Banking Stability and Shadow Banking: A New Overview for the United States

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Abstract

This paper analyses commercial banking and shadow banking, with the intention of understanding different channels of instability that can occur through both types of banking for the United States. The work is pioneering a comprehensive vision of shadow banking and its interrelation with commercial banking. The results of the work are designed to encourage reflection on possible mediums to promote the stability of shadow banking, through new risk indicators. Finally, these indicators are tested using machine learning techniques.

Keywords: shadow banking, bank stability, canonical analysis, random forest.

JEL classification: C40, E47, Y21

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1. INTRODUCTION

In this work, an analysis of shadow banking in the United States and its links with traditional banking is carried out. There are several studies that analyze shadow banking, from different points of view from its influence on risk, for instance Vento and La Langa (2013), Adrian (2014), Maeno et al. (2014) and Martinez-Miera and Repullo (2019). In this present work, the aim is to obtain a comprehensive vision of the influence of shadow banking on traditional banking and vice versa. One of the advantages of the work is that it approaches the subject from a holistic position, in which all the institutions of shadow banking are collected and allows us to analyze their interaction with traditional banking.

Another novelty is the use of a methodology, which is canonical analysis, rarely applied in works of this type, which allows us to have a temporary evaluation of interactions. Once the most important relationships between both types of banking have been described, and what may be the bridges of instability between the two, an attempt is made to propose a possible macroprudential regulation of shadow banking. For this, the methodology used by the Basel committee based on the Hodrick Prescott filter is used, but with different variables obtained from shadow banking. The time series cluster is also applied and finally a Random Forest algorithm to evaluate the results of the instability of shadow banking on the losses that are caused in traditional banking.

Some shadow banking risk indicators could coexist with traditional banking and serve as a complement to macroprudential policy for future regulation. In our opinion, said policy suffers from weaknesses because part of the financial system is not regulated. Therefore, the regulation used by the Basel committee for the formation of countercyclical capital could be improved using one of the landmarks of Basel III, to avoid procyclicality.
It starts with the state of the art. In section 2, a general analysis of shadow banking in the United States and the canonical analysis that puts it in relation to traditional banking are carried out, using various variables. In section 3, the gaps of the shadow banking indicators are obtained and a cluster of time series is performed to analyze their evolution. Finally, in section 4, machine learning evaluates the shadow banking indicators to study their prediction of the instability of traditional banking.

2. State of the art

We begin by establishing a classification of shadow banking according to different perspectives. For the FSB (2011) the shadow banking system is the credit intermediation system that involves entities and activities outside the regular banking system. Specifically, shadow banking covers all financial activities and entities that increased systemic risk due to maturity transformation, leverage, liquidity or regulatory arbitrage. The FSB (2015) identifies five economic functions through which non-bank credit intermediation can present similar systemic risks to banks for the financial system. The economic functions defined by the FSB and the entities that typically participate in activities related to each function are: i) Management of collective investment vehicles as different types of funds; ii) provision of loans with short-term financing, such as financial companies; iii) intermediation in the market that is dependent on short-term financing or secured financing from clients, for example brokers or dealers; iv) facilitation of credit creation; and iv) credit guarantors and securitisation based on credit intermediation as securitization vehicles. Another type of classification of shadow banking is established according to the relationship with traditional banking and its degree of specialization, carried out by Pozsar et al. (2012). They establish four groups: i) the first is defined as internal shadow banking and consists of activities carried out by bank holding subsidiaries, these activities are included in the structure of traditional banking; ii) external shadow banking, consists of independent and regulated institutions that carry out shadow banking activities, but these do not represent its main business; for example independent stockbrokers, independent wealth management institutions, credit hedge funds and financial companies, iii) independent shadow banking, consists of entities that specialize only in shadow banking, such as structured investment vehicles, independent money market funds; and iv) government-sponsored shadow banking, includes government-sponsored companies such as Fannie Mae and Freddie Mac in the United States.

One of the outstanding characteristics of banking in the shadow of the previous definitions is its fragility. In fact, McCulley (2007) highlights that it does not benefit from a safety net or other official guarantees. This leads to greater fragility for said type of banking. Likewise, Agirman et al. (2013) highlight the fragility of such banking and define shadow banking as a great variety of highly leveraged institutions that do not take deposits that lend a lot and borrow shortly in liquid markets. Fragility occurs from a point of solvency as well as liquidity; although it can be argued that not having a safety net is very unwise, the moral hazard problems created by deposit insurance would be alleviated, as stated by Benveniste and Berger (1987).

The regulation of shadow banking would be one of the solutions to this fragility. Currently, the regulation of traditional banking can be considered as an element that favored the development of shadow banking, for Górnicka (2016) shadow banking arises as a result of regulatory arbitration and for Plantin (2014), banking in the shadow arises from a high capital requirement that is suboptimal. This forces banks to switch to off-balance sheet intermediation, where adverse selection problems are more severe. In this line Irani et al. (2020) investigate the connections between bank capital regulation and shadow banking in the US corporate loan market. The USA finds that less capitalised banks retain fewer loans, and increase volatility from asset sales. This occurs due to the fragility of shadow banking financing.

Although the fragility of shadow banking is one of its major problems, there are several authors who highlight advantages, for example, Irani et al. (2020) find that non-bank entities may have the flexibility to provide substitute credit when bank capital restrictions are tightened, thus allowing borrowers to maintain access to credit. They also note that non-banks may be more diversified and less systemically important, and therefore shifting risks to the non-banking sector could improve overall financial stability. But considering that the reallocation of credit could be counterproductive if the risks are simply transferred to unregulated entities, this also presents significant risks to the financial system.

Another advantage of shadow banking, although nuanced, according to the cycle of the economy, as maintained by Moreira and Savov (2014), shadow banks provide money-like and information-insensitive values. When there are no financial strains, additional liquidity encourages household savings, encourages investment, and increases growth. In contrast, in shocks, the values of shadow banking become illiquid, deleveraging accelerations and the execution of guarantees occurs. This occurs as explained by Adrian et al. (2013), because the shadow bank's leverage tends to be high when the balance sheets are large and credit intermediation is expanding. Furthermore, capital is countercyclical, as intermediaries tend to hold as little capital as possible during booms, but are forced to increase capital during recessions when market risk increases. In this line, Deutsche Bundesbank (2014) shows that in the United States, leverage is managed more actively by shadow banks than by commercial banks, thus highlighting that it is shadow banking that generates volatility for the transfer of assets. Growth in asset prices increases the assets of shadow banking, financed with short-term debt. This creates a self-reinforcing process that includes balance sheet growth, increased leverage, reduced risk premiums, and increased loans to the nonfinancial sector. In fact, for Sieron (2016), shadow banking shows that non-banking institutions can also carry out credit expansion and generate the economic cycle. Importantly, the latter activity also allows shadow banks to expand credit on their own. This is because they can create liquid promissory notes that work like money and are used as collateral against credit. The reuse of this guarantee amplifies the creation of credit. Supporting these approaches are Fève el al. (2019), by estimating a DSGE model of the United States economy with traditional and shadow banks that interact. They prove that shadow banking amplifies the transmission of structural shocks. They show how the leak to shadow entities reduces the ability of macroprudential policies aimed at traditional credit to reduce economic volatility. They suggest that a countercyclical capital buffer, if applied only to traditional banks, would have amplified the boom-bust cycle associated with the 2007-2008 financial crisis. On the other hand, a broader regulatory scheme targeting both traditional credit and shadow credit would have helped stabilise the economy. Moosa (2017) agrees with these ideas, concluding that it does not make sense to regulate deposit institutions while giving shadow banks a free hand to do as they please. Agresti and Brence (2017) propose several additional risk indicators for shadow banking that could potentially be included in the ESRB (European Systemic Risk Board) risk metrics framework, such as leverage liquidity indicators and maturity transformation. They also present several ratios of shadow banking that present these risks, but with the advantage that they are related to commercial banking. This constitutes one of the objectives of our work, but from a macroprudential perspective.

Although there are some advances in regulation by the Dodd-Frank Law, as stated by Gorton and Metrick (2010), there are still significant regulatory gaps; the regulation of money market mutual funds, securitisation and repos. They suggest that these areas require further regulation because they played "the central role in the recent crisis." It should be noted that the fund industry is one of the most important according to the size of shadow banking. The FSB (2017) and Gerety (2017) highlight that an increase in assets held in certain investment funds has increased the risks of liquidity transformation, underscoring the importance of addressing structural vulnerabilities in asset management activities. Likewise, Bellavite et al. (2017) conclude that money market funds, a significant part of shadow banks, increased systemic risk in the UK before the 2008 crisis, show that the liquidity mismatch increases systemic risk. Evidence indicates that shadow banking is highly vulnerable to liquidity shocks and is highly procyclical, posing problems for financial and macroeconomic stability.

3. ANALYSIS OF BANKING IN SHADOW AND TRADITIONAL BANKING

It begins with an analysis of the evolution and consideration for the purposes of the work of shadow banking in the United States. The institutions that are listed as shadow banking are the same ones that Pollin and Heintz (2012) consider in their work on the United States financial system. The institutions are represented in this first Figure, showing the total financial assets of different entities considered shadow banking over domestic financial assets. It is observed how the mutual funds present the highest growth, and in the crisis of 2002 and 2009, they present a great decrease (in the Figures the assets of the various institutions are presented over the total of the domestic financial assets).

Figure 1

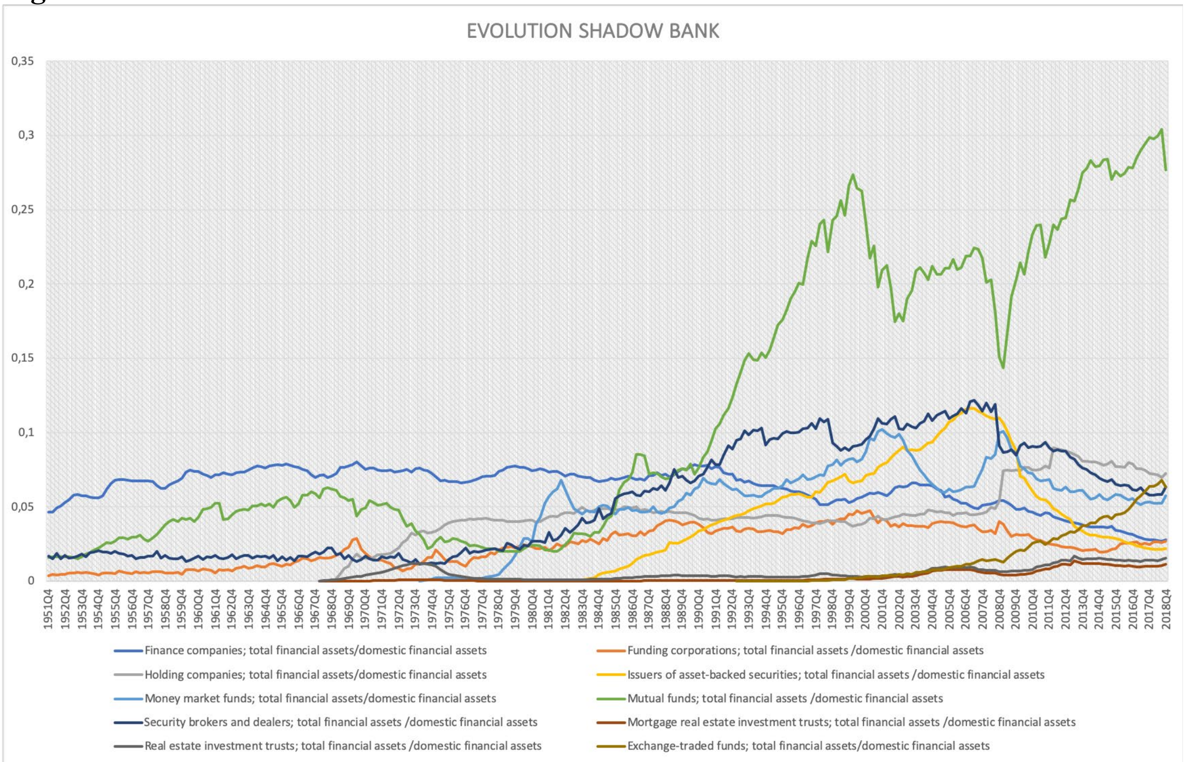


Figure 2.a represents mutual funds with respect to private deposit institutions, due to their importance. Throughout the historical series, the decrease in the weight of the assets of private deposit entities is observed, compared to the increase in assets in mutual funds. In figure 2.b this time is represented against the total number of shadow banks. It is evidenced from 1992, which is when the Basel I accord is implemented in the United States. Precisely from that year, specifically in 1993, the assets of shadow banks exceed the assets of traditional banks.

Figure 2a.

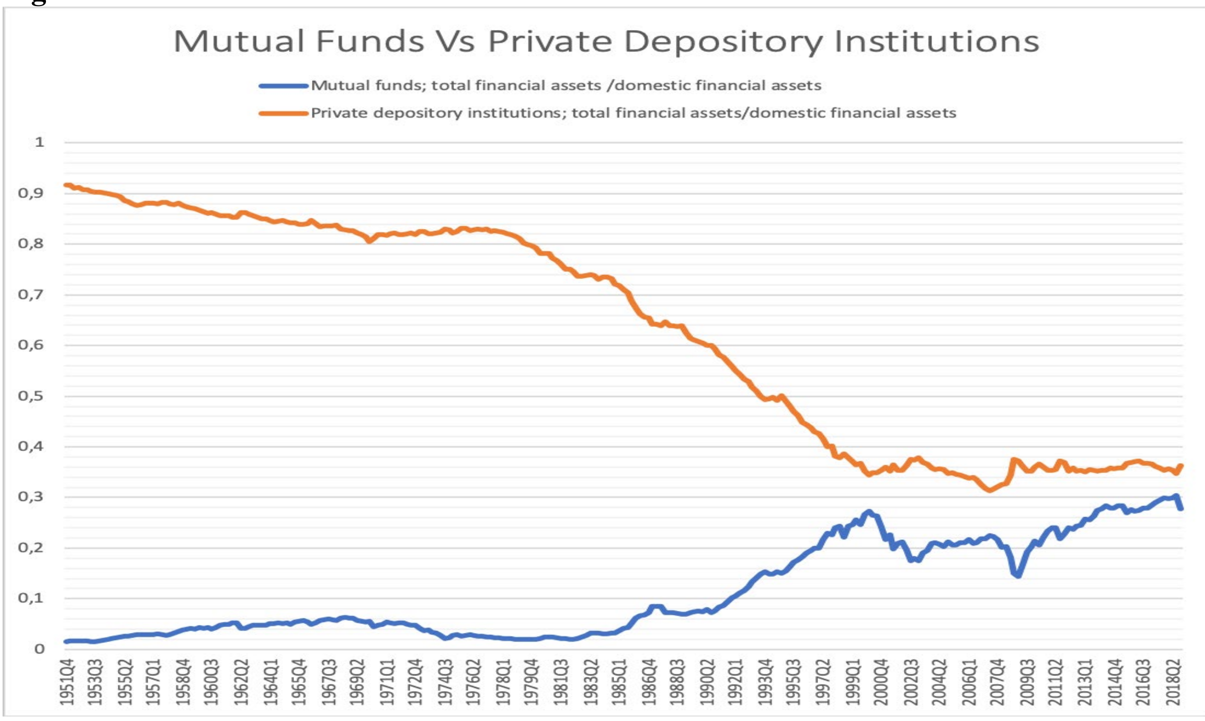
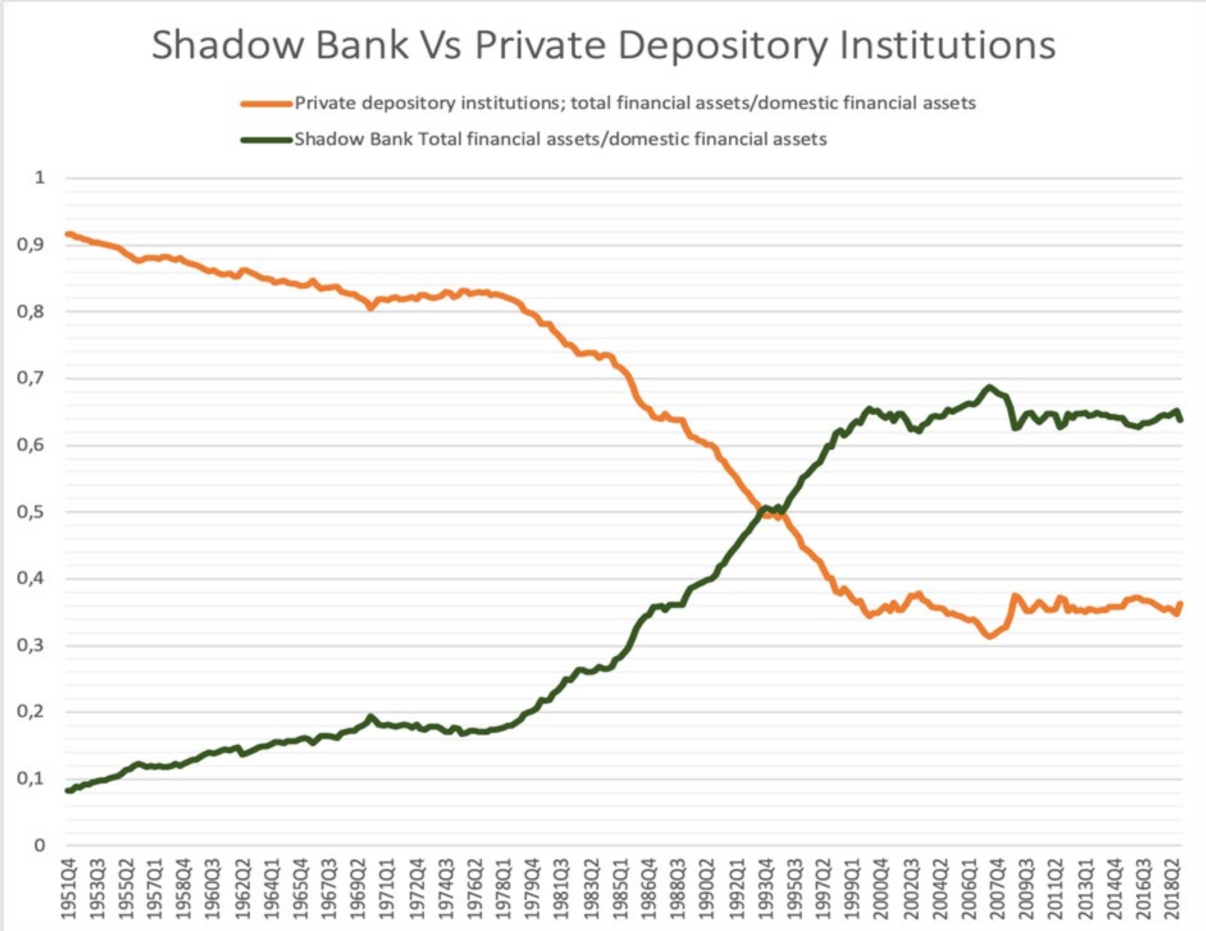


Figure 2b.



2.1 Canonical Analysis

First, a canonical analysis is carried out, the study period covers from the first quarter of 1993 to the last quarter of 2018 (the years in which we have data from all the series are taken). The variables used are listed in Annex 1, different aspects of both types of banks, solvency, liquidity, growth are covered of assets, financing structure and investment among others. The data used to form the variables is collected from the FED for shadow banking and directly from the FDIC for commercial banking. Canonical analysis is used, which consists of finding two sets of base vectors, one for x that represents the set of variables of the traditional bank and another set for y, that represents the set of variables of the shadow bank, such that the correlations between the projections of the variables in these base vectors are maximized mutually represented by ρ.

$$\rho = \frac{\mathrm{E}[x\mathcal{Y}]}{\sqrt{\mathrm{E}[x^2]\mathrm{E}[\mathcal{Y}^2]}} = \frac{\mathrm{E}\left[\,\hat{\mathrm{w}}_x^{\mathrm{T}}\, x\mathcal{Y}^{\mathrm{T}}\hat{\mathrm{w}}_{\mathcal{Y}}\right]}{\sqrt{\mathrm{E}[\hat{\mathrm{w}}_x^{\mathrm{T}}\, xx^{\mathrm{T}}\hat{\mathrm{w}}_x\,]\mathrm{E}[\hat{\mathrm{w}}_x^{\mathrm{T}}\, yy^{\mathrm{T}}\hat{\mathrm{w}}_y\,]}} = \frac{w_x^{\mathrm{T}}\, C_{x\mathcal{Y}}\, W_{\mathcal{Y}}}{\sqrt{W_x^{\mathrm{T}}\, C_{xx}\ W_x W_{\mathcal{Y}}^{\mathrm{T}} C_{\mathcal{Y}\mathcal{Y}} W_{\mathcal{Y}}}}$$

Being W_{x} y W_{y} projections on x and y, which are called canonical variables.
Being C_{xx}, $C_{\mathcal{Y}\mathcal{Y}}$ the covariance matrices of the sets and $C_{x\mathcal{Y}}$ the variance matrix between sets.
Subsequent canonical correlations are uncorrelated for different solutions:

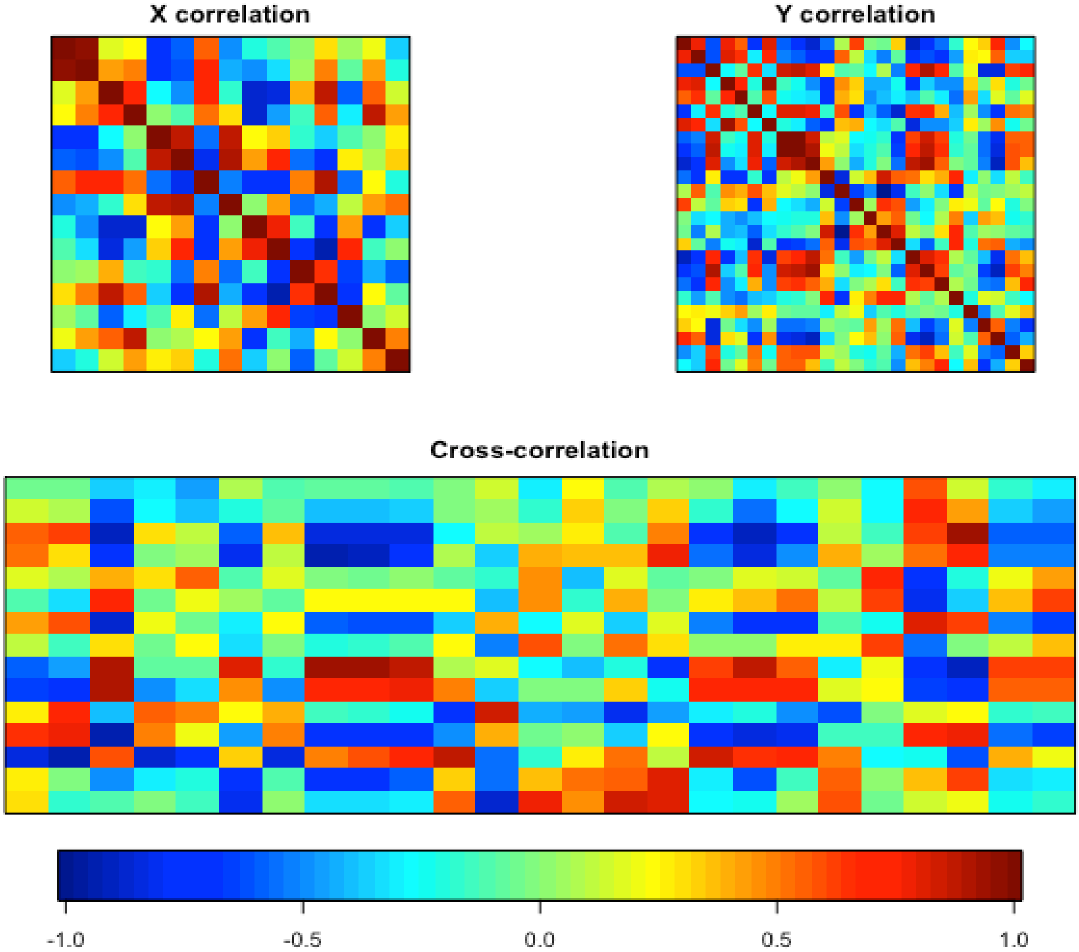
$$\mathrm{E}\left[x_i x_j\right] = \mathrm{E}\left[W_{xi}^{\mathrm{T}} xxC^{\mathrm{T}} W_{xj}\right] = W_{xi}^{\mathrm{T}} C_{xx} W_{xj} \ = 0$$

$$\mathrm{E}\ [\mathcal{Y}_i\mathcal{Y}_j] = \mathrm{E}[W_{\mathcal{Y}i}^{\mathrm{T}}\ xx\ C^{\mathrm{T}}\ W_{\mathcal{Y}j}] \ = \ W_{\mathcal{Y}i}^{\mathrm{T}} C_{\mathcal{Y}\mathcal{Y}} W_{\mathcal{Y}j} \ = 0 \quad \text{for } i \neq j.$$

$$\mathrm{E}\left[x_i\mathcal{Y}_j\right] = \mathrm{E}\left[W_{xi}^{\mathrm{T}} x\mathcal{Y}C^{\mathrm{T}} W_{\mathcal{Y}j}\right] = W_{xi}^{\mathrm{T}} C_{x\mathcal{Y}} W_{\mathcal{Y}j} \ = 0$$

Figure 3 shows the correlation of matrix X and matrix Y of the values that represent the variables defined for shadow banking and for commercial banking. The cross-correlation matrix between both matrices is also represented.

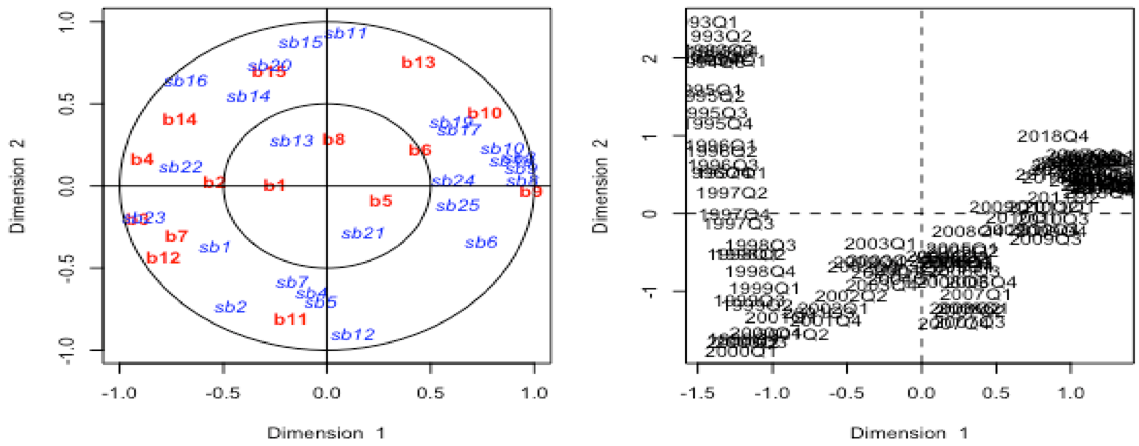
Figure 3



2.1.1 First dimension

This dimension is called shadow banking and bank solvency. (As bank solvency increases, the growth of total shadow banking assets over total domestic assets increases). Annex 1 shows the correlations of the variables with the dimension. It can be concluded that when bank solvency, and specifically regulatory solvency, a leak of financial resources to shadow banks occurs. However, when bank solvency deteriorates, due to unfavorable economic conditions, the growth of shadow banking assets is reduced, seeking the safety net of the regulated sector. Figure 4 represents dimension 1 versus dimension 2.

Figure 4



In the first dimension, it is observed that various ratios of shadow banking assets to GDP are observed, saturating in a positive way in this dimension. Specifically, sb3 (Holding companies; total financial assets), sb6 (Mutual funds; total financial assets), sb8 Mortgage real estate investment trusts; total financial assets), sb9 (Real estate investment trusts; total financial assets), sb 10 (Exchange-traded funds; total financial assets).

As well as bank solvency ratios b9 (Equity Capital to Assets) and b10 (Total Risk-Based Capital Ratio (PCA)) and a solvency ratio sb17 (Financial assets / Financial Liabilities (Security broker and dealers)) and liquidity sb18 (Checkable deposits / Financial Assets (Security broker and dealers)) of security brokers and dealers, as well as a liquidity ratio of holding companies sb19 (Total Time and savings deposits; asset / total financial assets).

With a negative sign that saturates in this dimension, we have bank financial profitability (b2), net interest margin (b4), the cost of financial assets (b3), net loans on total assets (b12) and deposits insured on total deposits (b14) and coverage ratio (b7). It also correlates the ratio of municipal assets to the total assets of the Mutual Funds (sb16) and debt assets to financial assets (sb22), as well as the commercial role on financial assets of holding companies (sb23).

For higher values of this dimension, shadow banking occupies a greater position of assets over domestic financial assets, there is greater financial solvency of commercial banks and security brokers as well as greater liquidity of security brokers and holdings companies.

For smaller dimension values, the following indicators: the bank's financial performance is higher, as well as its interest margin, as well as net loans on total assets and the proportion of provisions on loans. The cost of financing also increases, as well as the interest margin that favors financial profitability.

Municipal bonds on the total assets of mutual funds increase as this dimension becomes more negative. The latter ratio saturates inversely to the ratio of financial assets of mutual funds to domestic financial assets. This can be explained because when there is a decrease in the financial assets of the funds over the domestic financial assets, the investment in these financial assets that are safe and with good returns will grow.

In holding companies, when the ratio of assets that have debt to total assets becomes higher, their subsidiaries are likely to have less capital. This last ratio correlates negatively in the dimension, as well as the regulatory capital ratios. Financial profitability also correlates jointly with this ratio, negatively in this dimension. On the other hand, the commercial paper on the financial assets in the holding companies correlates negatively in the dimension, it is assumed that the debts are greater in the system and the emissions in the short term are increased to be financed.

2.1.2. Second dimension

This dimension is called latent risk in traditional banking and in shadow banking, which increases as the dimension decreases. Specifically, they correlate negatively on the dimension: risk-weighted assets on total assets (b11), financing companies assets /total domestic assets (sb2), the assets of issuers of asset-backed securities on total domestic assets (sb4), the assets of the monetary funds over the total domestic assets (sb5), Security brokers and dealers on total financial assets over total domestic assets (sb7) and shares of corporations / total assets (Mutual Funds) (sb 12).

It correlates positively in the dimension, indicating a lower risk in the dimension of the financing of deposits on total assets (b13).

In contrast, the total assets of depository institutions over national financial assets (b15), the proportions of treasury assets with respect to the total assets of mutual funds (sb11) and holding companies (sb 20), agreements of repurchase of securities / Total assets (sb14) and debt securities / total assets (sb15) are positively correlated with the dimension.

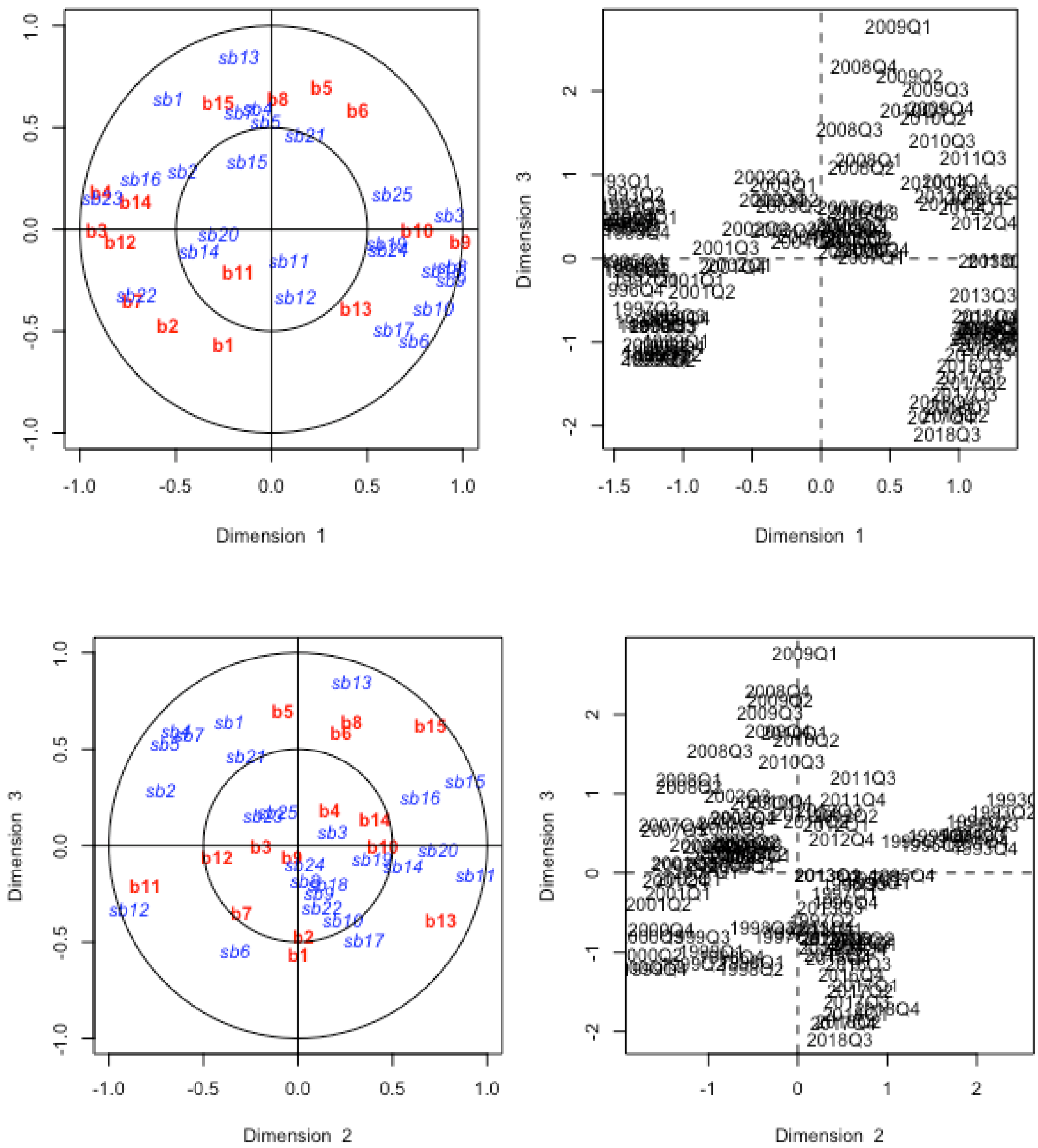
The joint explanation for this dimension may be that when risk increases in traditional banking, there is an increase in the business of the entities of the issuers of asset-backed securities with loans that leave the balance sheet and are securitised. It also increases the business of finance companies and the activity of security brokers and dealers. The risks that traditional banking does not assume begin to be undertaken by this shadow bank. Therefore, the assets of deposit institutions over total domestic assets, correlates negatively with this dimension. Regarding the structure of mutual funds, investment in debt and in security repurchase agreements correlates inversely in the dimension to investment in stocks. This may be due to at times of less risk taking, investment shifts from equities to debt securities versus investments in equities.

In the first quadrant (see Figure 4) it is demonstrated how b15 (Assets of deposit institutions / domestic financial assets) corresponds with sb 20 (Treasury securities / Financial assets (Holding Companies)). When the financial assets of depository institutions increase, at the holding level the proportion of treasury securities over financial assets increases. It may be due to a security search by the holding entity.

In the second quadrant (see Figure 4), the bank solvency (b10) and the solvency sb17 (Financial assets / Financial Liabilities (Security broker and dealers)) correlate between them, this is because in times of recession when there is a greater risk, a greater solvency is required for both entities. Holding companies also seek to increase their liquidity, to provide support to their investees. For this reason, it also correlates positively sb19 (Total term deposits and savings; assets / total financial assets (Holding Companies)).

In the third quadrant b9 (Equity Capital to Assets) (See Figure 4), which represents a solvency ratio, it is highly correlated with sb8 (Mortgage real estate investment trusts; total financial assets / domestic financial assets), indicating that the greater the bank solvency, the more financing in the mortgage market due to the increase in shadow banking.
In the fourth quadrant, b3 (cost of Earning Funding Assets) and sb23 (Commercial paper / Financial assets (Holding Companies)) are highly aligned with each other and negatively with dimension 1. The correlation can be explained, due to the increase in financing costs, the issuance of commercial paper is more profitable and the holding companies make investments in this asset.
Figure 5 represents the third dimension versus the first and second dimensions.

Figure 5



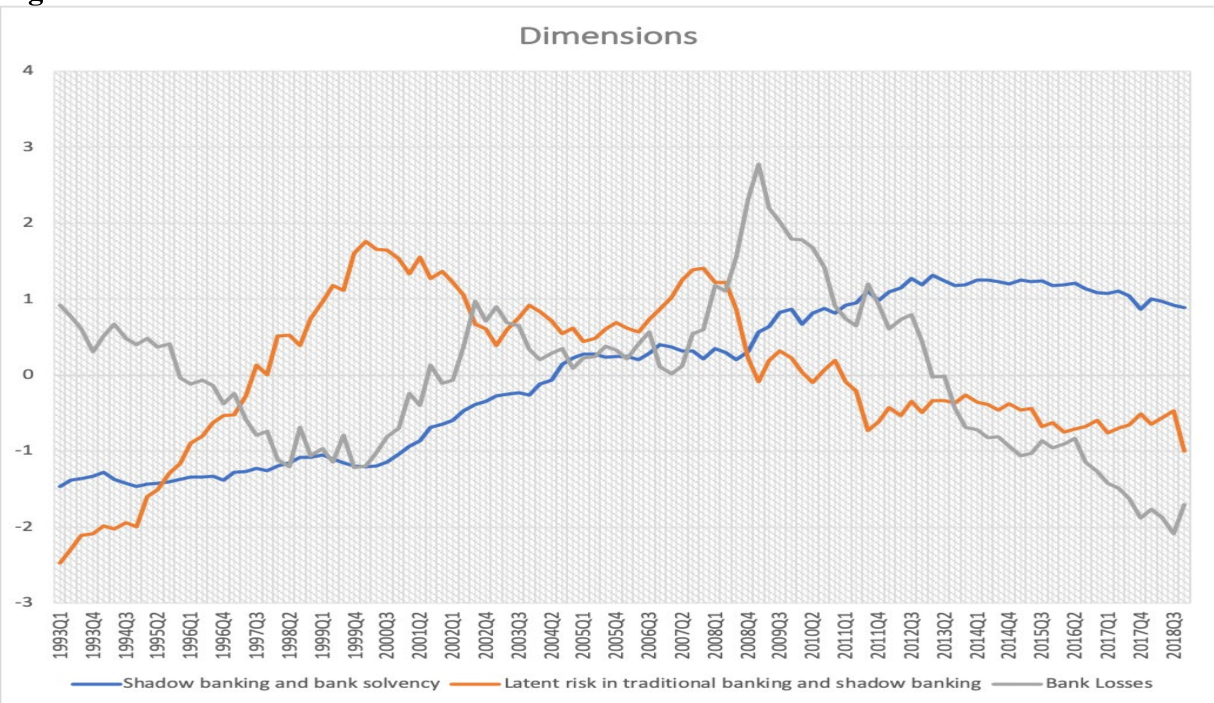
2.1.3 The third dimension

It is called losses from traditional banking; A correlation of all the provision and loss ratios in a positive way. Security repurchase agreements / financial assets (Holding Companies) sb21, correlates positively, because the holding entities are granting liquidity to their investees. On the other hand, economic profitability is negatively affected, therefore it is negatively correlated.
Dimension 4 and 5 are not taken since the connections are exceptionally low and have a low explanatory power, the Figure can be seen in Annex 2 (the correlations are very low and are within the circle radius 0.5).

2.1.4 Temporal analysis of dimensions

In the temporal analysis (see figure 6), dimension 2 the latent risk in traditional banking has been inverted so that a higher value implies greater risk. It can be seen that the increase in solvency requirements together with shadow banking grow evenly throughout the entire sample (dimension 1), specifically from 2002. Exactly, on July 4, Internal Ratings-Based Systems for Corporate Credit and Operational Risk Advanced Measurement Approaches for Regulatory Capital is issued, which together with Basel II becomes more demanding from the bank asset. As of 2009, with the 2009 issuance of the Basel Accords and subsequent implementation, the solvency of traditional banking, along with shadow banking in this dimension, increases again. It can be inferred that before the implementation of Basel III, by the United States there is already an increase in solvency, along with an increase in shadow banking.

Figure 6



Regarding dimension 2 of latent risk in both types of banking, a decrease is observed from 2009 as a result of the crisis; with very high growth in the face of the crisis of 2003 and 2008. On the other hand, dimension 3, bank losses is seen to manifest just as the growth of dimension 2 (latent risk), reaching its maximum just 2 years later to reach the maximum both in the period 2000-2002, and in the period 2008-2010.

3.Analysis of Shadow Banking Gaps

In this section, the objective is to obtain the gaps and group them, through the ratio of total shadow banking assets to GDP. It seeks to obtain a measure of risk from shadow banking. The gap of each of the 10 series that reflect each type of shadow banking is extracted, as well as the gap of the series formed by the ratio of total assets to GDP for deposit institutions[2]. Annex 3 presents the series and their gaps according to all available data. For this, the Holdrick Precott filter is used, which extracts the trend, T_t, minimising the following function:

$$min_{\mathrm{T}t} \sum_{t=1}^{\mathrm{T}} (\mathcal{Y}t + \mathrm{T}t)^2 + \lambda \sum_{t=2}^{\mathrm{T}-1} [(\mathrm{T}_{t+1} - \mathrm{T}_t) - (\mathrm{T}_t - \mathrm{T}_{t-1})]^2$$

Being λ the correction factor [3].

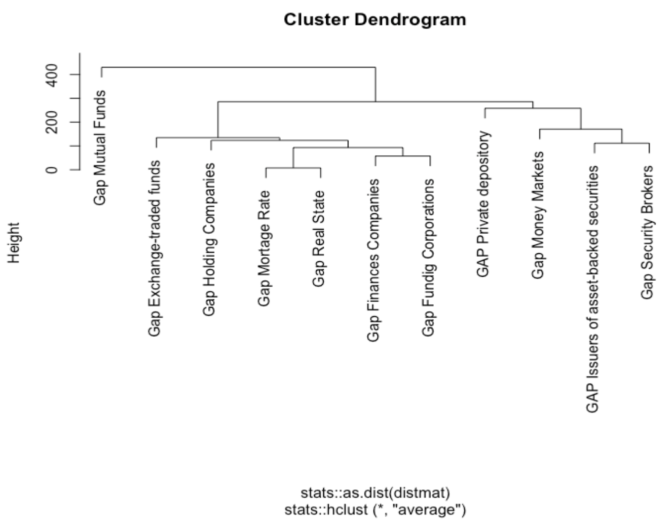
Then we use the time series cluster, in this case the data from the first quarter of 1993 to the last quarter of 2018 are used (the years in which we have data from all the series are taken), with the same data the regression tree and Random Forest will be performed. All values are present in this time range. The distance between clusters is calculated with the following formula:

$$d(i \cup j, k) = \alpha_i d(i,k) + \alpha_j d(j,k) + \beta d(i,j) + \gamma \left| d(i,k) + d(j,k) \right|$$

$d\,(q,r)$ is the distance between the clusters C_q and C_r, $d(i \cup j, k)$ is the distance between the clusters $C_i \cup C_j$ y C_K and the parameters $\alpha_i, \alpha_j, \beta$ *and* γ which, together with the distance function, determines the method for the agglomerative hierarchical grouping.

With the time series cluster it is observed how the gaps are grouped and the groups that present a similar behavior are interpreted. Below is the dendogram (Figure 7) that allows us to differentiate the groups according to height.

Figure 7



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[2] To see different evaluation measures for the establishment of countercyclical capital see Basel Committee on Banking Supervision (2018) "Towards a sectoral application of the countercyclical capital buffer: a literature review"

[3] Galán (2019) In his work he discusses the smoothing parameter to be used for the Holdrick Precot filter.

We chose 7 groups, according to the dendogram. A cut is made at a height of 100. Groups let you see how gaps behave. The groups that are formed are (Annex 4 presents the Figure of the grouped series):

Group 1: The Private depository Gap is grouped.

Group 2: The Finances Companies Gap, the Funding Corporations Gap, the Mortage Rate Gap and the Real State Gap are grouped. This group groups the entities with a great impact on financing.

Group 3: The Holding Companies Gap is grouped.

Group 4: The Issuers of asset-backed securities Gap and the Security Brokers Gap are grouped. In this group, a large cyclical component is observed due to the observed gap, inside the bench in the shade. It is observed that its gap is the one with the most amplitude presentingwithin all groups. It is the type of shadow banking that is furthest from the trend both in times of shocks and expansion.

Group 5: The Money Markets Gap is grouped.

Group 6: The Mutal funds Gap is grouped.

Group 7: The Exchange-traded funds Gap is grouped.

4. Gap and delinquency analysis

In this section, the aim is to analyse which gap is more important in determining bank losses, for this, the Percent of Loans and Leases Noncurrent (b6) is used as a predictor. With this, it is intended to study the influence of these gaps on bank losses and with it on banking crises.

A regression tree is then performed in which, in addition to the gaps previously calculated, the credit gap over GDP is added, as a predictor variable. The analysis is performed for the same period as the canonical analysis and the time series cluster. The gaps have the following codes represented in Table 1:

Table 1

Codes	Gaps
Gap 1	Gap Private depository
Gap 2	Gap Finances Companies
Gap 3	Gap Funding Corporations
Gap 4	Gap Holding Companies
Gap 5	Gap Issuers of asset-backed securities
Gap 6	Gap Money Markets
Gap 7	Gap Mutual Funds
Gap 8	Gap Security Brokers
Gap 9	Gap Mortage Rate
Gap 10	Gap Real State
Gap 11	Gap Exchange-traded funds

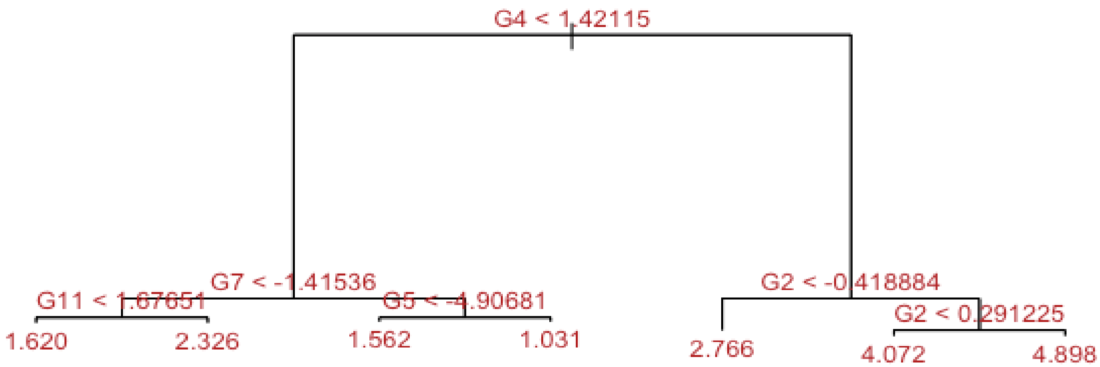
A regression tree is used [4], which is a machine learning method to build prediction models from data. As advantages, these methods have an easy interpretation and their solidity at extreme values. It also enables capturing linear and non-linear relationships and there may be a link between variables. As problems, this methodology presents a remarkably high variance, that is, a small change in the data can cause different partitions of the data. This will be corrected with the use of different Machine Learning ensemble methods.

The regression tree follows the following model:
Let Y be a response variable and let p be predictor variables x1, x2, ..., xp, where the xs are taken fixed and Y is a random variable. The statistical problem is to establish a relationship between Y and the X's in such a way that it is possible to predict Y based on the values of the X's. To do this, we want to estimate the function of its probability such as:
E[Y|x1,x2,...,xp]
It seeks to obtain a minimum variance within each node τ of the tree,
$i(\tau)= \sum_{i\in\tau}((Yi - Y(\tau))^2$

Where Y (τ) is the average of Y´s within the node τ.
To divide a node τ into two child nodes, τ_L (left node) and τ_R (right node), the goodness of a division s is defined as:
$\Delta I(\tau) = i(\tau) - i(\tau_L) - i(\tau_R)$
With this last equation, the impurity reduction is obtained when the parent node is passed to the child node, the impurity reduction is sought to be maximum.
The objective is to obtain the maximum homogeneity of those of the terminal nodes.
It is sought that R (τ) be minimized as:
$R(\tau)= \sum_{\tau\in\zeta} i(\tau)$
Where ζ represents the set of terminal nodes.

In the regression tree (see Figure 8) it is proven that G4 representing the Gap of holding companies is the most important variable to predict insolvency in the traditional banking system, when the gap is greater than 1.42 and G2 (the gap of the Finances companies) is greater than 0.29. Bank losses are in the order of 4,898. In the extreme case of less losses we have for G4 values of 1.42 and for values greater than G7 (Gap of the Mutual Funds) higher than -1.41 and for G5 values (Gap Issuers of asset-backed securities) higher at -4,9068 the lower bank solvency values.

Figure 8



[4] The strengths and weaknesses of the regression trees is developed by Loh (2011) and the development of the algorithm by Breiman et al. (1984).

The MSE we get 0.200686, which means the error is 0.4479. These results may lead us to reflect on a regulatory surcharge on the gap for certain entities, according to their influence on bank losses, which we will examine with the application of Random Forest, we use this methodology with the intention of improving the prediction. In prediction trees like all statistical models, the balance between bias and variance must be taken into account. By the concept of bias, it is understood how far the predictions from the real values are on average. Variance is understood as the variation of the model, depending on the sample used in the training phase. More complex models tend to reduce bias, increasing the predictability of the model. On the other hand, an overfit can occur, that is, the model adjusts so much to the training data that it does not correctly predict new data. Therefore, a model with a balance between bias and overfit is pursued.

In predictive tree models with many nodes, they tend to fit the training sample very well, but at the cost of greater variance. With the assembly method used in this work, a balance between bias and variance is pursued. In the method of Random Forest[5], repeated sampling is carried out. A model is fitted with the different samples of the population, and the result is averaged, reducing the variance. For this, bootstrapping is used, generating different samples through resampling. With each of these samples a tree is made, which is not pruned, having a reduced bias but a greater variance. The algorithm's stop system is the minimum number of observations that the final nodes must have. It is a modification of the bagging model by mitigating the correlation between the trees; this is achieved by selecting the predictors at random. It prevents a very influential predictor from dominating the construction of the trees. The MSE estimates the prediction error of the model considering these observations that have been "left out of the training sample". This error is calculated as follows: $\frac{1}{n}\sum_{i=1}^{n}(\text{yi} - \text{yiOOB})^{2}$

Being yi_{OOB} the prediction for observation is obtained by averaging the individual predictions of the trees for which that observation has been left out of the training sample and real the actual value of the response variable.

We managed to improve the prediction by obtaining an MSE of 0.1794699, improving the prediction that we obtained using the regression tree.
To calculate the importance of the predictors, the increase in the MSE and the increase in the purity of the nodes are used. The increase in the MSE identifies the influence of each predictor on the MSE of the model estimated by the out of bag error.

MSE OOB (Xj permuted) = $\frac{1}{n}\sum_{i=1}^{n}(\text{yi} - \text{yiOOB}(\text{Xj permuted}))^{2}$

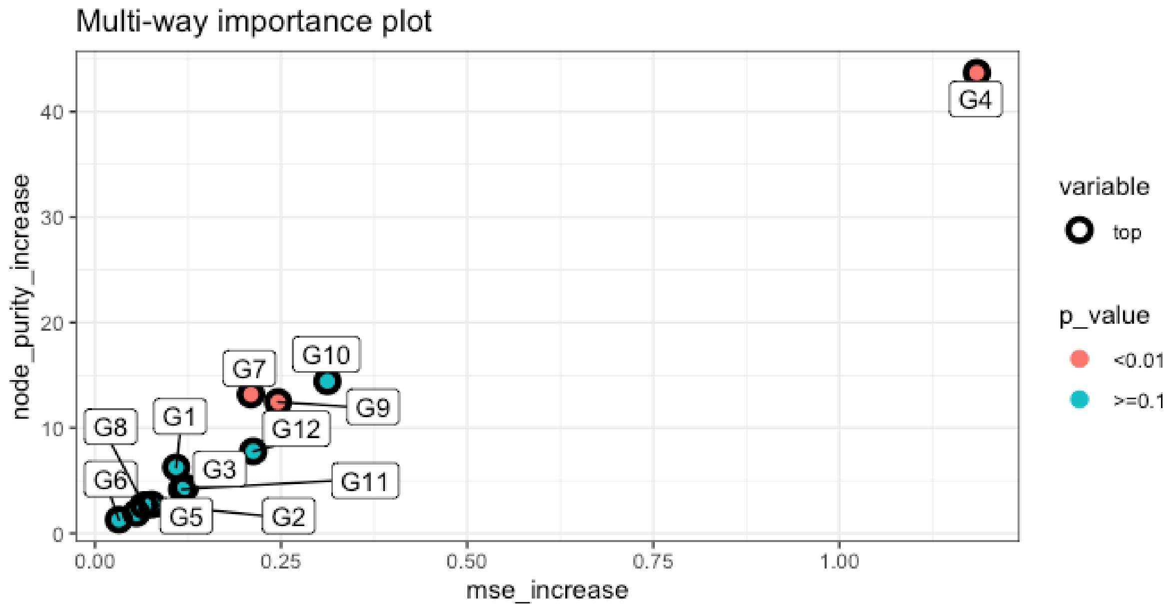
After this, for each variable X in each tree t, the difference between the two measures MSE OOB ($X\ permut$ed) and MSE OOB is calculated. This difference, for each variable, is summed in all the trees, averaged and normalised between the standard deviation of the differences. The result of this process is a measure of the importance of each variable. If the predictor that is not included provides information about the model, the MSE will increase.

The increase in the purity of the nodes is calculated by the decrease in the MSE, which is calculated as the average decreases. Therefore, the higher the value, the greater the contribution of the predictor to the model (see Figure 9).

[5] Breiman (2001) develop the advantages of random forest.

In the Figure we see the most important variables for the model, they are G4 (Gap Holding Companies), G10 (Gap Real State); G9 (Gap Mortgage Rate) and G7 (Gap Mutual Funds), to predict bank insolvency.

Figure 9



We will now see within the model how these variables interact in the prediction of bank delinquencies. It is shown in Figure 10 how when the G4 is greater than 2% and the G7 is less than approximately 1%, the highest percentage of failures occurs. This is supposed to be caused by the rapid takeover of liquidity from such funds. Something similar happens with G10.

Figure 10 a

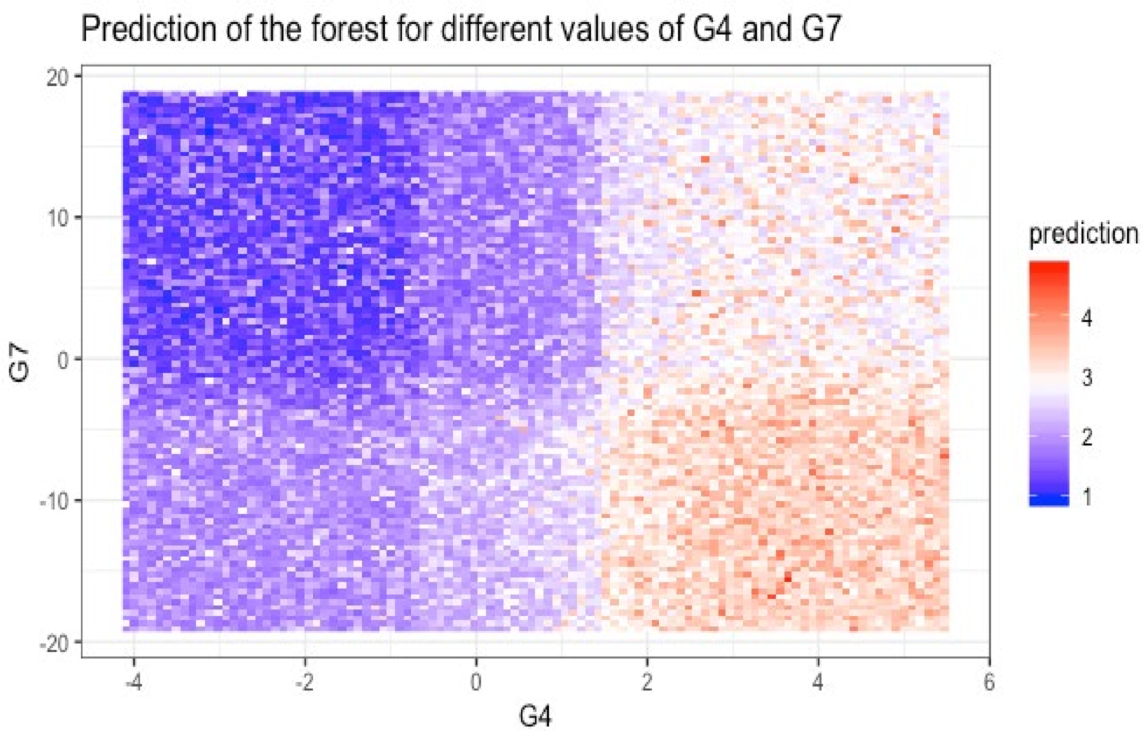
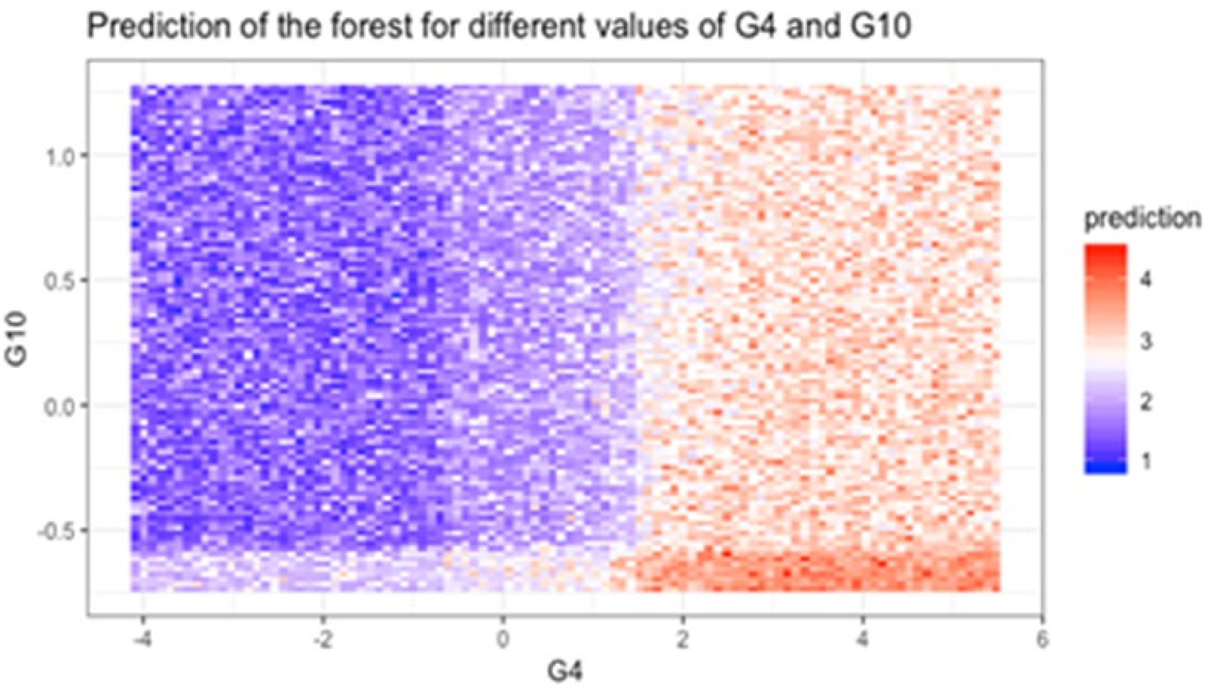


Figure 10 b



In the prediction (Figure 10 a) for G7 that represents the gap of the Mutual Funds and G4 that represents the Gap of the Holdings companies, it is displayed that for a higher Gap of the Holdings Companies, the highest percentage of failures is predicted, together with a lower Gap value of mutual funds below zero. However, exactly when the Gap G10 (Gap Real State) is less than -0.5 major failures occur (see Figure 10 b) and G4 exceeds 2%.

This constitutes a system that could be used to establish regulatory surcharges for shadow banking, based on calculated gaps. Taking into account those entities that may have a greater influence on financial stability, for example by focusing more on gaps than those determined by our model and previously explained.

CONCLUSIONS

With the canonical analysis, three dimensions are obtained that allow establishing various ratios of shadow banking and traditional banking, the dimensions are the first shadow banking and bank solvency, the second dimension latent risk in traditional banking and in shadow banking and the lost third dimension of traditional banking. It is concluded that when bank solvency increases, there is a growth in shadow banking. The increase in bank risk is accompanied by an increase in certain activities of shadow banking, such as issuers of asset-backed securities and financing companies, among others. The risks that traditional banking does not assume begin to be assumed by banking in the shade.

Shadow banking is largely determined by regulation, in times of strict regulation there is an increase in such banking. A part of the credit and financial activity is directed towards this type of banking, avoiding the stricter regulation of traditional banking. On the other hand, in times of crisis, shadow banking rapidly reduces its size, resources are quickly transferred to the regulated sector, benefiting from its safety net, increasing the procyclicality of the system. Therefore, Basel III's attempts to reduce procyclicality through countercyclical capital, we believe are incomplete in not considering shadow banking, the main responsibility for the procyclicality of the system.

The gaps of the assets of different shadow banking institutions on GDP are proposed as possible instruments to measure risk. With the time series cluster, 7 groups of gaps are obtained. These instruments can be used to extend the macroprudential regulation of shadow banking and avoid leaks that occur from the regulated to the unregulated sector and vice versa according to economic status.

One of the great advantages of the work is the approximation of the identification of instability in traditional banking, understood as delinquency through the gaps of shadow banking and traditional banking, evaluating its importance according to machine learning. Specifically, the gaps according to the random forest algorithm that best predict bank delinquencies are, in order of importance, the Holding Companies Gap, Real State Gap, Mortage Rate Gap, and the Gap Mutual Funds Gap.

This analysis can also be used as an early warning mechanism to detect imbalances in shadow banking that can revert to traditional banking.

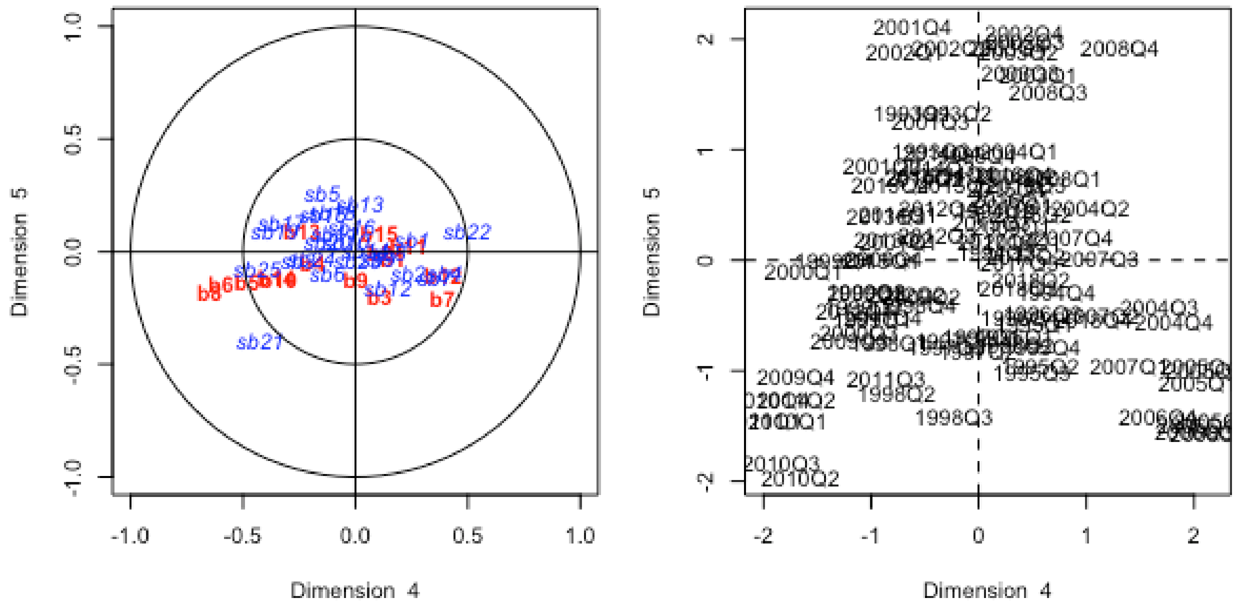
Appendix 1

Codes	Banking variables	Dimension 1	Dimension 2	Dimension 3	Dimension 4
b1	Return on Assets	-0.24888380	0.004483917	**-0.555530613**	0.164376340
b2	Return on Equity	**-0.54000601**	0.029116607	-0.466907946	0.107758914
b3	Cost of Earning Funding Assets	**-0.91090671**	-0.195078100	0.002845710	0.106382717
b4	Net Interest Margin	**-0.88890539**	0.166769401	0.180498610	-0.187531148
b5	Net Charge offs to loans and leases	0.26032463	-0.081264157	**0.698145481**	-0.473457379
b6	Percent of Loans and Leases Noncurrent	0.45063712	0.227678386	0.584733155	**-0.590059537**
b7	Loss Allowance to non-current Loans & Leases (Coverage ratio)	**-0.72389117**	-0.297851456	-0.343528045	0.381603069
b8	Loss Allowance to Loans and Leases	0.03450898	0.283938177	**0.643075605**	-0.639635763
b9	Equity Capital to Assets	**0.98442774**	-0.032264518	-0.060793003	0.002262065
b10	Total Risk-Based Capital Ratio (PCA)	**0.76100810**	0.448037896	0.002100055	-0.337550936
b11	Risk-Weighted Assets to Total Assets	-0.17271690	**-0.804713418**	-0.206499265	0.232846178
b12	Net Loans & Leases to Total Assets	**-0.78667846**	-0.427995850	-0.059456931	0.385338528
b13	Total Deposits as a % of Total Assets	0.44164940	**0.754063417**	-0.386445171	-0.233189900
b14	Insured Deposits as a Percent of Total Deposits	**-0.70759407**	0.406359582	0.142943338	-0.345767544
b15	Assets of deposit institutions / domestic financial assets	-0.27779258	**0.699424109**	0.619227016	0.104927570

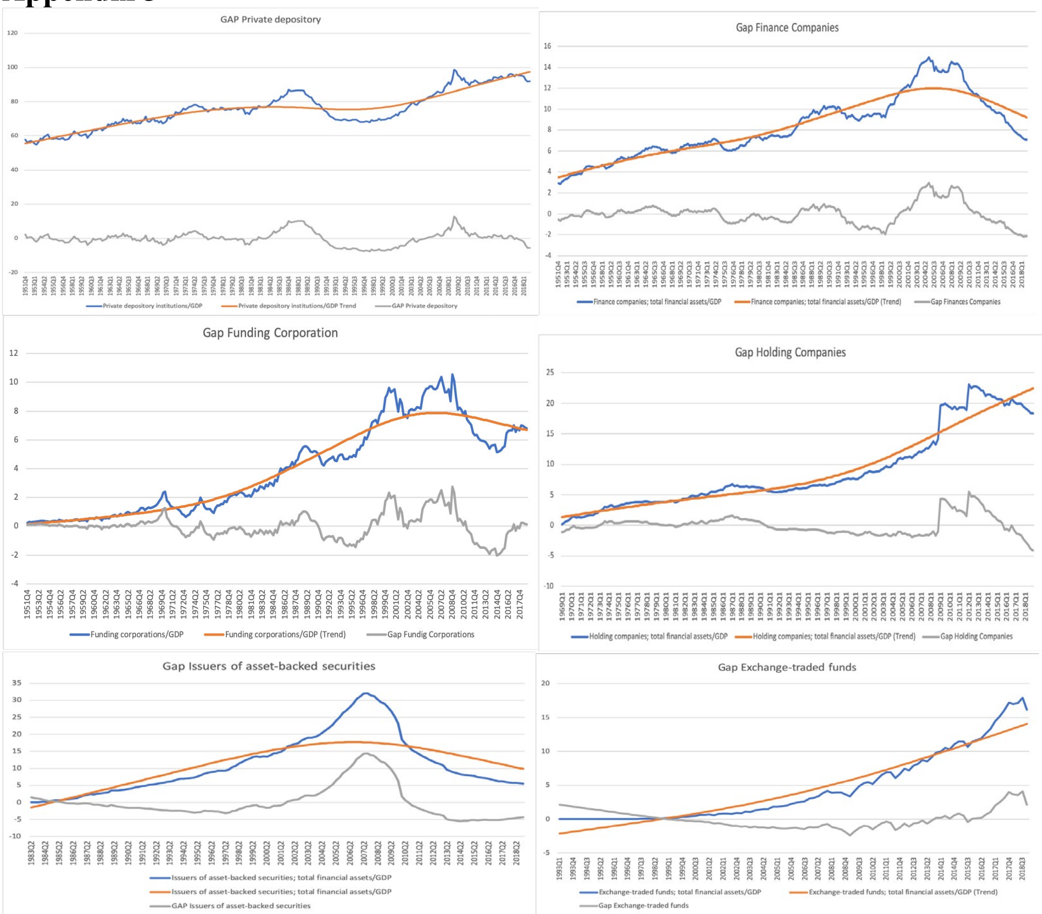
Codes	Shadow banking variables	Dimension 1	Dimension 2	Dimension 3	Dimension 4
sb1	Finance companies; total financial assets/ domestic financial assets	-0.54115778	-0.36634820	**0.64948903**	0.254277281
sb2	Funding corporations; total financial assets/ domestic financial assets	-0.46755070	**-0.72971227**	0.28867522	0.235878313
sb3	Holding companies; total financial assets/ domestic financial assets	**0.92761724**	0.18111119	0.07489467	-0.259532005
sb4	Issuers of asset-backed securities; total financial assets/ domestic financial assets	-0.07510023	**-0.64930809**	0.60532254	0.399014562
sb5	Money market funds; total financial assets/ domestic financial assets	-0.03316528	**-0.70701426**	0.53947530	-0.151977913
sb6	Mutual funds; total financial assets/ domestic financial assets	**0.74325177**	-0.33468202	-0.54292708	-0.127664205
sb7	Security brokers and dealers; total financial assets/ domestic financial assets	-0.17006740	-0.57931600	**0.58296888**	0.357006168
sb8	Mortgage real estate investment trusts; total financial assets/ domestic financial assets	**0.94157695**	0.03512861	-0.18372190	0.146800530
sb9	Real estate investment trusts; total financial assets/ domestic financial assets	**0.93652712**	0.11071235	-0.24560593	0.099156753
sb10	Exchange-traded funds; total financial assets/ domestic financial assets	**0.84522940**	0.23495232	-0.39123327	-0.045755793
sb11	Treasury securities / total assets (Mutual Funds)	0.08946181	**0.93892619**	-0.14828566	-0.095129454
sb12	shares of corporations / total assets (Mutual Funds)	0.12249028	**-0.89689983**	-0.33144758	0.142518834
sb13	Gse backed securities / total assets (Mutual Funds)	-0.17159972	0.28287264	**0.85238037**	0.017307047
sb14	security repurchase agreements / Total assets (Mutual Funds)	-0.38058341	**0.55508625**	-0.10622338	0.042707637

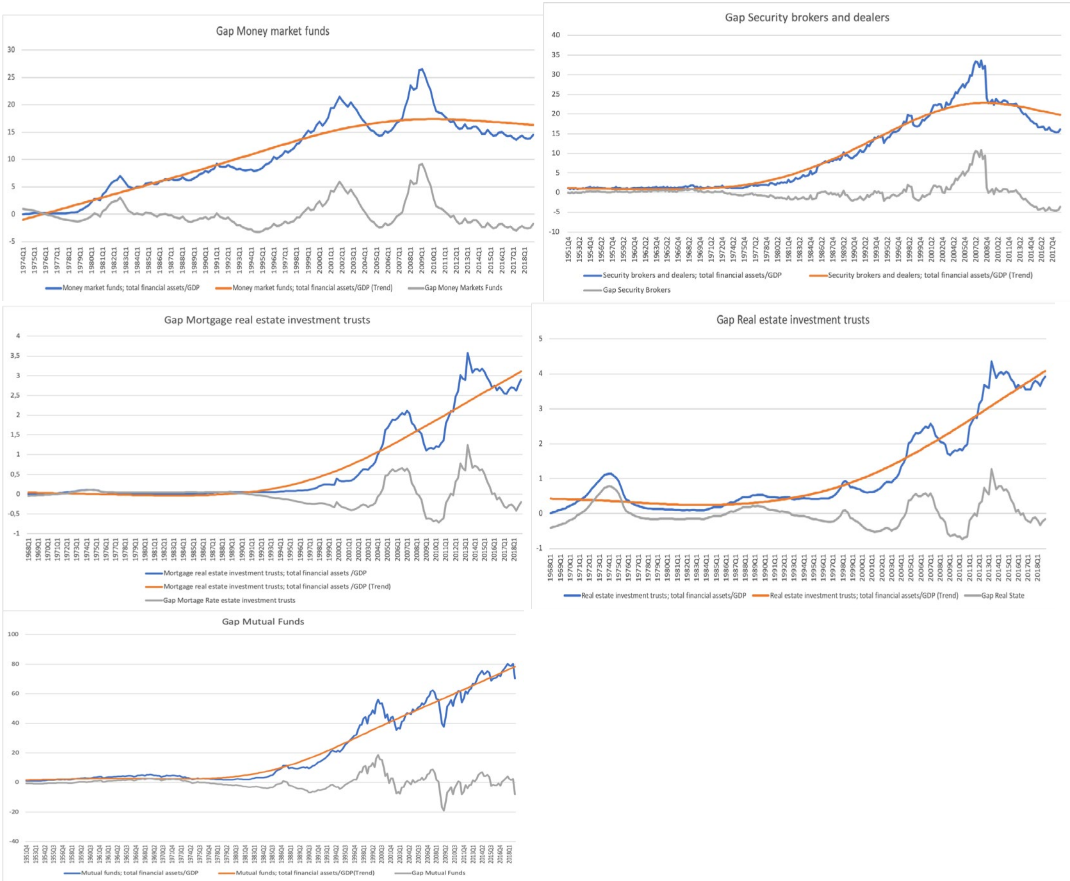
sb15	Debt securities / Total assets (Mutual Funds)	-0.13089916	**0.88215261**	0.33670933	-0.147350322
sb16	Municipal Securities / total assets (Mutual Funds)	**-0.68610198**	0.64676317	0.25204025	-0.019843913
sb17	Financial assets / Financial Liabilities (Security broker and dealers)	**0.63600609**	0.34791303	-0.48739166	-0.335072642
sb18	Checkable deposits / Financial Assets (Security broker and dealers)	**0.88914940**	0.15674380	-0.19719617	-0.108404850
Sb19	Total Time and savings deposits; asset/total financial assets (Holding Companies)	**0.59956126**	0.39106557	-0.06713752	-0.364931094
sb20	Treasury securities/Financial assets(Holding Companies)	-0.27889965	**0.74009250**	-0.01817269	-0.127490768
sb21	security repurchase agreements /financial assets (Holding Companies)	0.17375804	-0.27783085	**0.47403229**	-0.429769323
sb22	Debt assets/financial assets (Holding Companies)	**-0.70783432**	0.12458720	-0.32120143	0.501664047
Sb23	Commercial paper/Financial assets (Holding Companies)	**-0.88698906**	-0.18699191	0.16332653	0.008208795
sb24	Checkable deposits and currency; asset/Financial assets (Money Markets)	**0.60746843**	0.03496400	-0.09832170	-0.201502985
sb25	Total time and savings deposits; asset/Financial asset (Money Markets)	**0.62905545**	-0.11093040	0.17970024	-0.443637047

Appendix 2

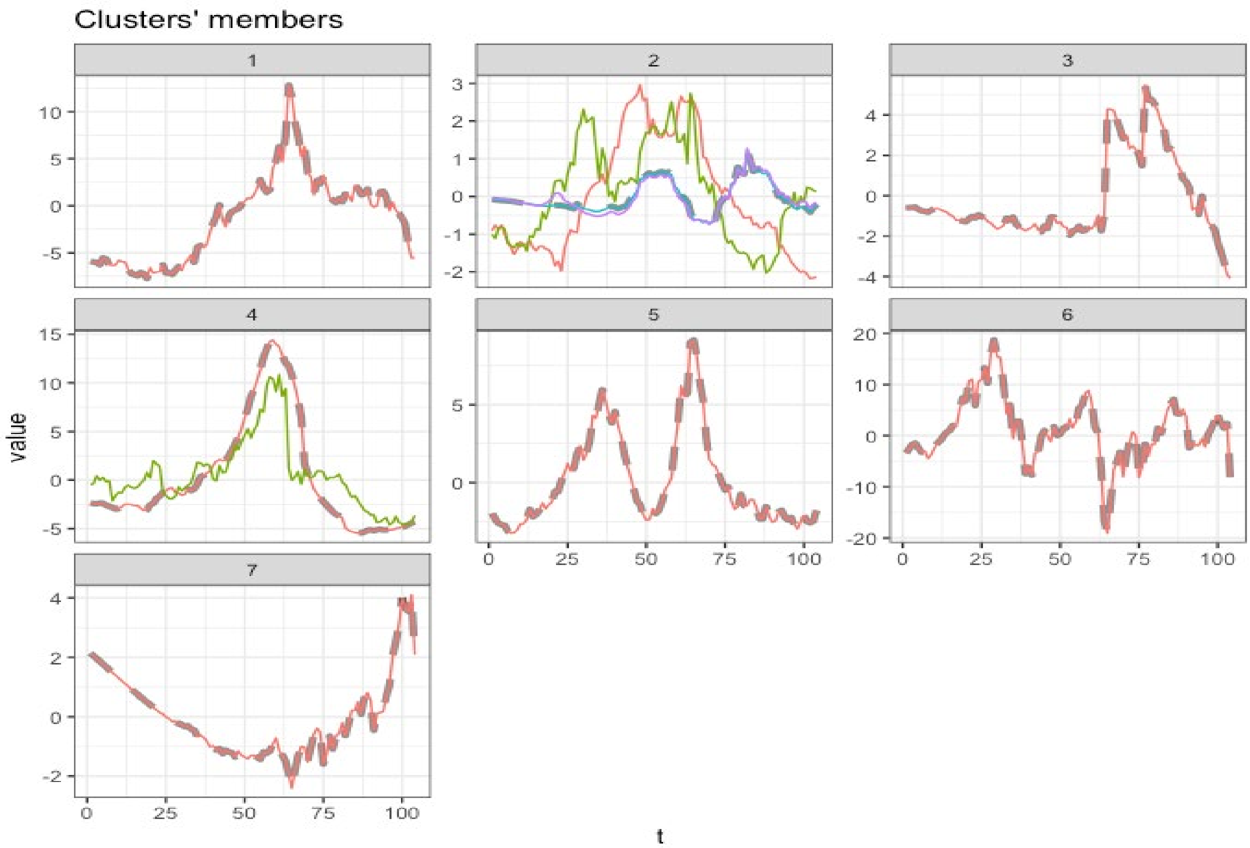


Appendix 3




Gap Money market funds
Gap Security brokers and dealers
Gap Mortgage real estate investment trusts
Gap Real estate investment trusts
Gap Mutual Funds

Appendix 4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