Transportation	16,151	35,913	52,063	340	52,403	18,930
Other Transportation Activities	6,776	66,448	73,224	905	74,129	15,608
Communication	7,663	15,395	23,057	293	23,350	9,650
Financial Intermediation	**46,774**	**41,837**	**88,610**	**171**	**88,781**	**46,035**
Financial Institutions	40,806	25,647	66,453	77	66,530	23,659
Loans Extended to Banks*	28,072	30,477	58,548	9	58,558	49,906
Other Financial Instruments	2,356	12,186	14,542	33	14,576	15,355
Insurance and Pension Excluding Compulsory Social Sec. Institutions	320	519	839	18	858	3,853
Other Financial Intermediation	3,291	3,485	6,776	41	6,817	3,169
Real Estate Brokerage, Renting and Business Activities	**31,440**	**177,681**	**209,121**	**10,165**	**219,286**	**30,931**
Real Estate Brokerage	3,065	34,837	37,902	3,835	41,737	3,573
Rent (Vehicle, Machine, Device)	4,537	23,515	28,052	1,533	29,585	1,833
Computer and Related Activities	2,590	16,163	18,754	331	19,085	4,832
Research, Consulting, Advertising and Other Activities	21,247	103,165	124,413	4,466	128,879	20,693
Defense, Public Administration And Social Security Institutions	**3,588**	**60,556**	**64,143**	**284**	**64,428**	**9,656**
Education	**3,084**	**10,374**	**13,458**	**1,169**	**14,627**	**1,194**
Health and Social Services	**3,203**	**23,948**	**27,152**	**656**	**27,808**	**4,959**
Other Services	**10,595**	**49,785**	**60,380**	**3,277**	**63,657**	**9,908**
Arranging of Drainage and Waste	413	930	1,343	39	1,382	461
Organizational Activities	1,217	5,076	6,293	147	6,439	823
Cultural, Entertainment and Sportive Activities	3,069	12,609	15,678	408	16,086	3,000
Other Personel Services	5,896	31,170	37,066	2,683	39,749	5,624
Private Person Employing Worker	**65**	**138**	**202**	**48**	**250**	**272**
International Organizations and Institutions	**12**	**30**	**42**	**3**	**45**	**10**
Individual Housing Credit	**93**	**279,088**	**279,180**	**915**	**280,095**	**0**
Individual Automobile Credit	**449**	**11,399**	**11,847**	**151**	**11,999**	**0**
Individual Credit-Other	**31,963**	**354,775**	**386,738**	**10,549**	**397,287**	**0**
Credit Cards**	**198,483**	**5,419**	**203,902**	**7,110**	**211,012**	**344,470**
Other	**6,688**	**19,308**	**25,996**	**4,043**	**30,039**	**29,661**
TOTAL	962,441	2,612,184	3,574,625	152,480	3,727,105	1,296,812

Note: * "Loans Extended to Banks" is provided for information and not included in overall calculation in this table.
** For credit cards non-cash loans figure expresses credit cards limit commitments.
Prepared by using Finance Subject Codes in the Risk Operations Circular issued by CBRT.

Appendix B

PANEL COINTEGRATION TESTS

```
Kao test for cointegration

Ho: No cointegration                         Number of panels       =     33
Ha: All panels are cointegrated              Avg. number of periods = 67.303

Cointegrating vector: Same
Panel means:          Included               Kernel:          Bartlett
Time trend:           Not included           Lags:            1.48 (Newey-West)
AR parameter:         Same                   Augmented lags:  1
------------------------------------------------------------------------------
                                             Statistic        p-value
------------------------------------------------------------------------------
 Modified Dickey-Fuller t                     -6.4984         0.0000
 Dickey-Fuller t                              -6.7713         0.0000
 Augmented Dickey-Fuller t                    -2.6663         0.0038
 Unadjusted modified Dickey-Fuller t         -10.5337         0.0000
 Unadjusted Dickey-Fuller t                   -8.1008         0.0000
------------------------------------------------------------------------------
```

```
Pedroni test for cointegration

Ho: No cointegration                         Number of panels       =     33
Ha: All panels are cointegrated              Avg. number of periods = 68.485

Cointegrating vector: Panel specific
Panel means:          Included               Kernel:          Bartlett
Time trend:           Not included           Lags:            1.00 (Newey-West)
AR parameter:         Panel specific         Augmented lags:  1
------------------------------------------------------------------------------
                                             Statistic        p-value
------------------------------------------------------------------------------
 Modified Phillips-Perron t                    2.0518         0.0201
 Phillips-Perron t                            -0.9890         0.1613
 Augmented Dickey-Fuller t                    -2.5634         0.0052
------------------------------------------------------------------------------
```

```
. xtcointtest westerlund LoansAssets NPLrate dCPI dIP

Westerlund test for cointegration

Ho: No cointegration                        Number of panels       =     33
Ha: Some panels are cointegrated            Avg. number of periods = 69.727

Cointegrating vector: Panel specific
Panel means:          Included
Time trend:           Not included
AR parameter:         Panel specific
```

	Statistic	p-value
Variance ratio	11.8772	0.0000

```
Kao test for cointegration

Ho: No cointegration                        Number of panels       =     33
Ha: All panels are cointegrated             Avg. number of periods = 67.303

Cointegrating vector: Same
Panel means:          Included              Kernel:          Bartlett
Time trend:           Not included          Lags:            2.61 (Newey-West)
AR parameter:         Same                  Augmented lags:  1
```

	Statistic	p-value
Modified Dickey-Fuller t	1.8640	0.0312
Dickey-Fuller t	1.3910	0.0821
Augmented Dickey-Fuller t	3.5372	0.0002
Unadjusted modified Dickey-Fuller t	3.0285	0.0012
Unadjusted Dickey-Fuller t	2.6793	0.0037

```
Pedroni test for cointegration

Ho: No cointegration                        Number of panels       =     33
Ha: All panels are cointegrated             Avg. number of periods = 68.485

Cointegrating vector: Panel specific
Panel means:          Included              Kernel:          Bartlett
Time trend:           Not included          Lags:            3.00 (Newey-West)
AR parameter:         Panel specific        Augmented lags:  1
```

	Statistic	p-value
Modified Phillips-Perron t	6.0557	0.0000
Phillips-Perron t	7.1778	0.0000
Augmented Dickey-Fuller t	5.7442	0.0000

```
Kao test for cointegration
__________________________

Ho: No cointegration                      Number of panels      =    27
Ha: All panels are cointegrated           Number of periods     =    64

Cointegrating vector: Same
Panel means:          Included            Kernel:           Bartlett
Time trend:           Not included        Lags:             2.63 (Newey-West)
AR parameter:         Same                Augmented lags:   1
```

	Statistic	p-value
Modified Dickey-Fuller t	-2.1285	0.0166
Dickey-Fuller t	-3.7123	0.0001
Augmented Dickey-Fuller t	-3.2140	0.0007
Unadjusted modified Dickey-Fuller t	-2.3374	0.0097
Unadjusted Dickey-Fuller t	-3.8136	0.0001

```
Pedroni test for cointegration
______________________________

Ho: No cointegration                      Number of panels      =    27
Ha: All panels are cointegrated           Number of periods     =    65

Cointegrating vector: Panel specific
Panel means:          Included            Kernel:           Bartlett
Time trend:           Not included        Lags:             3.00 (Newey-West)
AR parameter:         Panel specific      Augmented lags:   1
```

	Statistic	p-value
Modified Phillips-Perron t	-1.6796	0.0465
Phillips-Perron t	-4.2526	0.0000
Augmented Dickey-Fuller t	-3.3855	0.0004

```
Westerlund test for cointegration
_________________________________

Ho: No cointegration                      Number of panels      =    27
Ha: Some panels are cointegrated          Number of periods     =    66

Cointegrating vector: Panel specific
Panel means:          Included
Time trend:           Not included
AR parameter:         Panel specific
```

	Statistic	p-value
Variance ratio	3.5626	0.0002

Appendix C

MODEL SELECTION TESTS

The accuracy of coefficient estimations in panel VAR model relies on the determination of optimal lag order in panel VAR specification. Several criteria for model and moment selection are used to determine the optimal lag length. CD stands for coefficient of determination, MBIC stands for Bayesian-Schwarz Information Criteria, MAIC stands for Akaike Information Criteria and MQIC stands for Hannan-Quinn Information Criteria. Objective functions to minimize for each criterion are:

$$\begin{aligned} BIC_n(k,p,q) &= J_n(k^2p,k^2q) - (|q|-|p|)k^2 log(n) \\ BIC_n(k,p,q) &= J_n(k^2p,k^2q) - 2k^2(|q|-|p|) \\ HQIC_n(k,p,q) &= J_n(k^2p,k^2q) - Rk^2(|q|-|p|)log(log(n)), \quad R>2 \end{aligned} \tag{C.1}$$

Where $J_n(k^2p, k^2q)$ is the J statistic of over-identifying restriction for a k-variable panel VAR of order p and moment conditions based on q lags of the endogenous variables with sample size n.

We also use the coefficient of determination (CD) as a criterion, which can be used in just-identified GMM models [Abrigo and Love, 2016]. Denote by ψ the k×k unconstrained covariance matrix of dependent variables. CD can be calculated as

$$CD = 1 - \frac{det(\Sigma)}{det(\psi)} \tag{C.2}$$

Table C.1: Model Selection Tests: $LoansAssets$, $NPLrate$, ΔCPI, ΔIP (Baseline Model)

lag	CD	Hansen's J Statistic	MBIC	MAIC	MQIC
1	.9935369	9,509,311	-3,584,313	5,989,311	2,445,334
2	.9929959	7,247,882	-4,655,413	4,047,882	8,260,848
3	.99117	7,260,646	-3,452,319	4,380,646	1,481,029
4	.9663627	5,747,135	-3,775,501	3,187,135	6,096,968

Table C.2: Model Selection Tests: $LoanShare$, $secNPL$

lag	CD	Hansen's J Statistic	MBIC	MAIC	MQIC
1	.9994792	1,736,603	-9,977,298	-1,463,397	-4,633,869
2	.9993267	6,929,232	-8,092,503	-1,707,077	-4,084,931
3	.9993675	6,999,858	-5,156,965	-9,000,142	-248,525
4	.9983851	1,329,973	-2,795,478	-6,670,027	-1,459,621

Table C.3: Model Selection Tests: Public Banks, $LoansAssets$, $NPLrate$, ΔCPI, ΔIP

lag	CD	Hansen's J Statistic	MBIC	MAIC	MQIC
1	.9994964	1,478,613	-2,184,481	1,986,131	-754,469
2	.9984775	8,941,069	-1,853,214	-658,931	-7,807,047
3	.9949436	5,197,457	-1,311,802	-1,202,543	-5,967,954
4	.9859823	2,477,517	-6,680,219	-7,224,829	-3,105,188

Table C.4: Model Selection Tests: Private Banks, $LoansAssets$, $NPLrate$, ΔCPI, ΔIP

lag	CD	Hansen's J Statistic	MBIC	MAIC	MQIC
1	.9870972	5,356,018	6,207,943	4,076,018	2,794,333
2	.9622282	270,447	-8,469,477	174,447	7,832,064
3	.893778	1,124,705	-1,242,907	484,705	-1,561,372
4	.5261475	4,469,928	-736,813	1,269,928	-1,934,283

Appendix D

FORECAST ERROR VARIANCE DECOMPOSITION

Table D.1: FEVD: $LoansAssets$, $NPLrate$, ΔCPI, ΔIP

		Impulse Variable			
Response Variable	Forecast Horizon	$LoansAssets$	$NPLr$	ΔCPI	ΔIP
$LoansAsset$	1	1	0	0	0
	2	.9955903	.0017396	.0000465	.0026237
	3	.9891682	.0060263	.00029	.0045154
	4	.9812586	.0128136	.0005119	.0054159
	5	.9717614	.021886	.0006421	.0057104
	6	.9606808	.0329246	.0006997	.0056948
	7	.9482025	.0455411	.0007138	.0055425
	8	.9346367	.0593074	.0007057	.0053503
	9	.9203554	.0737843	.0006885	.0051719
	10	.9057452	.0885495	.0006703	.0050351
$NPLr$	1	.0528288	.9471712	0	0
	2	.0335472	.9635145	.0000255	.0029127
	3	.0232408	.9704274	.0002654	.0060664
	4	.0191715	.9715371	.0005856	.0087058
	5	.0196539	.9685979	.0008903	.0108578
	6	.0234483	.9627576	.0011574	.0126367
	7	.0295883	.9548928	.0013881	.0141309
	8	.0373137	.9456984	.0015877	.0154001
	9	.0460312	.9357224	.0017612	.0164852
	10	.0552831	.9253887	.0019123	.0174159
ΔCPI	1	.001924	.0017729	.996303	0
	2	.0068121	.0020223	.9893342	.0018315
	3	.0137451	.0022458	.9819237	.0020855
	4	.0194836	.0025737	.9758674	.0020753
	5	.0237181	.0030455	.9711621	.0020744
	6	.026719	.0036602	.9675421	.0020787
	7	.0287874	.0043985	.9647346	.0020795
	8	.0301703	.0052338	.962519	.0020769
	9	.0310595	.006137	.9607303	.0020732
	10	.0316013	.0070803	.9592481	.0020703
ΔIP	1	.0003554	.0039119	.0013112	.9944214
	2	.0299936	.0131613	.0429394	.9139058
	3	.0617426	.0213375	.0493898	.8675301
	4	.0881229	.0271332	.0483499	.8363941
	5	.1088967	.0308811	.0469897	.8132326
	6	.1251963	.0331815	.0459827	.7956396
	7	.1380347	.0345126	.045243	.7822096
	8	.1481671	.0352118	.0446863	.7719349
	9	.1561573	.0355128	.0442621	.7640678
	10	.1624385	.0355768	.0439374	.7580473

Table D.2: FEVD: $RealLoans$, $RealNPL$, ΔCPI, ΔIP

		Impulse Variable			
Response Variable	Forecast Horizon	$realLoan$	$realNPL$	ΔCPI	ΔIP
$realLoan$	1	1	0	0	0
	2	.8202085	.0021373	.1657004	.0119538
	3	.7099479	.0059471	.271219	.012886
	4	.6365299	.0091467	.3409686	.0133548
	5	.5879487	.0118872	.3867532	.0134109
	6	.5538737	.0142745	.4184993	.0133526
	7	.5288368	.0164145	.4415046	.0132441
	8	.5096623	.0183737	.4588469	.0131171
	9	.4944597	.0201952	.4723608	.0129843
	10	.4820493	.0219072	.483192	.0128516
$realNPL$	1	.4793431	.5206569	0	0
	2	.4326977	.3718133	.1941701	.0013188
	3	.377723	.2880485	.3313862	.0028423
	4	.3419363	.2442424	.410123	.0036983
	5	.3181053	.2195262	.4581634	.0042052
	6	.301339	.2047879	.4893692	.0045039
	7	.2888629	.1957424	.5107172	.0046775
	8	.2791228	.1901941	.5259114	.0047715
	9	.2712098	.1869208	.5370562	.0048132
	10	.264573	.1851944	.5454131	.0048195
ΔCPI	1	.1920308	.0262616	.7817076	0
	2	.1639358	.0214145	.808212	.0064377
	3	.1614415	.0207256	.8110226	.0068103
	4	.16072	.0204022	.8117782	.0070996
	5	.1609181	.0202761	.8115969	.0072088
	6	.1613145	.0202192	.8111981	.0072682
	7	.1617541	.0201945	.8107496	.0073018
	8	.1621853	.0201851	.8103061	.0073235
	9	.1626012	.0201844	.8098755	.0073389
	10	.163006	.0201893	.8094536	.007351
ΔIP	1	.4654692	.0872517	.0098647	.4374144
	2	.3154006	.0582395	.3039009	.322459
	3	.3056718	.0557242	.3341866	.3044174
	4	.3001611	.0545185	.3472035	.2981168
	5	.2987508	.0542149	.3505262	.296508
	6	.2983854	.0541897	.3512641	.2961608
	7	.2983553	.0542651	.351281	.2960986
	8	.2983889	.0543722	.351216	.296023
	9	.2984074	.0544851	.3512282	.2958793
	10	.2983964	.0545948	.3513266	.2956823

Table D.3: FEVD with $NPLr$ as the Impulse Variable

		Public Banks			$Private Banks$		
Response Variable	Forecast Horizon	Dec.2002-Dec.2015	Jan.2016-Dec.2020	Dec.2002-Dec.2021	Dec.2002-Dec.2015	Jan.2016-Dec.2020	Dec.2002-Dec.2021
$LoansAsset$	1	0	0	0	0	0	0
	2	.0014229	.0528366	.0051325	.0013901	.1318621	.0014144
	3	.0040044	.1399781	.0152141	.0048131	.3355342	.005423
	4	.0072457	.2222152	.0280421	.0101851	.4653248	.012458
	5	.0108348	.2832402	.0418822	.0172854	.5392679	.0226733
	6	.0145608	.3245384	.0555881	.0258183	.5882489	.0360206
	7	.0182784	.3515382	.0684942	.0354411	.6277627	.0522857
	8	.0218894	.3690106	.0802672	.0457899	.661635	.0711149
	9	.0253305	.380316	.0907845	.0565067	.6900421	.0920461
	10	.0285635	.387659	.1000479	.0672634	.713482	.1145473
$NPLr$	1	.9438248	.9945293	.966039	.9494799	.9147103	.9473196
	2	.9378634	.9292586	.9389779	.9641504	.8312628	.9663022
	3	.9332675	.8867633	.9144912	.9708333	.8360004	.9773911
	4	.9299108	.8424201	.8982384	.9714708	.8488464	.9821358
	5	.9272636	.7847528	.8874741	.9675464	.8558131	.9821507
	6	.9250469	.7178203	.8799169	.9604242	.8584712	.9788241
	7	.9231341	.6500869	.8742679	.9512445	.8597193	.9732466
	8	.9214628	.5887493	.8698284	.9408942	.8607808	.966236
	9	.9199962	.5377745	.8662155	.9300319	.8617724	.9583868
	10	.9187084	.4980838	.8632085	.9191276	.8625939	.9501233
ΔCPI	1	.0040908	.0811799	.0029794	.001102	.025127	.0015002
	2	.0093478	.084861	.0055699	.0020738	.1455287	.0014288
	3	.0131200	.0844798	.0071103	.0027965	.1460621	.0013897
	4	.0156696	.0834408	.0080854	.0034369	.1471384	.0013601
	5	.0174686	.085005	.0087622	.004086	.1482898	.0013737
	6	.0187826	.0909117	.0092584	.0047668	.1482224	.0015327
	7	.0197582	.1018432	.0096337	.0054723	.1482745	.0019159
	8	.0204885	.1182335	.0099232	.0061857	.1482973	.0025629
	9	.0210385	.1403945	.0101496	.0068901	.1482968	.0034853
	10	.0214554	.1681622	.0103288	.007571	.1482969	.0046768
ΔIP	1	.0000649	.0171683	.0034601	.0026947	.0027911	.0011451
	2	.0013249	.1105000	.0090147	.0027669	.0596969	.0066309
	3	.0028093	.208406	.0183855	.0034079	.0638187	.0125151
	4	.0039044	.2681024	.0253437	.0040118	.0704593	.0171318
	5	.0046090	.3059358	.0293906	.004486	.0973892	.0203917
	6	.0050447	.3313856	.0314908	.0048484	.1180745	.0226502
	7	.0053085	.3496788	.0324898	.0051247	.1323904	.024218
	8	.0054642	.3634733	.0329157	.005335	.1460015	.0253059
	9	.0055526	.3740442	.0330652	.0054944	.1616044	.0260548
	10	.0056000	.3820572	.033095	.0056145	.1790691	.0265625

Table D.4: FEVD for *SectoralLoans*

		Impulse Variable					
		Total Loans		Medium to Long Term Loans		Short Term Loans	
Response Variable	Forecast Horizon	*LoanShare*	*secNPL*	*LoanShare*	*secNPL*	*LoanShare*	*secNPL*
LoanShare	1	1	0	1	0	1	0
	2	.9981581	.001842	.997892	.002108	.9997393	.0002607
	3	.9943161	.0056839	.9933025	.0066975	.9991871	.0008129
	4	.9889117	.0110883	.9865842	.0134158	.9983996	.0016003
	5	.9823163	.0176837	.9780719	.0219281	.9974337	.0025663
	6	.9748414	.0251586	.9680764	.0319236	.9963442	.0036558
	7	.9667464	.0332536	.9568822	.0431179	.9951821	.0048179
	8	.9582452	.0417548	.944745	.055255	.9939925	.0060074
	9	.949513	.050487	.9318927	.0681073	.9928136	.0071864
	10	.9406925	.0593075	.9185258	.0814743	.9916758	.0083242
secNPL	1	.0590062	.9409938	.0388591	.961141	.0380184	.9619816
	2	.0498726	.9501274	.0337223	.9662777	.0249762	.9750238
	3	.0422098	.9577903	.0292158	.9707843	.0184355	.9815645
	4	.0360883	.9639117	.0253469	.9746532	.0170672	.9829329
	5	.0315554	.9684446	.0221209	.9778792	.0195974	.9804026
	6	.0286311	.9713689	.0195402	.9804597	.0248915	.9751084
	7	.0273061	.9726939	.0176043	.9823956	.0319948	.9680052
	8	.0275399	.9724601	.0163092	.9836908	.0401404	.9598597
	9	.0292614	.9707385	.015647	.984353	.0487381	.9512619
	10	.0323709	.9676291	.0156061	.9843939	.0573525	.9426475

Appendix E

GRANGER CAUSALITY TESTS

We conduct panel VAR Granger-causality Wald test. Null and alternative hypothesis are as follows:

H_0 :Excluded variable does not Granger-cause Equation variable

H_a :Excluded variable Granger-causes Equation variable

Table E.1: Granger Causality Tests: $LoansAssets$, $NPLrate$, ΔCPI, ΔIP

Equation	Excluded	χ^2	*df*	$Prob > \chi^2$
$LoansAssets$	$NPLrate$	12,532	1	0.000
	ΔCPI	0.283	1	0.595
	ΔIP	6,285	1	0.012
	ALL	19,273	3	0.000
$NPLrate$	$LoansAssets$	27,060	1	0.000
	ΔCPI	0.174	1	0.676
	ΔIP	11,850	1	0.001
	ALL	51,467	3	0.000
ΔCPI	$LoansAssets$	7,807	1	0.005
	$NPLrate$	0.734	1	0.392
	ΔIP	3,486	1	0.062
	ALL	31,688	3	0.000
ΔIP	$LoansAssets$	42,858	1	0.000
	$NPLrate$	22,819	1	0.000
	ΔCPI	118,416	1	0.000
	ALL	121,938	3	0.000

Table E.2: Granger Causality Tests: $RealLoan$, $RealNPL$, ΔCPI, ΔIP

Equation	Excluded	χ^2	*df*	$Prob > \chi^2$
$realLoan$	$realNPL$	3,779	1	0.052
	ΔCPI	137539	1	0.000
	ΔIP	39,334	1	0.000
	ALL	160,702	3	0.000
$realNPL$	$realLoan$	14,213	1	0.000
	ΔCPI	151228	1	0.000
	ΔIP	4,301	1	0.038
	ALL	161,132	3	0.000
ΔCPI	$realLoan$	0.191	1	0.662
	$realNPL$	0.030	1	0.862
	ΔIP	11,580	1	0.001
	ALL	13,238	3	0.004
ΔIP	$realLoan$	2,257	1	0.133
	$realNPL$	1,693	1	0.193
	ΔCPI	103,132	1	0.000
	ALL	104,044	3	0.000

Table E.3: Granger Causality Tests: $LoanShare$, $secNPL$

Equation	Excluded	χ^2	*df*	$Prob > \chi^2$
$LoanShare$	$secNPL$	19,683	1	0.000
	ALL	19,683	1	0.000
$secNPL$	$LoanShare$	2,971	1	0.085
	ALL	2,971	1	0.085

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