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A Multivariate Analysis of SIEFORE Daily Returns*

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Abstract: This document presents a multivariate analysis of the relations among daily returns of pension funds in Mexico from 1997 to 2019. Evidence of a positive relation among daily returns through five statistical methods is provided. We find Granger causality of the returns of some funds to others, showing that some managers' decisions have influence on the investment decisions of others. We introduce financial connectedness indicators for daily returns, finding a high degree of linkage and spillovers. The high levels of financial connectedness observed suggests that shocks on the economy affect the SIEFORE returns in the same direction and broadly similar magnitude.

Keywords: pension funds, private pension, financial stability

JEL Classification: G23, J32

Resumen: Este documento presenta un análisis multivariado de la relación entre los rendimientos diarios de los fondos de pensiones en México de 1997 a 2019. Se provee evidencia de una relación positiva entre los rendimientos de los fondos de pensiones como resultado de cinco métodos estadísticos. Se encuentra causalidad de Granger de los rendimientos de unos fondos a otros, mostrando que las decisiones de algunos administradores tienen influencia sobre las decisiones de inversión de otros. Se introducen indicadores de conectividad financiera de rendimientos diarios, encontrando un alto grado de vinculación y derrama. La alta conectividad financiera observada sugiere que los diversos choques a la economía, tanto reales, como financieros, afecten los rendimientos de las afores del sistema en la misma dirección y similar magnitud.

Palabras Clave: fondos de pensiones, pensiones privadas, estabilidad financiera

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1. Introduction

In Mexico, the defined contribution pension system in force since 1997 has contributed to deepen the financial markets. Pension assets have increased gradually to 15.4 percent of GDP, and 28.1 percent of domestic savings in September 2019. They have created a demand for securities that has made possible to build a longer and more complete yield curve.^{1, 2} Pension funds provide a flow of resources, as well as liquidity to financial markets.³ However, some trading strategies or portfolio adjustment mechanisms can lead to an increase in volatility or deviation of asset prices from their fundamentals. These periods of market stress have been a concern for pension supervisory authorities. Through a multivariate analysis, this paper examines whether daily returns of pension funds in Mexico relate to each other.

Although in general there are mixed views on the role of pension funds in the financial sector, from a positive contribution to stability to a potential negative impact on stock market volatility and on asset prices, caused by pension funds' managers buying and selling decisions, we relate with those that find a positive contribution and find a deep financial connectedness of returns. On the positive view, trading by pension funds professional managers interacts with trading by other investors with more limited information, helping restore potential equity price deviations from their fundamentals. On the negative view, an increase in the demand of risky assets from pension funds can cause a surge in equity prices, deviating them from their fundamentals. Given the importance in size and connectedness of pension funds, periods of market stress may surge, particularly when fund managers follow

¹ Following banks, private pension funds are the second most important financial intermediary in Mexico and manage 18.6 percent of the financial system's net assets.

² At the end of 2018, assets under management in the saving system in Chile, El Salvador and Peru were equivalent to 72%, 43% and 21% of their GDP, respectively.

³ Mexican regulation establishes mandatory retirement savings; thus, pension funds provide financial markets with a periodic flow of resources based on the number of active workers affiliated to social security institutes. Given that the system has not yet reached its decumulation stage, currently partial withdrawals are lower than the inflows of resources from mandatory contributions. In 2019, an average of 20 million 440 thousand formal jobs were registered. Each of the accounts associated with these workers registered contributions equivalent to 6.5% of their base contribution salary.

each other's investment decisions, as our results suggest.⁴ Studies have found mixed evidence on these views in different countries or periods.⁵

The institutional design of the pension systems can also impose constraints on investment decisions. Constraints can affect the choice of strategic and tactical asset allocations. For example, an investment regime allowing few assets or asset classes can impede diversification. The lack of diversification implies a riskier portfolio. With a risky portfolio, for example, sudden changes such as the downgrade of an asset can cause a selloff of this security, with few options where to reinvest.

We analyze the relation across pension funds' daily returns from July 1997 to September 2019 using different tools: goodness of fit tests of their distribution with respect to two theoretical distributions; the verification of positive correlation between funds; Granger causality tests; and impulse response functions. Finally, we introduce financial connectedness indicators for daily returns. These indicators draw from a variance decomposition of the returns of a fund on others. Since connectedness may vary across time, we also explore dynamic connectedness indicators. Though we consider changes in the investment regime a feature that can affect investment behavior and lead to aggregate changes in the portfolio, we do not deepen into its analysis since it does not have an impact on daily returns because it affects funds of all pension fund managers in the same manner.

Our results provide evidence of a clear positive relation among different pension funds in Mexico. Most of the daily return's distributions show an asymmetry to the left, indicating that for an extreme scenario, the probability of loss is higher than for profits. Daily returns correlate positively; correlation has increased over time and remains at a high level. Additionally, we confirm a relation among funds returns through Granger causality tests. We find that some funds affect others.

To deepen the study of the relationship among daily returns, we measure the response of an impulse in the daily return of a fund on the rest of them. For most cases, we find an almost

⁴ According to Bauer et al. (2018), institutional investors display a tendency to follow each other's investment decisions.

⁵ Alda (2018) provides a complete review of studies analyzing the impact of pension funds in financial markets.

immediate response that disappears after some days. Most of the effects on different funds turn out in similar responses, presenting a high degree of interconnection.

Finally, to explore the relation among different funds and linkages in the pension system, we analyze financial inter-connectedness. We confirm a high level of connectedness among funds in returns. There is a high degree of linkage and spillovers, characterized by the transmission of shocks within funds and across the system. We find that connectedness has remained at high levels during almost a decade.

In Section 2, we present a literature review and the contribution of this paper to the financial literature. A description of the data used is included in Section 3, while Section 4 presents a multivariate analysis to verify the relation among daily returns in Mexican pension funds. Section 5 introduces the concept of financial connectedness and estimations for daily returns. Finally, we present conclusions and recommendations.

2. Literature Review

There are positive and negative views on the role that pension funds play in financial markets. On the positive side, Fama (1965) considers that financial institutions (e.g. pension funds asset managers) are more sophisticated and informed investors than individuals are. When non-justified changes in prices take place, pension funds can help to restore market equilibrium. In addition, the presence of pension funds in the financial system has positive features, such as contributing to deepen debt and equity markets and providing liquidity to financial markets.

Han et al. (2018) find evidence of a counter-cyclical behavior in some countries and consider this to be positive for the stability of financial markets and the economy in the long run. According to Raddatz and Schmuckler (2008), another positive feature of pension funds includes promoting private sector savings and reducing the cost of capital for corporations, as a mean to achieve more developed market-oriented financial systems. Pensions funds provide a stable source of capital in the long run, since workers contribute for years until their retirement.

On the other hand, some authors are not so positive regarding the role of pension funds in financial markets. Several authors studied the case of herding in financial markets, and particularly on pension funds.⁶ According to Lakonishok et al. (1992) institutional investors can destabilize financial markets by driving asset prices beyond their fundamental values, increasing long-run price volatility. Additionally, there are agency problems among managers and fund sponsors. Managers may hold the same stock to avoid falling behind a peer group by following a unique investment strategy. However, the authors acknowledge that if institutional investors herd in a timely manner, they might contribute to market efficiency.

Active trading by investors implies buying and selling decisions that may move stock prices. Blake et al. (2016) study if pension funds herd in the UK and whether herding impacts asset prices. They find evidence of herding in the asset allocations of pension funds; however, in the long run the average fund is not able to react to changes in expected returns and risks on the assets. Consequently, investment behavior does not move asset prices towards their fundamental values and hence, does not play a stabilizing role on financial markets.

Alda (2018), states that financial literature has documented the existence of convergence behavior among institutional investors. Supposedly, fund managers should act according to the fund investment objective. However, managers' words and actions frequently influence other fund managers.

There is scant research for the case of Mexico. Han et al. (2018) analyze if pension funds were a stabilizing factor in financial markets in some countries during and after the 2008-2009 financial crisis. They present evidence of counter-cyclical behavior for the case of Poland, Italy and Chile. However, there is non-conclusive evidence in Mexico.

Fuentes et al (2014) use the returns of a specific life-cycle fund between 1997 and 2013 to perform returns' goodness of fit tests and Granger causality tests. They accept Granger causality from some funds to others. We use the same methodology for all funds, extending

⁶ Herding in pension funds has been studied by Lakonishok et al. (1992), Jones et al. (1999), Wermers (1999), Badrinath and Wadal (2002), Blake et al. (2002), Voronkova et al. (2005), Olivares (2005), Andreu et al. (2009) and Raddatz and Schmuckler (2013).

the study period from October 2008 to September 2019, and to have a more complete interpretation of the information obtained, we estimate the moments of the distribution. Our results show that, in accordance with distributions of financial variables characterized with fat tails, extreme values are stronger in losses than in profits. In addition, we contribute by applying Granger causality tests to the life-cycle funds and by highlighting the funds that have an impact on others, as well as those that are affected by the first ones.

This paper contributes to the literature providing measures that point to a high relation of daily returns in Mexican pension funds through different methodologies. We add an impulse-response analysis, which shows that for most cases there is an almost immediate response, which disappears after some days. Granger causality shows that the investment behavior and, daily returns of some funds have a strong influence on other ones.

We also introduce the concept and estimation of financial connectedness among pension funds. This novel methodology shows the spillovers of shocks among funds, providing pairwise (from one fund to another) net global connectedness indicators and a system indicator.

Since connectedness is not a static concept, we estimate dynamic connectedness and provide a graphic representation of the pension system's connectedness. We show how the indicator increases with the appearance of specific events.

3. Overview of the Individual Accounts Pension System

In order to help to understand the following sections, we provide the reader with an overview of the Mexican Pension System, and in particular of the individual accounts pension system on which we will focus.

The Mexican Pension System is composed by 4 different pillars, according to the World Bank classification. The first pillar refers to non-contributive pensions, such as the Universal Pension, financed by the government. The second pillar encompasses mandatory public pensions, of which some are contributive, and others have financial reserves. This is the case of autonomous institutions and public universities, local and municipal governments, armed

forces, and some development banks. An important reform took place in 1997 creating a defined contribution system (DC) in a third pillar, composed by individual accounts where resources are invested in specialized investment funds. A fourth pillar encompasses voluntary savings. This can be individual accounts managed by *Retirement Fund Managers* (AFORE), Social Prevision Funds (resources from public and private institutions to finance pensions), occupational pension plans or private plans offered by financial institutions.

In this paper we will analyze returns of individual accounts from the third pillar. These are linked to employment and their assets are completely financed, originally encompassing workers in the private sector affiliated to the Mexican Social Security Institute (IMSS). A second reform took place in 2008 paving the way for individual accounts and a DC pension system for the public sector workers affiliated to the State Workers Social Security Services Institute (ISSSTE). The system that regulates the management of these individual account resources is commonly known as the Savings for Retirement System (SAR). In addition, some public autonomous institutions pension plans have been reformed and now have a defined contribution system.⁷

Compulsory contributions equivalent to 6.5% of the salary are managed AFORE, which administer the SAR or Mexican DC pension system.⁸ They invest compulsory savings of private workers affiliated to the IMSS and federal government's public workers affiliated to ISSSTE of the third pillar in individual accounts in specialized pension funds called *Investment Companies Specialized in Retirement Funds* (SIEFORE) according to the age distribution of workers. The ruling body of *National Commission of Retirement Savings System* (CONSAR), the pension system supervisory authority, authorizes the investment regime.

Up to December 2019 there have been six SIEFORE:

- SIEFORE Básica de Pensiones, hereon SB0: workers aged 60 or older that are soon to retire. Created in March 2016.

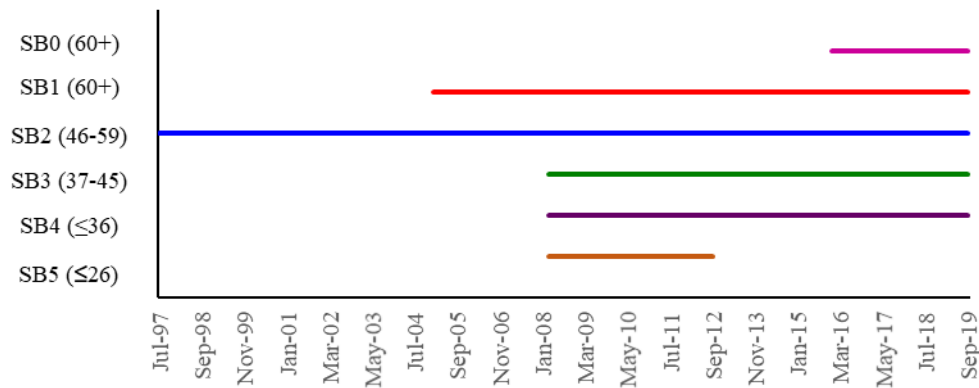
⁷ This is the case of the pension plans of IMSS, CFE and PEMEX workers.

⁸ AFORE manage the resources of workers that entered to work after July 1997 (IMSS) and March 2008 (ISSSTE). They also manage the savings of transition workers who entered the labor force before that dates.

- SIEFORE Básica 1, hereon SB1: workers aged 60 years or older. Created in January 2005.
- SIEFORE Básica 2, hereon SB2: workers with an age between 46 and 59 years. This was the original investment fund until January 2005, when SB1 was created. In March 2008, new SIEFORE were created to manage resources of those workers with less than 46 years old.
- SIEFORE Básica 3, hereon SB3: workers with an age between 37 and 45 years. Created in March 2008.
- SIEFORE Básica 4, hereon SB4: workers with an age of 36 years or less. Created in March 2008.
- SIEFORE Básica 5, hereon SB5: workers with an age of 26 years or less. Created in March 2008. However, this fund was short-lived and merged with SB4 in October 2012.

Figure 1 illustrates the date of creation and lifespan of each SB.

Figure 1: SIEFORE Básica Lifespan



Source: Own elaboration with data from CONSAR.

CONSAR authorizes the investment regime for each SB based on the investment horizon of its affiliates. Figure 2 shows the upper limits for risky investments for each SB. Funds with the resources of younger workers (SB4) have a more flexible investment regime so they can attain a higher return and accumulated balance in the accounts. Since resources will be

invested more time, they can recover in case of losses. On the other side, funds with resources of older workers (SB0 or SB1), who are closer to retirement have a more conservative investment regime. The idea is to protect them from strong losses in the years close to retirement, since they would not have many years left to recover.

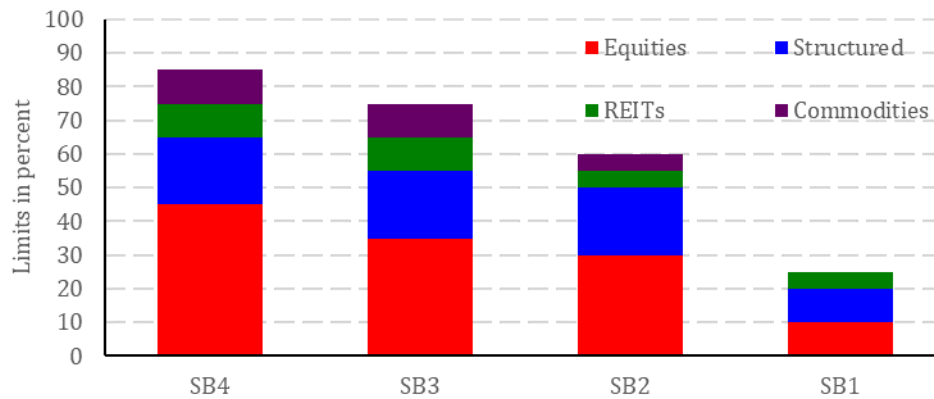
The resources in the SB can be invested in different asset classes, like public debt (domestic or foreign), equities (domestic or foreign), structured instruments, REITS, commodities, derivatives, and cash deposits. There are maximum investment limits in some of these instruments.

When the system started in 1997, SIEFORE could only invest in bonds. The more important changes by asset class are the following: in 2005, when the SB1 was created, the SB2 was allowed to invest in equity. Two years later, securitized assets, Development Capital Certificates and REITs were allowed. In 2011, the investments in commodities were integrated to the set of assets allowed. In 2013, some derivatives were allowed and three years later, Investment Projects Certificates (CERPIs) and REITs for infrastructure and energy joined to the set.

Up to November 2019, there was a limit regarding the country of emission of the assets, of 20 percent. This limit was the only one that has been near to being surpassed. In July 2014, foreign assets represented 19.8% of the total of investments of SB.

The maximum investment limit for different asset classes according to SB during September 2019 are shown in Figure 2. Figures 5 to 9 in Annex A shows the limits and the actual investment for each asset class and fund.

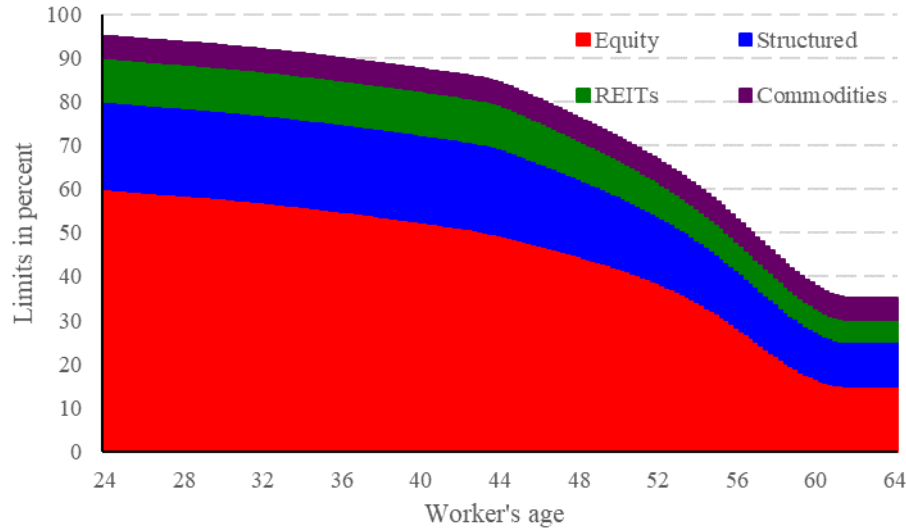
Figure 2: Investment regime for SIEFORE Básica
(September, 2019)



Source: CONSAR

In December 2019, resources of SB1, SB2, SB3 and SB4 were divided into 10 target dated funds, that accumulate and invest the resources of a certain cohort of workers. For example, initial SIEFORE Básica holds the savings of workers younger than 25 years old, while SB 90-94 holds the ones of workers born between 1990 and 1994. The general idea is that each SIEFORE will invest its resources accordingly with the horizon these will be in the account, in an attempt to maximize the accumulated amount. Given that it is a structural change, we do not include this new phase in our analysis. The SIEFORE Básica de Pensiones Fund was not modified. Since the time series of prices of target date funds are no longer compatible with those of the SB, we will not include these in our analysis. Figure 3 shows the glide path of investments with the new system of target date funds. As we can see, the portfolio will change as the workers age.

Figure 3: Authorized Investment Regime Glide Path
(December, 2019)



Source: CONSAR

At the beginning of the system in 1997 there were 17 original AFORE. Through the years, some of them left the market, new ones entered, and others were merged, sold or closed. The number of AFORE reached a maximum of 21 in 2006, in an effort by the regulator to promote competition through a higher number of participants.⁹ However, the system has gradually consolidated—as in other countries with individual accounts—to only 10 fund managers since May 2018.¹⁰

4. Data

The main variable of analysis is SIEFORE daily price returns of the SB1 to SB4 from all ten AFORE that were active at September, 2019, estimated as the daily price difference in logarithms. That is, they are daily returns in percent of the 40 different funds.

⁹ According to Calderón-Colín, Domínguez and Schwartz (2008) this policy was not effective.

¹⁰ In Chile, the number of fund managers, called Administradora de Fondos de Pensiones (AFP), decreased from a maximum of 14 in 1998 to 5, while in Peru it consolidated from 8 AFP at the beginning of the system in 1993, to 4.

Prices are an indicator of the value of the portfolio published by CONSAR. The data is public information available with daily periodicity since the start until the end of each fund.¹¹

We analyze daily returns for the 10 AFORE that had operations in September 2019, with their respective SIEFORE. For the AFORE that did not begin operations at the beginning of the system, we consider the information since the beginning of their operations.

For the goodness of fit tests and correlation analysis, we use information for SB2 since July 1, 1997, when the system began, until the end of September 2019. Since the other SB began their operations in different dates, SB1 analysis starts in January 2005, while for SB3, SB4 and SB5 it starts in March 2008. We do not analyze SB0 given that time series contain less than one thousand observations, which would not allow for a robust analysis.

In the case of VAR, Impulse-Response Functions and Connectedness, the analysis is done from October 2008 to September 2019, since there was a structural change in the series that would make the previous information not compatible.

5. Relation among SIEFORE

In order to analyze the existence of a relationship of daily returns among pension funds, we consider the following methodologies: goodness of fit tests, analysis of correlations; Granger causality tests; and impulse response functions. As a preview of results, all tools point to a high relation of daily returns.

5.1. Goodness of Fit Test

As a first step, we perform goodness of fit tests of the distribution of returns with respect to two theoretical distributions. We will assume that most SIEFORE have a similar behavior in the short-term if their returns have the same probability distributions with similar parameters.

¹¹ Data can be found at: <https://datos.gob.mx/busca/dataset/precios-de-gestion-de-las-siefores>.

We performed a goodness of fit statistical test with respect to the normal distribution. The hypothesis is strongly rejected, consistent with K  chler et al. (1999) and Trejo et al. (2006). This fact is not surprising; it is well-known that returns do not have a normal distribution.

Following Fama (1965) and K  chler et al. (1999) we test if the sample obtained has a hyperbolic distribution. Specifically, based on Trejo et al. (2006), we perform a goodness of fit test for the Normal Inverse Gaussian distribution (NIG). We do not reject the hypothesis in most cases. However, we reject the hypothesis for AFORE A, AFORE C and AFORE I in SB4. Hence, we use NIG parameters for the analysis of moments of the distribution.

To assess if the NIG samples belong to the same population, we perform a Kruskal-Wallis rank sum test, except for AFORE A, AFORE C and AFORE I of SB4, which, as mentioned below, we find not fitting into a NIG distribution and therefore cannot belong to the same distribution that other SIEFORE.

Results suggest that every group of SB belong to the same population, that is, the ten SB1 share the same parameters; the SB2 also share the same parameters, and so on for the rest of SB groups; these does not mean that each parameter vectors are identical.

Although the mean of all samples is positive, it has small values. The value of the first moment decreases gradually from SB4 to the other SB, having SB1 the lowest mean; that is, the expected value of returns is higher for the SIEFORES with more flexible investment regime. On average, daily variations in prices are minimal and though the positive and negative effects are usually compensated, there is a slight trend in the portfolio to be favorable. The medians of distributions have positive values, which reinforces the argument that SIEFORE have more positive than negative returns.

Table 1: SB Returns Distribution. NIG Goodness of fit test and Moments
(July 1997-September 2019)

AFORE	SB	p-value	E[X]	SD[X]	Skew[X]	K[X]	Med[X]
A	1	0.17	0.0004	0.0023	-0.7279	6,305	0.0005
B	1	0.22	0.0004	0.0021	-0.3800	7,647	0.0005
C	1	0.03 **	0.0004	0.0022	-0.4824	6,629	0.0005
D	1	0.71	0.0004	0.0022	-0.4701	6,680	0.0005
E	1	0.04 **	0.0004	0.0020	-0.6104	3,934	0.0005
F	1	0.08 *	0.0003	0.0021	-0.2904	6,231	0.0003
G	1	0.61	0.0003	0.0023	-0.2333	4,466	0.0004
H	1	0.45	0.0003	0.0036	-0.1795	147,948	0.0003
I	1	0.05 *	0.0004	0.0008	1.5193	798	0.0003
J	1	0.17	0.0003	0.0021	-0.4500	10,364	0.0003
A	2	0.01 **	0.0004	0.0030	-0.7897	8,239	0.0005
B	2	0.16	0.0004	0.0030	-0.7251	5,778	0.0005
C	2	0.01 **	0.0004	0.0031	-0.7739	7,221	0.0005
D	2	0.40	0.0004	0.0031	-0.7693	5,498	0.0005
E	2	0.11	0.0004	0.0029	-0.8158	5,117	0.0005
F	2	0.30	0.0003	0.0026	-0.2380	5,991	0.0004
G	2	0.68	0.0003	0.0030	-0.2541	4,300	0.0004
H	2	0.69	0.0003	0.0051	-0.2132	78,767	0.0003
I	2	0.03 **	0.0004	0.0009	0.3961	11,520	0.0004
J	2	0.18	0.0003	0.0029	-0.3000	21,698	0.0003
A	3	0.01 **	0.0004	0.0034	-0.8722	10,304	0.0005
B	3	0.06 *	0.0004	0.0035	-0.7592	7,793	0.0005
C	3	0.01 **	0.0004	0.0036	-0.8389	9,717	0.0005
D	3	0.31	0.0005	0.0036	-0.8080	7,525	0.0006
E	3	0.10	0.0004	0.0031	-0.8671	5,888	0.0005
F	3	0.33	0.0003	0.0028	-0.2341	6,090	0.0004
G	3	0.63	0.0003	0.0033	-0.1968	5,050	0.0004
H	3	0.63	0.0003	0.0058	-0.2051	99,477	0.0003
I	3	0.01 **	0.0004	0.0012	0.0499	1,027,640	0.0004
J	3	0.08 *	0.0003	0.0032	-0.2588	30,434	0.0003
A	4	0.00 ***	0.0004	0.0038	-1.0076	9,825	0.0005
B	4	0.09 *	0.0004	0.0040	-0.8012	10,524	0.0005
C	4	0.00 ***	0.0005	0.0042	-0.9129	11,806	0.0005
D	4	0.10	0.0005	0.0041	-0.8940	9,346	0.0006
E	4	0.04 **	0.0004	0.0035	-0.9138	7,155	0.0005
F	4	0.27	0.0003	0.0031	-0.2348	5,933	0.0004
G	4	0.81	0.0003	0.0035	-0.2076	3,965	0.0004
H	4	0.54	0.0003	0.0062	-0.2332	56,173	0.0004
I	4	0.00 ***	0.0004	0.0014	-0.1850	119,276	0.0004
J	4	0.06 *	0.0003	0.0032	-0.2510	30,131	0.0003

Source: Own elaboration with data from CONSAR.

Significance codes: one asterisk indicates the SIEFORE whose samples fit to a NIG distribution according to the goodness of fit test at 10% significance (* $p < 0.10$), ** 5% significance ($p < 0.05$), and 1% significance *** ($p < 0.01$).

SB4 returns have a greater dispersion than those of SB3, which in turn are more volatile than those of SB2, leaving SB1 as the category with lowest dispersion in returns. This result is consistent with a more flexible investment regime for SIEFORE with younger workers' resources, which allows a greater risk since the resources remain in the fund for a longer time and can recover from possible losses. As funds manage resources from older workers, their investment regime is more conservative.

As is often the case with returns' distributions, all SIEFORE have high kurtosis, which indicates that most values are close to the mean. That is, the expected value of the portfolio does not change much every day.

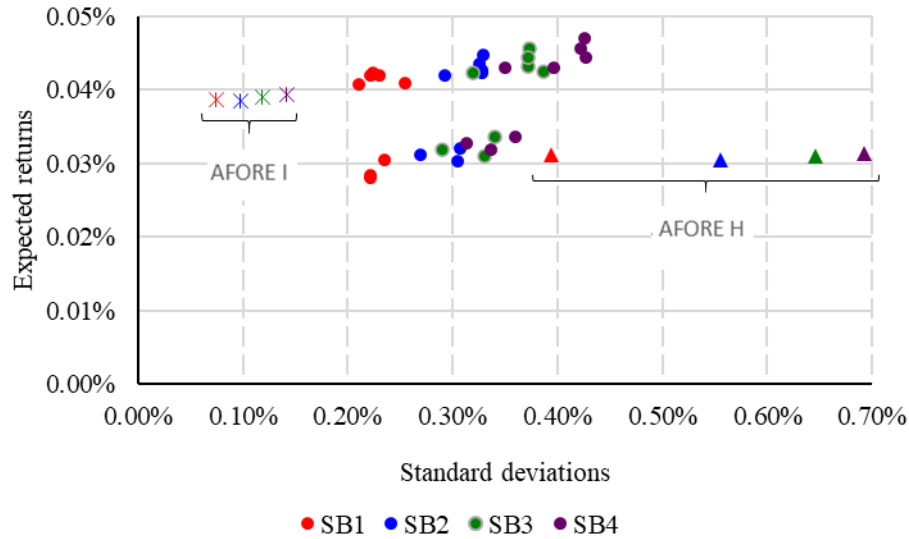
Most SIEFORE's daily returns are positive and the average and the median are also positive, so most of the distributions show a bias towards daily profits; the probability that a return is positive is around 0.57. However, the left tail of the distribution is longer than the right tail, which means that extreme returns move more from the average downwards than upwards. This suggests that extreme values are greater in losses than in profits.

The probability that a return is lower than the mean minus two standard deviations is 2.5% compared to the probability that the return is higher than the mean plus two standard deviations, which is 2.4%. Furthermore, the probability that a return is lower than the mean minus two standard deviations given a negative result is around 5.8% while the probability that a return is higher than the mean plus two standard deviations given a positive result is around 4.2%.

That is, in general, a positive return has a higher probability of occurring than a negative return. However, in extreme scenarios, a negative result is more probable than a positive one. Therefore, although SIEFORE have positive returns every day, these are low compared with the negative ones that are higher in absolute value.

Figure 4 presents a scatter plot with the standard deviations of the returns on the x-axis and the expected returns on the y-axis.

Figure 4: Expected returns and risk of pension funds



Source: Own elaboration with data from CONSAR.

It is possible to observe differences related to investment behavior. For example, although most dots are on the center of the graph, some call our attention: at the left, with a low standard deviation, we notice AFORE I's SIEFORE returns characterized by a conservative investment profile with low risk and low return; on the right side of the graph, we observe AFORE H's SIEFORE with the highest risk, although it does not have the highest expected returns.

5.2. Correlation

Once we have evidence that most SIEFORE belong to the same probability distribution, we study if their prices move in the same direction most of the time. If this is the case, we expect returns to be positively related. In the opposite case, the relation will be negative. Another possible case is the absence of a relation between the returns.

A simple and intuitive way to measure the relationship among daily returns is to estimate the correlation between them. Correlation measures strength and direction of the relationship

between variables. In the case of financial assets, some authors consider that a high degree of correlation among returns may lead to volatility and affect price stability (Hu, 2006).¹²

We estimate the Spearman correlation coefficient for all SIEFORE. Since we know that most SIEFORE belong to the same distribution, we expect high correlation coefficients, although it is possible that we obtain low correlations which is a signal that the prices of some SIEFORE are more volatile than others. Negative correlations are not expected.

We present only the results of SB2 given that estimations are similar for all type of funds. Table 2 presents the daily returns correlation matrix among the SB2 funds that still exist today, where a darker tone of blue depicts a higher correlation.¹³

As shown, with the exception of AFORE I, the daily return correlation among most fund managers is not only positive, but high. This result is consistent with the one obtained in Section 5.1 where AFORE I's SIEFORE returns have a different distribution than those of other SIEFORE.

Although the matrix presents only high correlations, every SIEFORE has an AFORE with which it is more correlated than to the others. This is an important result because the SIEFORE with the highest correlation coefficients (like AFORE A and AFORE C) could give different results in the following sections than the SIEFORE with minor relations (like AFORE G and AFORE I).

¹² Lakonishok et al. (1992) measure the degree of correlation across 341 institutional investors' money managers in buying and selling a single stock (or industry grouping) as a first approach to test for herd behavior.

¹³ We present the analysis of SB2 since it is the pension fund with a longer history, from the beginning of the savings system to the date. Daily return correlation matrices and tables for other SB showing correlations across time are included in the Appendix A and B.

Table 2: Daily return correlation matrix among SB2 AFORE
(July 1997-September 2019)

	A	B	C	D	E	F	G	H	I	J
A										
B	0.93									
C	0.95	0.94								
D	0.92	0.90	0.93							
E	0.93	0.91	0.95	0.94						
F	0.90	0.87	0.90	0.90	0.92					
G	0.87	0.84	0.88	0.86	0.89	0.87				
H	0.91	0.88	0.92	0.89	0.92	0.88	0.88			
I	0.63	0.61	0.64	0.67	0.66	0.68	0.56	0.59		
J	0.92	0.90	0.93	0.91	0.94	0.92	0.87	0.91	0.66	

$0 < \rho \leq 0.5$ $0.5 < \rho \leq 0.75$ $0.75 < \rho \leq 0.85$ $0.85 < \rho \leq 0.95$ $0.95 < \rho < 1$

Source: Own elaboration with data from CONSAR.

All coefficients are significant at a 95% and 99% level of confidence.

Since data covers a long period and the degree of correlation may have changed across time, the analysis can take into consideration matrices for different sub-periods. Every horizon time was defined by changes in the structure of the system, such as entrance or exit of AFORE. Thus, periods do not have the same length.

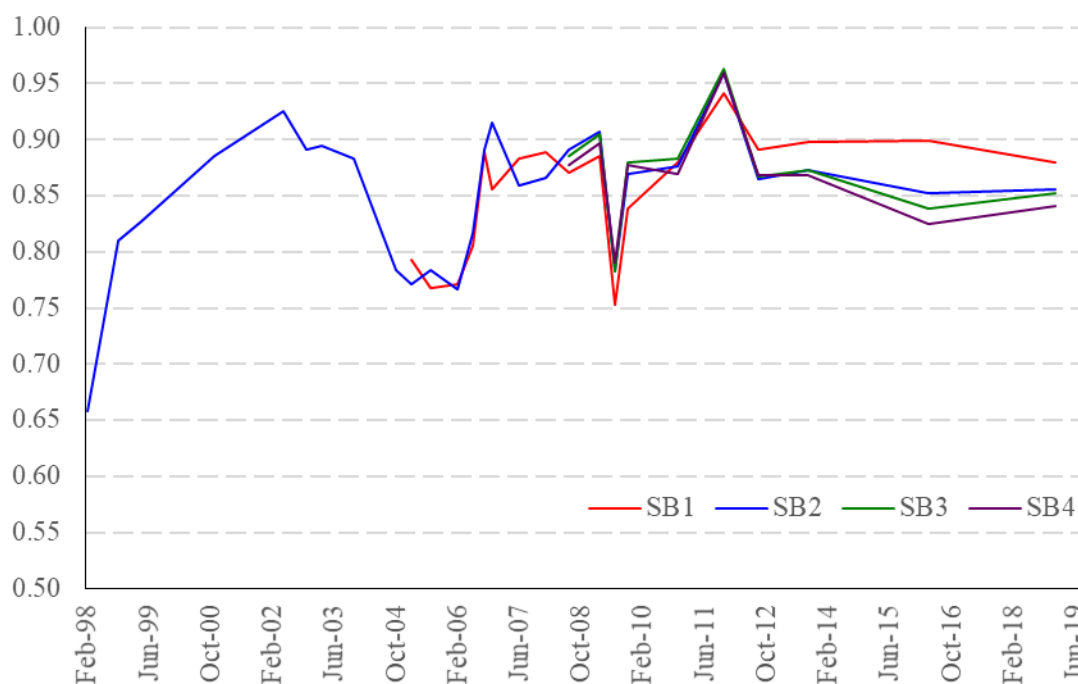
The daily return correlation between AFORES across time is presented in Table 3, which shows ten different matrices. Each one contains the correlation of an AFORE's returns with the other ones for SB2 across time.

Although correlation changes across time, in general it remains at a high level. It is lower at the beginning of the sample when SIEFORES began to build portfolios and increases along time, as resources accumulate, and managers engage in a more sophisticated process of asset allocation. Although further analysis is required, changes in correlation are probably related to changes in the investment regime, financial crises or the introduction of prudential benchmarks.

An average of the correlation's coefficients of different SIEFORES across time shows a clearer picture. As shown in Figure 5, correlation starts at $\rho=0.65$ at the beginning of the system, followed by a strong increase that leads near $\rho=0.9$ by mid-2002. During this period, several modifications to the investment regime were introduced and AFORES are

continuously adapting to build their portfolios. For example, operations with derivatives and investment in yens and euros were allowed in 2001, while states, municipal and public entities' debt was authorized in 2002–2003. However, in 2004 correlation decreases slightly, possibly related to the introduction of a more flexible investment regime that allowed a higher diversification through investment in equities, both in the domestic and foreign markets. The new SB1 fund was introduced in January 2005, for workers closer to retirement. Correlation continues to increase up to September 2008. As the financial crisis begun, correlation decreased slightly for nearly a year and has been relatively stable since then, except for a small decline at the end of 2011.

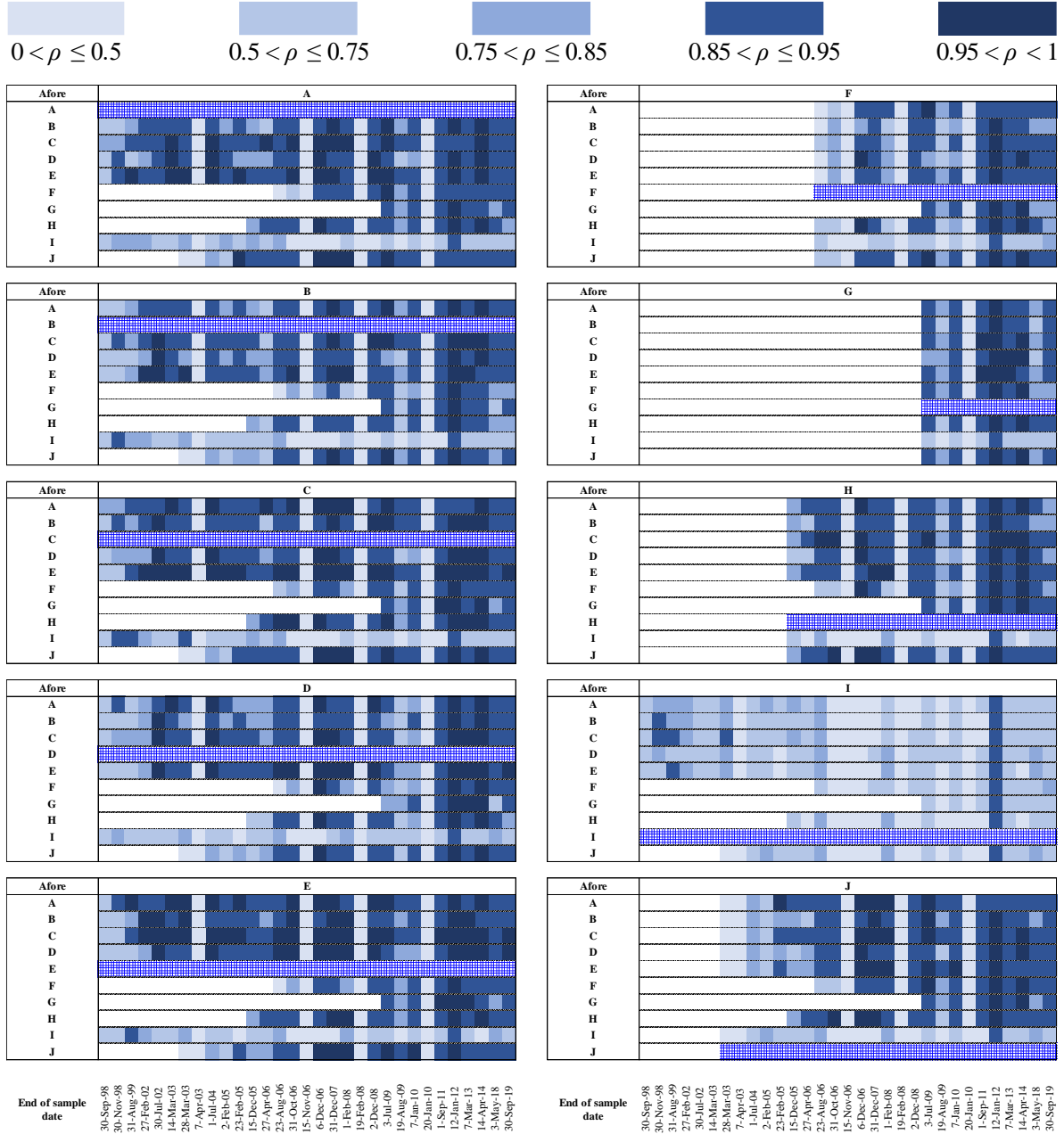
Figure 5: Average daily return correlation coefficient
(July 1997-September 2019)



Source: Own elaboration with data from CONSAR.

The Dickey-Fuller and Phillips-Perron tests show stationarity in three of the four time series in Figure 5. SB2 and SB3 series have not a unitary root at a significance level of 95%, SB4, has not a unitary root at a significance level of 90%. In contrast, SB1 presents a unitary root; therefore, SB1 is the only series that changes in the time with a trend.

Table 3: SB2 Daily returns correlation across time ¹



^{1/} Periods defined according to changes in the industrial organization, such as entries, exits or fusions among AFORE.

All coefficients are significant at a 95% level of confidence.

Source: Own elaboration with data from CON SAR.

A possible cause for high correlations among daily returns is a restrictive investment regime that does not allow SIEFORES to pursue different investment strategies. Another cause is

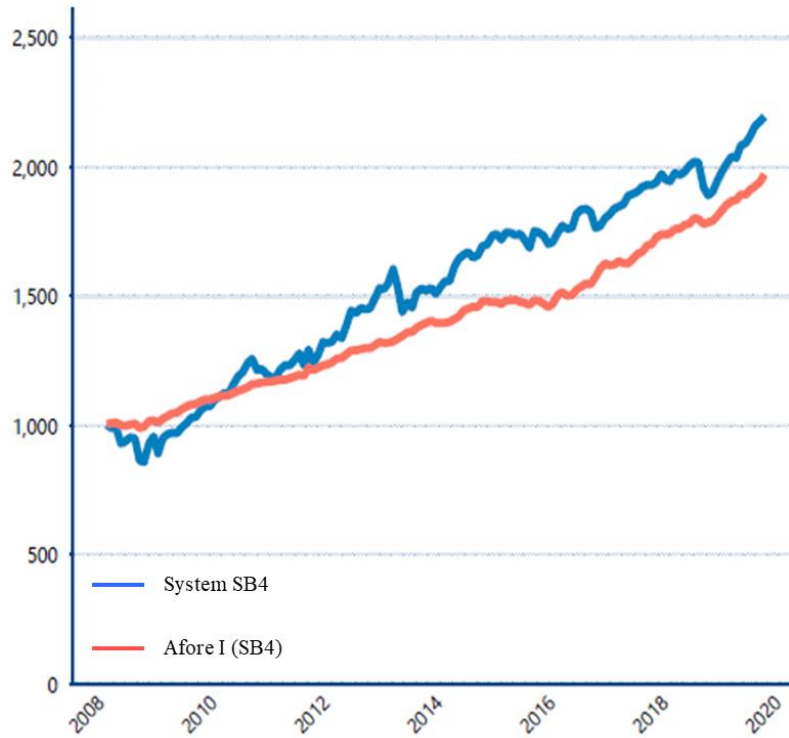
that the Mexican financial market is not so deep and there are not many alternatives for investment. For example, the market capitalization value of the Mexican stock market is 32.9 percent in terms of GDP compared to 147.9 in the USA and 72.2 in Chile. However, these explanations for high correlation do not impede a differentiated investment strategy. Figure 6 and 7 show the value of an investment of \$1000 pesos in two different SB4 funds, AFORE C and AFORE I, as well as the average return of all SB4 funds with observed returns. As seen, there is a striking difference -over 20 percent- in the final value of investment despite the existence of a limited investment regime and a shallow financial market.

Figure 6: Evolution of value of investment with initial MXP\$1,000



Source: Radiografía Financiera de las AFORE, November 2019, CONSAR.

Figure 7: Evolution of value of investment with initial MXP\$1,000



Source: Radiografía Financiera de las AFORE, November 2019, CONSAR.

5.3. Vector Autoregression

Correlation is a first indicator of association among SIEFORE's returns, although it does not provide evidence of causality or the magnitude of the effect that the behavior of a fund can have on other. Vector autoregression (VAR) analysis contributes to deepen our knowledge of the relation among funds.

We use vector autoregression with several objectives: first, we perform non-causality Granger tests for the prevailing AFORE; next, we analyze impulse-response functions. Finally, we use the VAR to estimate financial connectedness. The compact form of the autoregressive vectors used are:

$$R_t = c + \sum_{i=1}^T \Phi^i R_{t-i} + u_t$$

Each AFORE's return R_i ($i=1 \dots n$) in time t is explained by c , a constant, the set of its own lagged returns, as well as those of the other AFORE (also with lags). Based on Akaike, Hannan–Quinn and Schwarz information criteria, we decided to use two lags, so $T = 2$.

The results show similarities among the four types of SB. The coefficients corresponding to AFORE E, AFORE G and AFORE H are statistically significant in all cases. On the other hand, AFORE F's and AFORE J's coefficients are not significant for any SIEFORE.

On the other hand, the coefficient of AFORE E is significant given that the returns of this fund manager are very close to the market average return performance, in any type of SIEFORE.

5.3.1. Causality Tests

Raddatz and Schmuckler (2008) consider that some pension funds follow the investment behavior of others due to several reasons, mentioned in Section 2. In order to study the interaction among returns in the Mexican pension system, Fuentes et al. (2014), used daily information of some representative SIEFORE for the period 2000–2013 and accept the existence of Granger causality from some funds' daily returns to others, confirming the relation among funds. They considered this as evidence that, on average, SIEFORES have the similar behavior following some funds.

We also test the existence of Granger causality. A breakpoint unit root test showed a structural change in data's trends on October 29, 2008 probably caused by effects of financial crisis. Accordingly, we use the data from the end of October 2008 to September 2019, for different SIEFORE. Causality is not rejected when the p-value is lower than a significance level, implying an effect of the daily returns of an AFORE on others. Most SIEFORE show statistical significance at a level of 90%. Results imply causality of the daily returns of some AFORE to those of others. The following tables highlight the p-values where the hypothesis that the returns of the AFORE in the row do not "cause" those of the AFORE in the column is rejected.

In SB1, SB2 and SB3, results are consistent with those of the VAR: AFORE F and AFORE J Granger cause other AFORE, while AFORE E, AFORE G and AFORE H influence most of the other AFORE. Results in SB4 are slightly different since we find Granger influence from AFORE F and AFORE H to some AFORE.

In the case of SB1, in addition to AFORE E and AFORE H, AFORE B daily returns have an effect on most of the other AFORE.

Table 4: SB1 Granger Test p-value (row does not cause column)
(October 2008-September 2019)

	A	B	C	D	E	F	G	H	I	J
A		0.5975	0.8644	0.6009	0.8280	0.7869	0.8739	0.1971	0.4235	0.7789
B	0.0305 **		0.0064 ***	0.0094 ***	0.0213 **	0.0435 **	0.0255 **	0.0046 ***	0.1619	0.0355 **
C	0.1349	0.1661		0.1310	0.2208	0.3214	0.0755 *	0.3809	0.9767	0.3017
D	0.4470	0.5861	0.4357		0.5580	0.4234	0.1992	0.3795	0.2572	0.4993
E	0.0003 ***	0.0000 ***	0.0002 ***	0.0002 ***		0.0004 ***	0.0064 ***	0.0058 ***	0.1290	0.0014 ***
F	0.5539	0.3472	0.4771	0.4709	0.3526		0.6565	0.6316	0.0224 **	0.5793
G	0.1848	0.4577	0.0306 **	0.0422 **	0.0773 *	0.3817		0.5006	0.0535 *	0.3598
H	0.0000 ***	0.0001 ***	0.0000 ***	0.0064 ***	0.0009 ***	0.0141 **	0.1503		0.3995	0.0084 ***
I	0.0969 *	0.2172	0.1262	0.1012	0.0493 **	0.0679 *	0.0246 **	0.3224		0.2138
J	0.8627	0.6734	0.8470	0.8205	0.6536	0.0049 ***	0.4394	0.5610	0.2286	

Source: Own elaboration with data from CONSAR.

* Significant at 10%.

** Significant at 5%.

*** Significant at 1%.

Tests in other SIEFORE daily return data also confirm the effect of some AFORE on others. In SB2 there is also an effect on a lower number of AFORE by AFORE C and AFORE D. On the other hand, AFORE A, AFORE B and AFORE I seem to do not cause other AFORE's returns. AFORE A, AFORE B, AFORE F and AFORE G appear as the funds more affected by others.

Table 5: SB2 Granger Test p-value (row does not cause column)
(October 2008-September 2019)

	A	B	C	D	E	F	G	H	I	J				
A		0.3374	0.3021	0.2969	0.3410	0.6803	0.8434	0.8067	0.4963	0.2992				
B	0.2819		0.1110	0.2602	0.4193	0.2396	0.2555	0.2125	0.3976	0.2069				
C	0.0120	**	0.0005	***	0.0648	*	0.1296	0.0554	*	0.0243	**			
D	0.0636	*	0.2894	0.0500	**	0.0306	**	0.0337	**	0.0069	***			
E	0.0001	***	0.0000	***	0.0001	***	0.0016	***	0.0001	***	0.1261	0.0002	***	
F	0.2546		0.7296	0.3167	0.2872		0.4720		0.0377	**	0.1003	0.1357	0.3152	
G	0.0316	**	0.0389	**	0.0106	**	0.0900	*	0.0085	***	0.0232	**	0.0545	*
H	0.0002	***	0.0000	***	0.0007	***	0.0113	**	0.0002	***	0.0032	***	0.0001	***
I	0.9889		0.9663	0.6757	0.7809	0.7580	0.9042	0.4948	0.9586		0.1560		0.9981	
J	0.4156	0.4510	0.3154	0.3545	0.2344	0.2043	0.0780	*	0.3633	0.1114				

Source: Own elaboration with data from CONSAR.

* Significant at 10%.

** Significant at 5%.

*** Significant at 1%.

Causal relations also appear in SB3. AFORE C and AFORE I cause a larger number of other AFORE. In particular, AFORE I is the least diversified AFORE in SB3.¹⁴ Daily returns of AFORE A, AFORE D, AFORE F, AFORE G, AFORE H and AFORE J seem to be caused by other AFORE. In addition, AFORE A and AFORE B do not have an impact on others.

Table 6: SB3 Granger Test p-value (row does not cause column)
(October 2008-September 2019)

	A	B	C	D	E	F	G	H	I	J
A		0.1110	0.2151	0.2842	0.1688	0.4627	0.6101	0.3353	0.7878	0.3760
B	0.5912		0.3574	0.3319	0.7675	0.8050	0.8449	0.6848	0.4800	0.5889
C	0.0030	***	0.0004	***	0.0087	***	0.0281	***	0.0300	***
D	0.1155		0.3696	0.1544		0.1191	0.1109	0.0390	***	0.0070
E	0.0003	***	0.0003	***	0.0010	***	0.0000	***	0.0120	***
F	0.1223		0.4483	0.1811	0.2190	0.2903		0.0341	***	0.0945
G	0.0105	**	0.0054	***	0.0081	***	0.0142	**	0.0294	***
H	0.0002	***	0.0000	***	0.0005	***	0.0004	***	0.1015	***
I	0.0398	**	0.2145	0.0205	**	0.0327	**	0.0008	***	0.0047
J	0.8893	0.7069	0.6153	0.8278	0.5977	0.5994	0.2246	0.4275	0.2824	

Source: Own elaboration with data from CONSAR.

* Significant at 10%.

** Significant at 5%.

*** Significant at 1%.

Causality also appears in SB4. AFORE A, AFORE D and AFORE I are the AFORE that cause other AFORE returns. During the period of analysis, AFORE I had the least diversified portfolio in the market while AFORE A and AFORE D are the leaders in diversification for

¹⁴ See Section 3 for more information about diversification of portfolio.

these portfolios.¹⁵ Daily returns of AFORE A, AFORE B, AFORE C, AFORE D, AFORE E, AFORE H and AFORE J are now “caused” by other AFORE, while several of these AFORE continue not influencing others.

As in SB2, SB3 and SB4, AFORE I is not affected by other AFORE.

Table 7: SB4 Granger Test p-value (row does not cause column)
(October 2008-September 2019)

	A	B	C	D	E	F	G	H	I	J
A		0.0051 ***	0.0221 **	0.0205 **	0.0129 **	0.0847 *	0.0957 *	0.0276 **	0.4250	0.0157 **
B	0.3538		0.4669	0.1525	0.5559	0.9999	0.9229	0.7511	0.7701	0.7149
C	0.0212 **	0.0042 ***		0.0217 **	0.2727	0.0965 *	0.0098 ***	0.0630 *	0.9848	0.0534 *
D	0.0629 *	0.0831 *	0.1105		0.0636 *	0.0858 *	0.0204 **	0.0084 ***	0.9723	0.0630 *
E	0.0029 ***	0.0021 ***	0.0121 **	0.0193 **		0.0003 ***	0.0534 *	0.0149 **	0.1193	0.0157 **
F	0.0156 **	0.2450	0.0301 **	0.0550 *	0.0467 **		0.0053 ***	0.0285 **	0.0675 *	0.1038
G	0.0120 **	0.0025 ***	0.0163 **	0.0291 **	0.0267 **	0.0421 **		0.0214 **	0.0637 *	0.0362 **
H	0.0204 **	0.0008 ***	0.0270 **	0.1000	0.0220 **	0.0871 *	0.5314		0.0647 *	0.0113 **
I	0.0514 *	0.1189	0.0247 **	0.0235 **	0.0005 ***	0.0093 ***	0.0113 **	0.0101 **		0.0151 **
J	0.3431	0.6290	0.6482	0.4157	0.2604	0.0211 **	0.6537	0.7968	0.0139 **	

Source: Own elaboration with data from CONSAR.

* Significant at 10%.

** Significant at 5%.

*** Significant at 1%.

In addition to the high correlation exhibited among different daily returns of different funds, we confirm a strong relation given the Granger causality from the daily returns of some AFORE, to others. The exercise shows that the investment behavior and, daily returns of some funds have a strong influence on others, in terms of Granger causality. This is a result that should be kept in mind when we analyze dynamics in AFORE.

5.3.2. Impulse – Response Function

At this point, we confirmed the existence of a relation of SIEFORE’ daily returns through correlations and Granger causality tests. The next step is to measure the effect of the relation among funds. We do this with generalized impulse response functions based on the VAR estimates presented in the beginning of Section 5.3.

¹⁵ See Section 3 for more information about diversification of portfolio.

The impulse response function is defined as:

$$IRF_R(h, \delta, \Omega_{t-1}) = \mathbb{E}[R_{t+h}|u_t = \delta, \Omega_{t-1}] - \mathbb{E}[R_{t+h}|\Omega_{t-1}]$$

where IRF_R denotes the impulse – response function value in system R ; h is the horizon time in which the response will be evaluated; δ denotes the size of the impulse and Ω_{t-1} contains the historic information of R .

We introduce a one standard deviation shock in the daily return of a fund and observe if there is a response on the daily returns of other funds. The impact of the effects is estimated using the next function for some values of h .¹⁶

$$\begin{aligned} GI_R(h, \delta, \Omega_{t-1}) &= A_h \cdot \Sigma \cdot e_j \cdot \frac{\delta_j}{\sigma_{j,j}} \\ &= A_h \cdot \Sigma \cdot e_j \cdot \frac{\sqrt{\sigma_{j,j}}}{\sigma_{j,j}}, \\ &= \frac{1}{\sqrt{\sigma_{j,j}}} \cdot A_h \cdot \Sigma \cdot e_j \end{aligned}$$

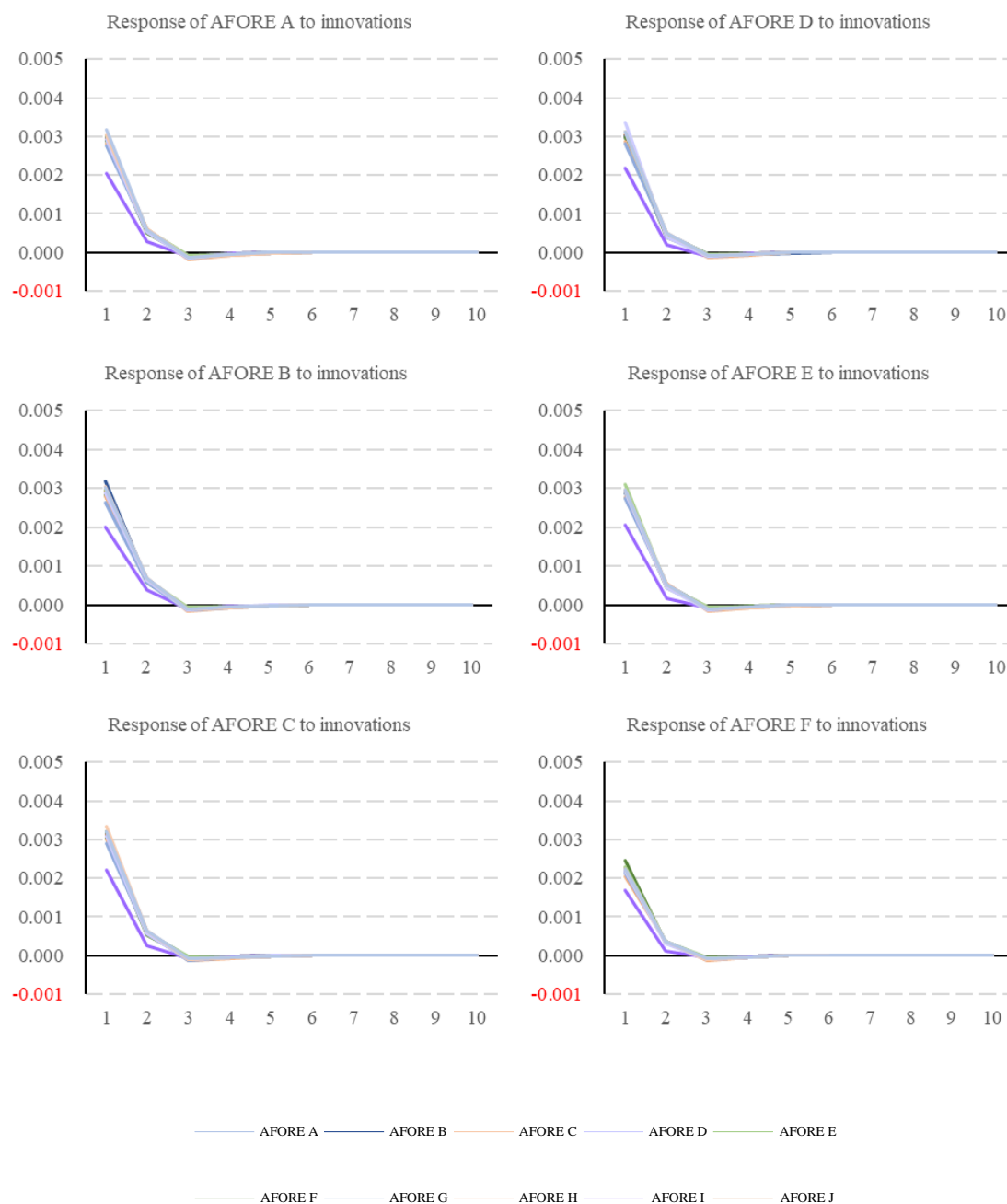
where A_h can be obtained recursively as follows:¹⁷

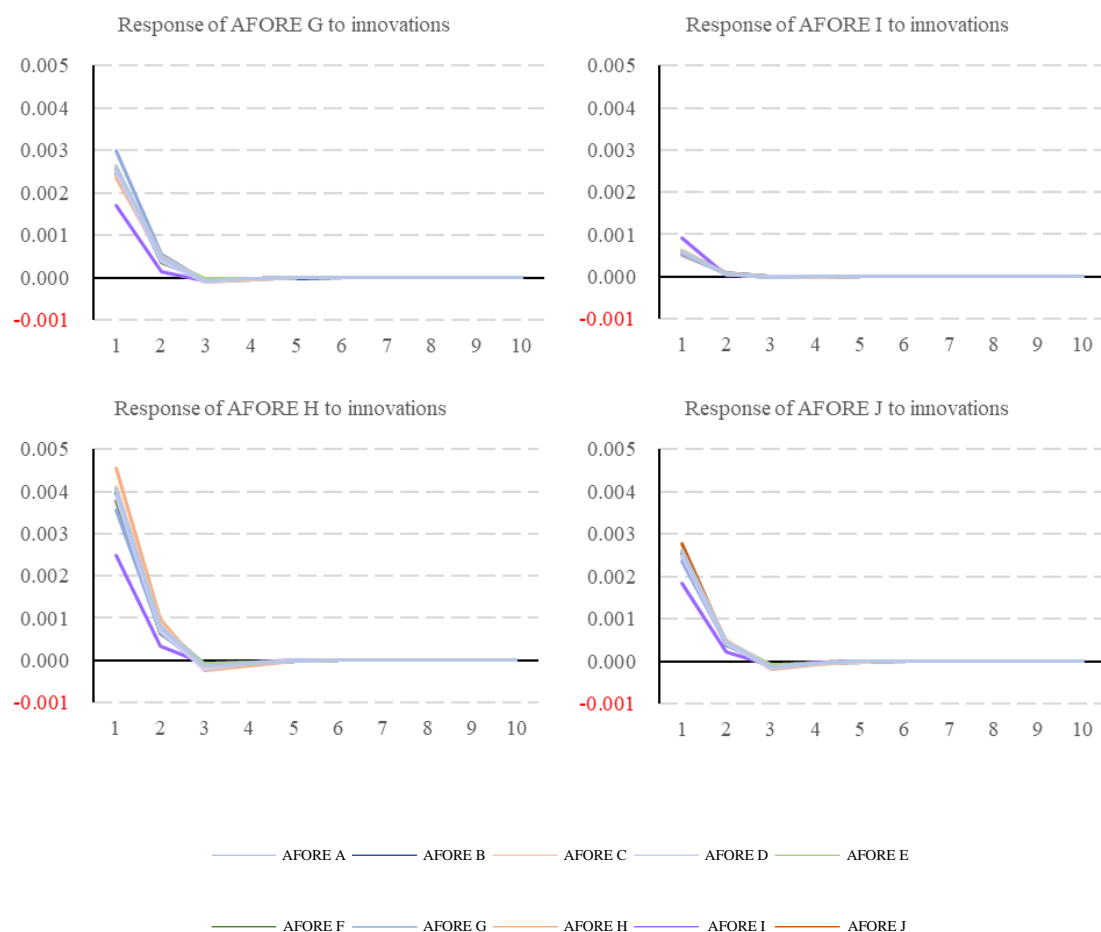
$$\begin{aligned} A_0 &= I_k \\ A_1 &= \Phi_1 \\ A_2 &= \Phi_1 A_1 + \Phi_2 \\ A_3 &= \Phi_1 A_2 + \Phi_2 A_1 + \Phi_3 \\ &\dots \\ A_h &= \Phi_1 A_{h-1} + \Phi_2 A_{h-2} + \dots + \Phi_p A_{h-p} \end{aligned}$$

¹⁶ For the construction of this function, go to Appendix C.

¹⁷ For more information about Impulse-Response Functions, see Potter (1999).

Figure 8: Response to Generalized one standard innovation shock on AFORE SB2
(October 2008-September 2019)





Source: Own elaboration with data from CONSAR.

We estimate generalized impulse – response functions across all AFORE, for the different SIEFORE. Results show an immediate effect that disappears generally after five days. Figure 8 shows the response of each AFORE to an innovation of a standard deviation on all other AFORE SB2. Notice that the impact, though positive, is lower on AFORE I, which is not subject to causality according to the Granger test.

There is a similarity in terms of a positive response and length of the effect among all funds, although the magnitude of the impact is slightly different. The similarity of the responses should not be surprising given the high level of correlation shown previously. In addition, the non-causality Granger tests show that, aside from the valuation effect due to similar portfolios, the SIEFOREs' returns react in the same direction with a similar magnitude, that

is, they are highly interconnected, which points out to the need for further and deeper analysis regarding the degree of connectedness among pension funds, in particular with respect to daily returns.

6. Pension Funds and Financial Connectedness

6.1. Financial and Macroeconomic Connectedness

Financial and macroeconomic connectedness is a concept used in order to understand how markets work, as well as an input for risk management, portfolio allocation and asset pricing.¹⁸ Connections among different assets, asset classes, portfolios, etc., are of interest for the study of financial markets, where often, the objects connected are typically returns or returns volatilities. The study of connectedness applies to networks of financial institutions and asset management firms.¹⁹ For Diebold and Yilmaz (2015), measuring connectedness among aggregate markets is important, but it also relevant to analyze it between individual institutions.

Financial markets are in part driven by macroeconomic fundamentals given that financial assets are claims on real output streams, which determine prices; however, the macroeconomy is also in part driven by the financial markets (as shown in the 2007-2008 Great Recession, preceded by a financial crisis).

Measuring connectedness can also be useful in crisis monitoring. In general, connectedness seems to increase sharply during crises, particularly that related to volatilities. In this paper, we will measure the financial connectedness among Mexican private pension funds, given their growing participation as financial intermediaries.

¹⁸ For a comprehensive view on financial and macroeconomic connectedness, see Diebold and Yilmaz (2015). This section is based on their work.

¹⁹ Retail, wholesale and investment banks are among the financial institutions where measuring connectedness is of interest. Among asset management firms, mutual funds and hedge funds are considered.

The approach of Diebold and Yilmaz to connectedness is based on assessing shares of h-step ahead forecast error variation in various locations due to shocks arising elsewhere, which is related to variance decomposition. A connectedness table is useful to understand different measures and relationships. This table is composed by a variance decomposition matrix denoted by $D = [d_{ij}]$, a column at the right containing row sums and a bottom row with column sums excluding the diagonal elements. Finally, a measure of total connectedness in a system, circled at the bottom right, results from the average of the sum of columns or rows. Since it is the average of the forecast error variance decomposition among the variables considered. It is defined as:

$$C = \frac{1}{n} \sum_{\substack{i,j=1 \\ i \neq j}}^N d_{ij}$$

In the table, each element represents the forecast error variance decomposition from row i due to column j . For example, the $d_{1,2}$ entry means that the shocks to X_2 are responsible for some percent of the h-step ahead forecast error variance in X_1 ; $d_{1,n}$ is the impact that variable 1 receives from variable n . The far-right cell is the sum of the forecast error variance decomposition –the total impact of other variables on variable 1. A similar interpretation works across columns, where element $d_{1,2}$ can be interpreted as how much of the variance of variable 1 is a response to the impulse of variable 2, and $d_{n,2}$ is the impact that variable 2 sends to variable n . The bottom cell of the X_2 column is the sum of the forecast error variance decomposition –the total impact of variable 2 on other variables, where i is different from 2.

Table 8: Connectedness Table

	X_1	X_2	...	X_n	From others
X_1	$d_{1,1}$	$d_{1,2}$...	$d_{1,n}$	$\sum_{j \neq 1} d_{1,j}$
X_2	$d_{2,1}$	$d_{2,2}$...	$d_{2,n}$	$\sum_{j \neq 2} d_{2,j}$
\vdots	\vdots	\vdots	\ddots	\vdots	\vdots
X_n	$d_{n,1}$	$d_{n,2}$...	$d_{n,n}$	$\sum_{j \neq n} d_{n,j}$
To others	$\sum_{i \neq 1} d_{i,1}$	$\sum_{i \neq 2} d_{i,2}$...	$\sum_{i \neq n} d_{i,n}$	$\frac{1}{n} \cdot \sum_{i \neq j} d_{i,j}$

Source: Diebold and Yilmaz (2015).

Connectedness among individual variables provides important information. The forecast error variance decompositions $d_{i,j}$ measure pairwise directional connectedness, which we can denote as:

$$C_{i \leftarrow j} = d_{i,j}$$

Which is different from $C_{j \leftarrow i} = d_{j,i}$

6.2. Connectedness in SB Daily Returns

The financial and macroeconomic connectedness methodology provides indicators among different pension funds, as well as a measure for the whole system.

We estimate the connectedness table for daily returns of the 10 AFORE for the different SIEFORE, considering information from December 2008 to September 2019:

Table 9: SB2 Connectedness Table
(December 2008- September 2019)^{1/}

Shock on Impact on	A	B	C	D	E	F	G	H	I	J	From others ²
A	12.06	10.86	11.19	10.36	10.95	10.01	9.21	9.76	4.93	10.66	87.94
B	11.32	12.48	11.52	10.16	10.78	9.77	8.61	9.76	4.92	10.70	87.52
C	11.13	10.99	12.07	10.25	10.97	9.78	9.15	9.92	5.11	10.62	87.93
D	10.97	10.28	10.92	12.63	11.02	9.95	8.96	9.45	5.34	10.47	87.37
E	10.96	10.35	11.05	10.39	12.01	10.38	9.37	9.65	5.18	10.67	87.99
F	10.68	10.02	10.50	9.99	11.05	12.70	9.47	8.96	5.81	10.81	87.30
G	10.75	9.70	10.73	9.86	10.91	10.31	14.18	8.78	4.46	10.33	85.82
H	10.92	10.50	11.19	10.00	10.78	9.38	8.42	13.81	4.04	10.95	86.19
I	8.98	8.59	9.37	9.14	9.48	9.97	7.03	6.59	21.36	9.50	78.64
J	10.87	10.48	10.89	10.07	10.85	10.30	9.05	9.97	5.30	12.22	87.78
To others ³	96.57	91.78	97.35	90.22	96.79	89.84	79.28	82.85	45.10	94.72	86.45

^{1/} Based on variance decomposition of 6 days.

^{2/} Column “From others” equals to the sum of the row except for the diagonal element. $C_{i,-} = \sum_{j \neq i} d_{ij} = \sum_j d_{ij} - d_{ii}$.

^{3/} Row “To others” equals to the sum of the column except for the diagonal element. $C_{-,j} = \sum_{i \neq j} d_{ij} = \sum_i d_{ij} - d_{jj}$.

Source: Own elaboration with data from CONSAR.

The table shows a high degree of total connectedness among daily returns, as shown by the indicator for the whole system, around 86 percent. This is also the result of a high degree of pairwise connectedness among AFORE.²⁰ Table 9 shows, for example, that AFORE B is responsible of the 10.5% of the forecast – error variance decomposition of AFORE H. Conversely, AFORE H is responsible of the 9.76% of the forecast error variance decomposition of AFORE B.

It is noteworthy that AFORE I has a low pairwise connectedness with other AFORE. This exception is consistent with: the lower correlation shown; the Granger non – causality tests in Section 5.3.1, where AFORE I’s daily returns do not “cause” those of others, nor are its returns caused by others; and the lower response to innovation shocks in other AFORE.

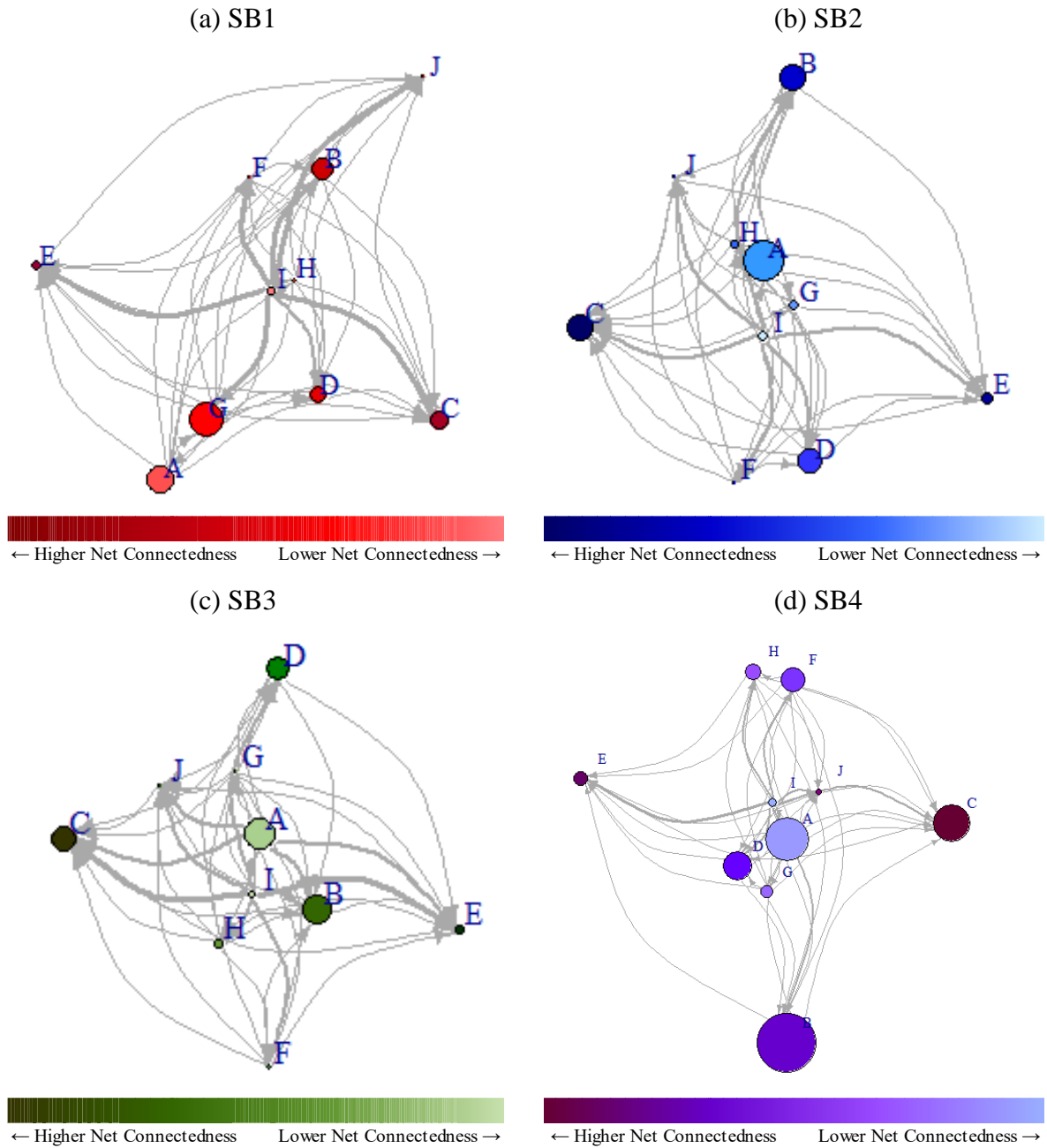
6.3. Connectedness Graphic Representation

Diebold and Yilmaz (2015) introduced a graphic representation of connectedness among systems in a point of time. Graphs contribute to depict several characteristics of

²⁰ See other tables in Appendix G.

connectedness in a glance. They also show the complex interactions among different agents of a system.

Figure 9: Connectedness among AFORE
(September 2019)



Source: Own elaboration with data from CONSAR.

In the Figure 9, we show the net financial connectedness among AFORE based on net connectedness table for each SB. Arrows show the direction of net connectedness and their width indicates the spillover; a narrower arrow means that an AFORE is responsible for a lower percent of the other manager's forecast error variance, compared with a wider arrow (pairwise connectedness). The size of the circles represents the importance of the AFORE according to its net assets, and the color is an indicator of the spillover of an AFORE on other pension fund managers (a darker circle means that a higher degree of the forecast error can be explained by exogenous shocks to other AFORE).

Figure 9 is based on the net connectedness table presented in Table 10.

Every element $e_{i,j}$ of this table represents the net connectedness between AFORE i and AFORE j for SB2.

$$e_{i,j} = \max\{d_{i,j} - d_{j,i}, 0\}.$$

In addition, it is possible to estimate net pairwise connectedness, which is analogous to a bilateral trade balance. Net pairwise connectedness is:

$$C_{ij} = C_{j \leftarrow i} - C_{i \leftarrow j}$$

Consequently, there are $\frac{N^2 - N}{2}$ net pairwise connectedness measures.

According to our example in Section 6.2 AFORE B is responsible of the 10.5% of the forecast error variance decomposition of AFORE H and AFORE H is responsible of the 9.76% of the forecast error variance decomposition of AFORE B. In Table 10 we present net connectedness (only net senders). For example, cell (2, 8) presents the difference of connectedness from AFORE B to AFORE H minus the connectedness from AFORE H to AFORE B which is 0.74, being AFORE B a net sender. Conversely, AFORE H is a net receiver.

Table 10: SB2 Net Connectedness Table
(December 2008-September 2019)^{1/}

Shock on Impact on	A	B	C	D	E	F	G	H	I	J
A			0.06							
B	0.45		0.52		0.43					0.21
C										
D	0.61	0.13	0.67		0.63					0.40
E	0.01		0.07							
F	0.67	0.25	0.72	0.05	0.68					0.51
G	1.53	1.09	1.58	0.89	1.53	0.84		0.36		1.28
H	1.16	0.74	1.26	0.55	1.13	0.42				0.99
I	4.05	3.67	4.26	3.80	4.30	4.16	2.57	2.55		4.20
J	0.21		0.26		0.18					
Net ²	8.63	4.26	9.41	2.85	8.79	2.54	-6.54	-3.34	-33.55	6.94

^{1/} Every element $e_{i,j}$ of this table represent the net connectedness between AFORE i and AFORE j for SB2.

$$e_{i,j} = \max\{d_{i,j} - d_{j,i}, 0\}.$$

^{2/} Bottom row “Net” is $C_j = C_{\leftarrow j} - C_{j\leftarrow}$.

Source: Own elaboration with data from CONSAR.

The results of net connectedness among AFORE for each SB are shown in Table 11 as a summary. Note that the SB2 row in Table 11 is the same that the bottom row in Table 10.

Table 11: Net connectedness among AFORE
(December 2008-September 2019)

	A	B	C	D	E	F	G	H	I	J
SB1	6.64	5.61	7.59	5.40	8.04	5.15	2.42	-8.99	-40.42	8.56
SB2	8.63	4.26	9.41	2.85	8.79	2.54	-6.54	-3.34	-33.55	6.94
SB3	8.66	4.74	9.84	2.26	9.25	1.42	-6.33	-2.25	-34.67	7.08
SB4	8.61	3.77	9.20	2.27	9.84	0.96	-6.53	1.23	-34.22	4.88

Source: Own elaboration with data from CONSAR.

These results can also be seen in Figure 9, where a high level of connectedness among daily returns of different AFORE in SB is confirmed.

The arrows show that AFORE J SB1, AFORE C SB2, AFORE C SB3 and AFORE D SB4 are the AFORE that send more spillover to others. No arrows go from other circles to these ones, indicating that they send more spillover than they receive. In all cases, the arrows to AFORE I are wider indicating that it receives more spillover than it sends, compared with other managers, where spillovers sent and received are similar. In addition, graph shows that the funds with more net assets are AFORE A, AFORE B and AFORE C. AFORE C, and

AFORE E –the darker circles– are the main players due to the net spillover they send to other AFORE forecast error variance, despite their size. On the other hand, AFORE G, AFORE H and AFORE I are the funds with the lowest levels of net connectedness as indicated. This is verified by the light color circle.

On a first approach, the low net connectedness of AFORE G and AFORE H is not consistent given that this AFORE exert Granger “causality” on others in Section 5.3. There is no contradiction given that results in Table 11 are obtained from a net connectedness table based on a variance decomposition matrix, while Section 5.3 is obtained from an auto regression vector.

In addition, the Granger causality test shows that an AFORE’s returns have an impact on the returns of other AFORE some days after, while the connectedness estimation shows the impact that the returns of an AFORE has on the forecast error variance decomposition.

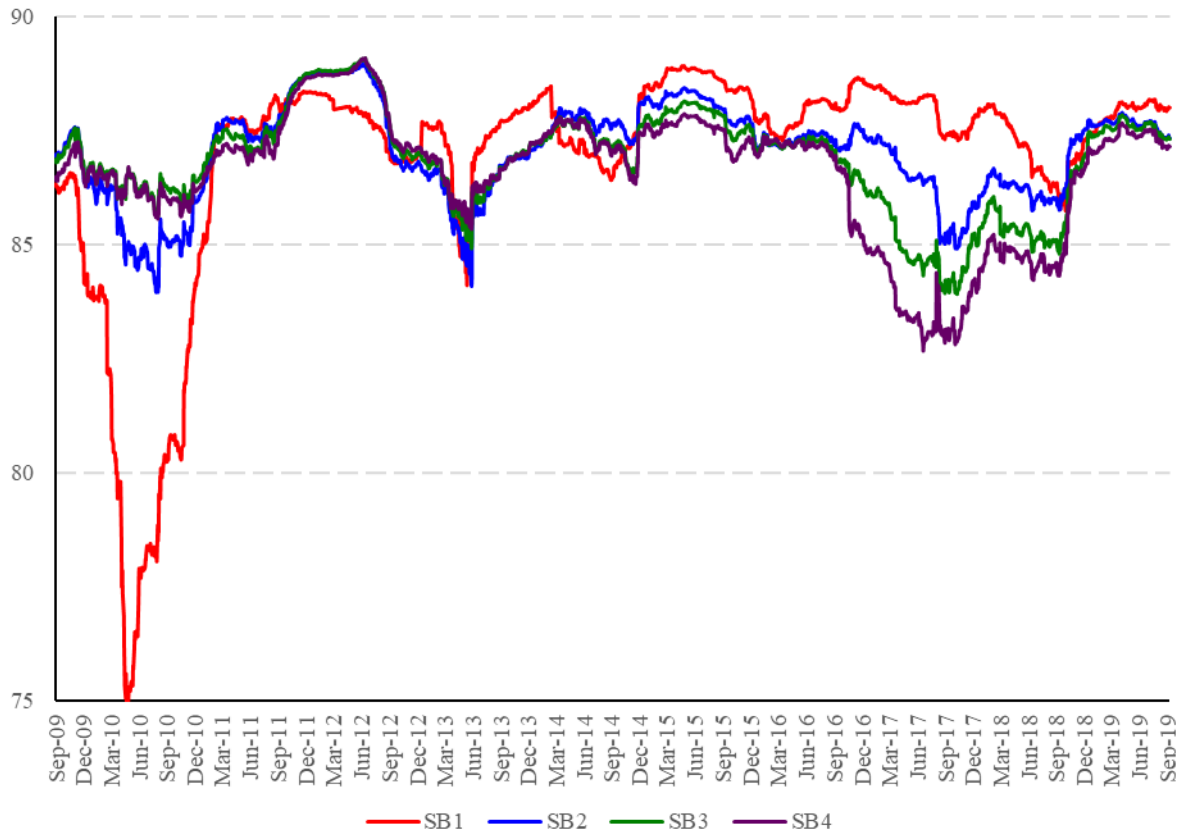
That is, connectedness and causality are different concepts. Granger results means that AFORE G and AFORE H are significant for other AFORE (although other AFORE are significant for AFORE G and AFORE H). On the other hand, the connectedness results mean that returns of AFORE G, AFORE H and AFORE I would have a higher forecast error than other AFORE as a response to a movement in the returns of other AFORE. AFORE E appears as a connected AFORE given to its proximity to the mean investors’ behavior.

6.4. Dynamics of Return Connectedness

As shown in the correlation analysis, the association among AFORE is not static. During our period of analysis, there have been changes in the financial landscape able to modify the level of connectedness. Hence, connectedness can be different at given points in time.

In order to have a more comprehensive view of connectedness, we can study its variation across time by moving from a static full – sample analysis to a dynamic rolling – sample analysis. We estimate total connectedness with 200 – day rolling samples and analyze the dynamics over time with a graph for the period December 2009 to September 2019, presented in Figure 10.

Figure 10: 200-day rolling window connectedness among AFORE
(December 2009-September 2019)



Source: Own elaboration with data from CONSAR.

In our sample, we begin with a high level of returns' connectedness, probably due to previous grouping of portfolio strategies during the financial crises. As the crisis recedes, connectedness returns to lower levels until May 2010. During the crisis, the connectedness diminishes, being the SB1 the fund with the lowest level. As time has passed, this situation has changed and now SB1 has the higher connectedness, while SB4 has the lowest. Further analysis of the determinants of changes in connectedness is required and can be the objective of further research.

We observe that the level of connectedness among AFORE throughout a period of ten years is high. During this time, the indicator has fluctuated slightly within a narrow band between 82 and 90 percent of connectedness.

7. Conclusions

We conduct a multivariate analysis of SIEFORE, with an emphasis on whether daily returns are related. Through different methodologies, we confirm the existence of this relation. The close relation of returns strengthens the possibility of an impact in financial markets.

There is a positive correlation of daily returns among AFORE, which has increased gradually and remains at a high level. We prove the existence of causality from some AFORE to others, implying that investment strategies and daily returns of some SIEFORE have an influence on others. The design of life-cycle funds is based on the premise that young workers can tolerate higher risk given that they have more time to recover from losses. We confirm this fact by showing that the daily returns distributions have a probability of high losses. This is an important finding for policy makers, which strengthens the need to protect resources of workers closer to retirement given that an extreme loss could damage badly a lifetime saving, but also to stress the importance of financial supervision of pension funds given the potential damage they could cause. On the other hand, it confirms the decision to allow funds for younger workers to accept a higher risk, since their resources will have more time to recover from a bad episode and receive positive returns most of the time.

A shock on returns of an AFORE has an immediate impact on others, which disappears after 5 days. Variance decomposition shows that return connectedness of the system is high, at 86 percent in average. Most AFORE send and receive spillovers. The AFORE that send more spillovers in net terms are AFORE C and AFORE E. AFORE I appears as less connected with other AFORE and hence has the lowest net connectedness. These findings show which AFORE are key players and leaders. While all managers are subject to financial supervision, authorities may take into account the systemic impact of their actions.

We estimate dynamic connectedness during a 10 year period and find that although it remains at high levels, it does fluctuate during time. Analyzing the determinants of connectedness is a possible avenue for further research.

Given the existence of a relation among returns, further work could study the existence of herding behavior or other trading strategies that could not be consistent with the objectives

of pension funds. Another interesting road for research is the role that pension funds have played during the financial crisis of 2008-2009 in Mexico. An interesting question is whether they have contributed to financial stability during this episode.

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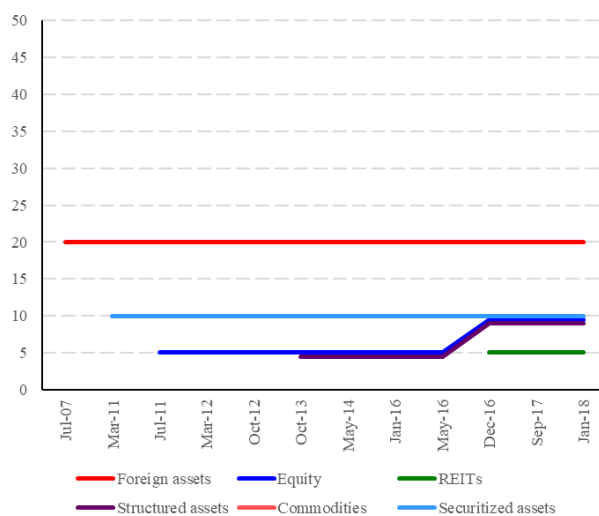
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9. Annex A. Evolution of Investment Regime

Figure 1: SIEFORE Básica 1

(July 2007-September 2019)

Percent of net assets

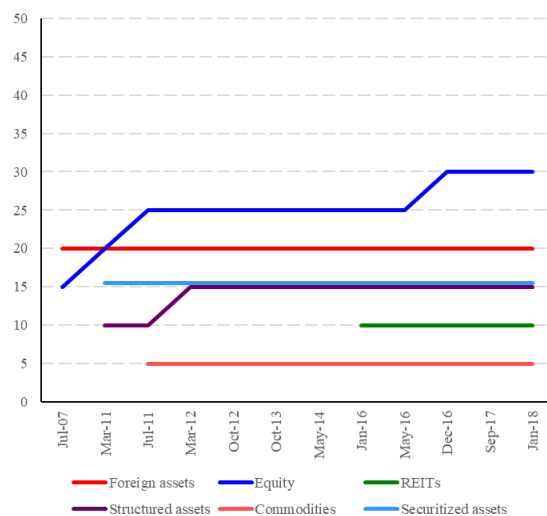


Source: Own elaboration with data from CONSAR.

Figure 2: SIEFORE Básica 2

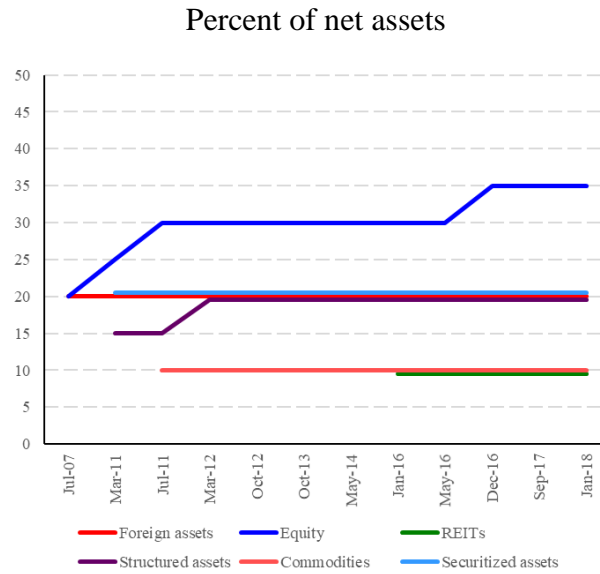
(July 2007-September 2019)

Percent of net assets



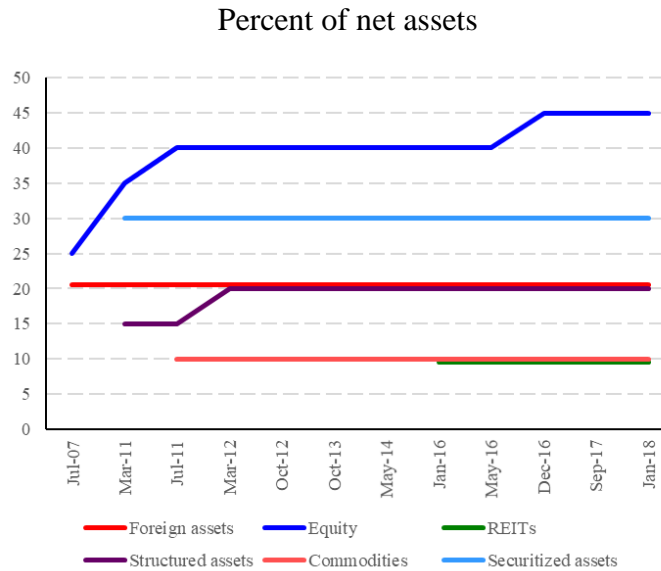
Source: Own elaboration with data from CONSAR.

Figure 3: SIEFORE Básica 3
(July 2007-September 2019)



Source: Own elaboration with data from CONSAR.

Figure 4: SIEFORE Básica 4
(July 2007-September 2019)

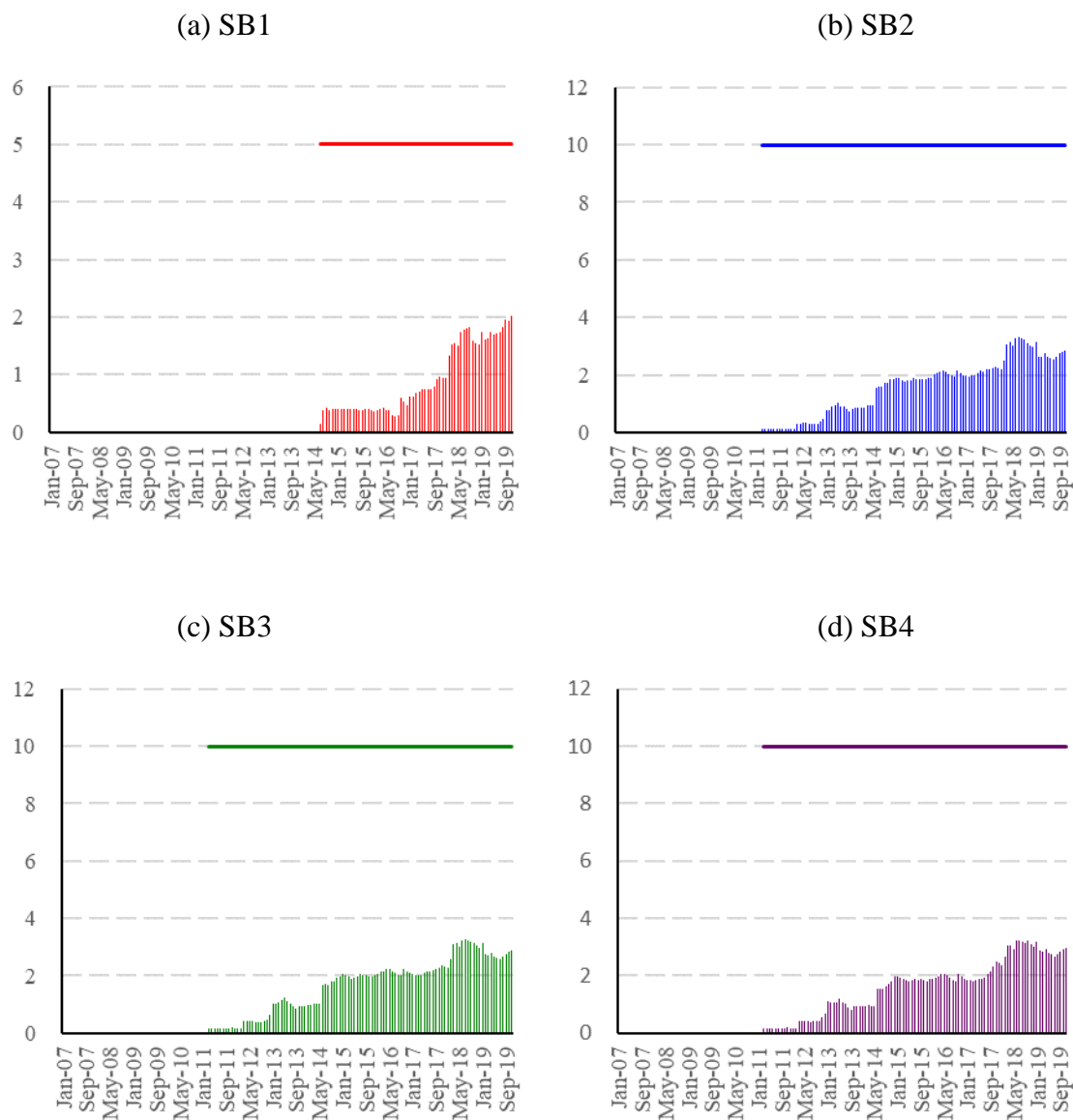


Source: Own elaboration with data from CONSAR.

Figure 5: Limits and actual investment on foreign assets

(July 2007-September 2019)

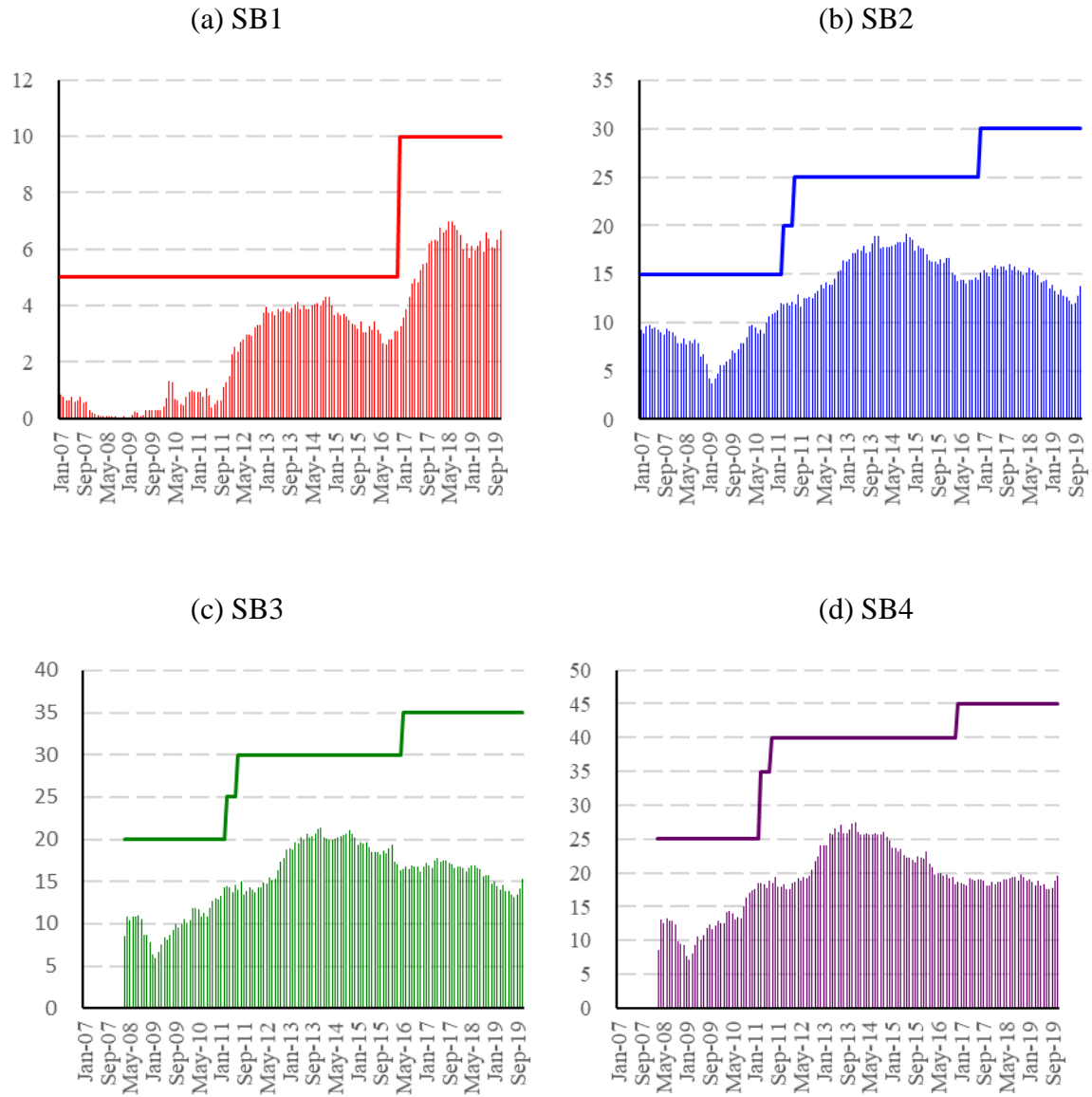
Percent of net assets



Source: Own elaboration with data from CONSAR.

Figure 6: Limits and actual investment on equity
(July 2007-September 2019)

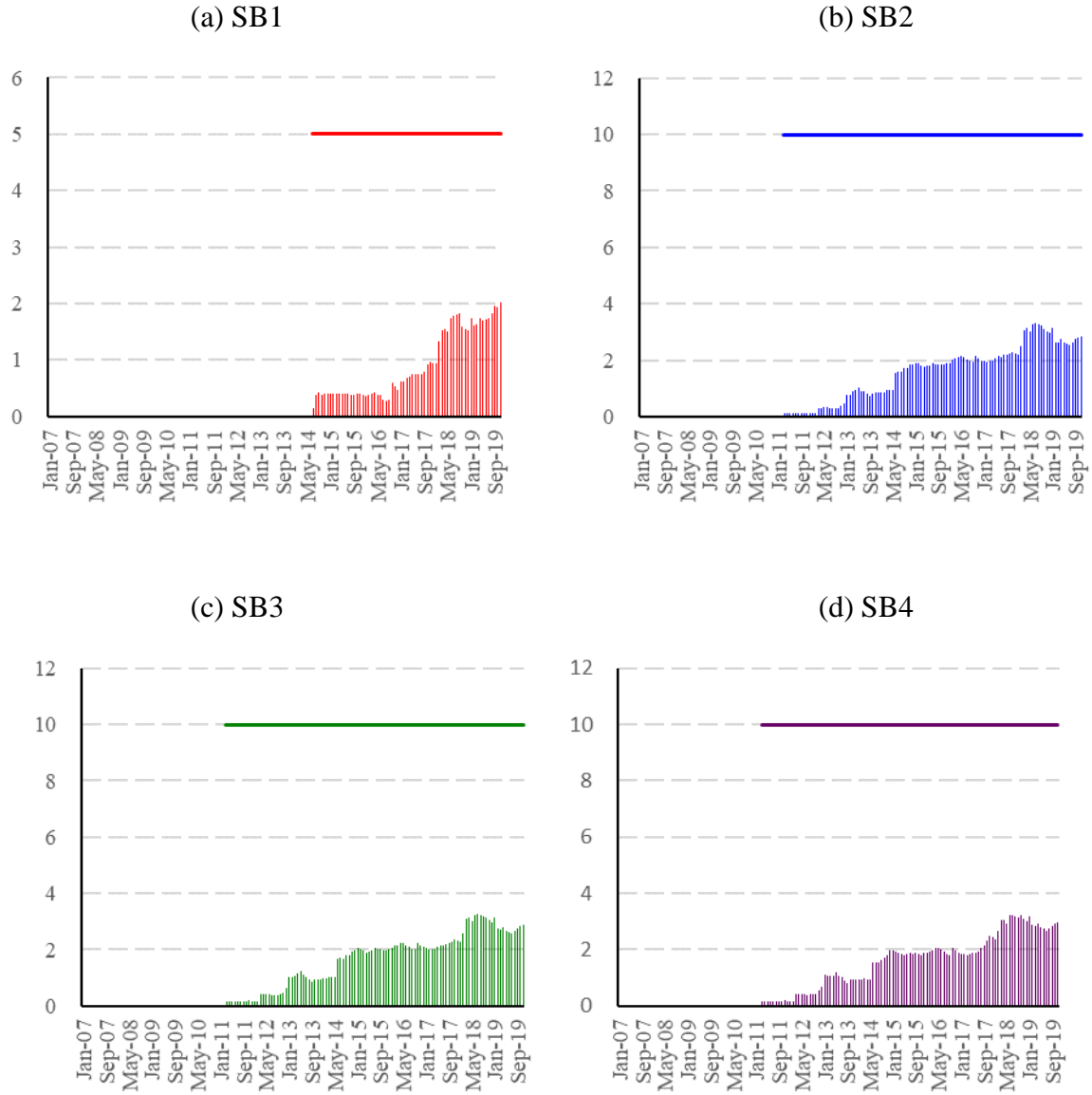
Percent of net assets



Source: Own elaboration with data from CONSAR.

Figure 7: Limits and actual investment on REITs
(July 2007-September 2019)

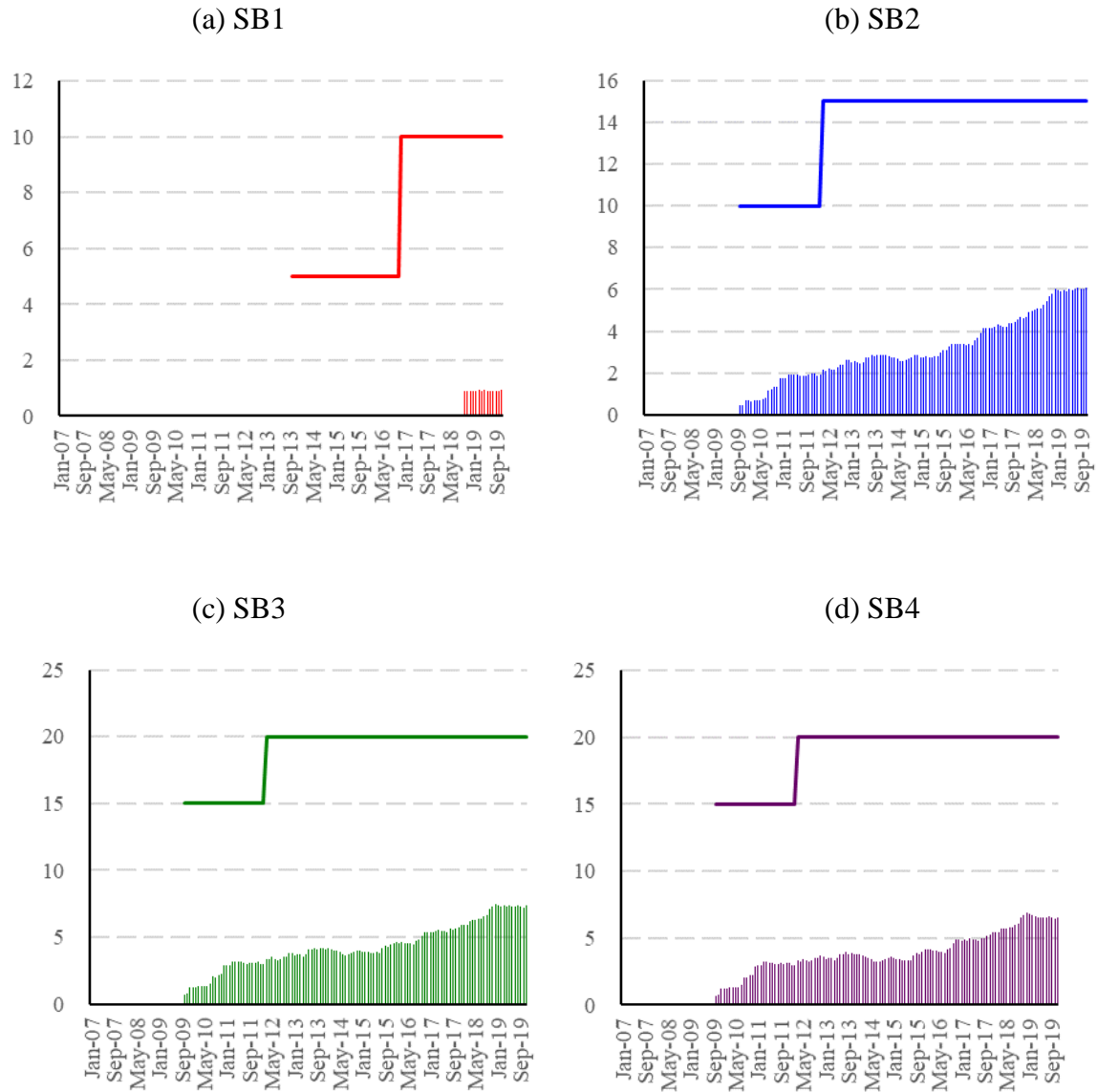
Percent of net assets



Source: Own elaboration with data from CONSAR.

Figure 8: Limits and actual investment on structured assets
(July 2007-September 2019)

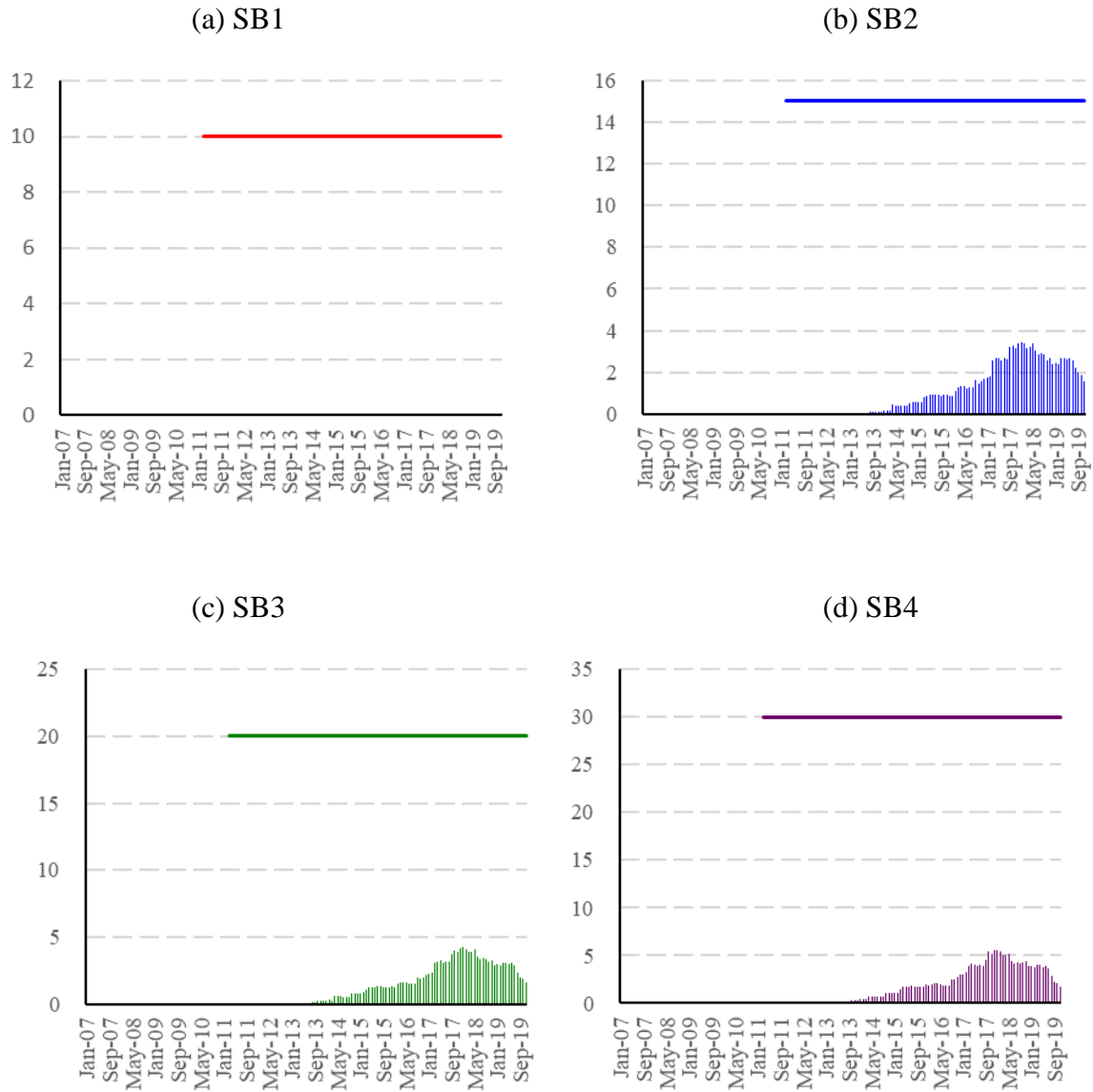
Percent of net assets



Source: Own elaboration with data from CONSAR.

Figure 9: Limits and actual investment on securitized assets
(July 2007-September 2019)

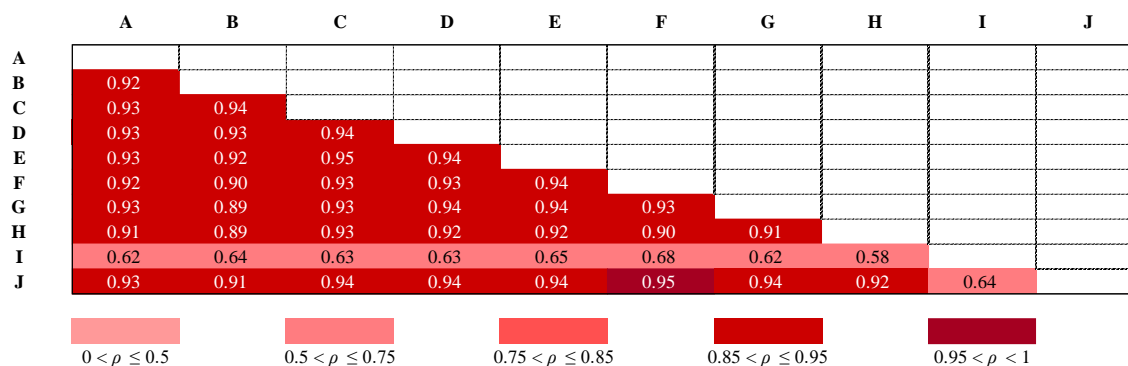
Percent of net assets



Source: Own elaboration with data from CONSAR.

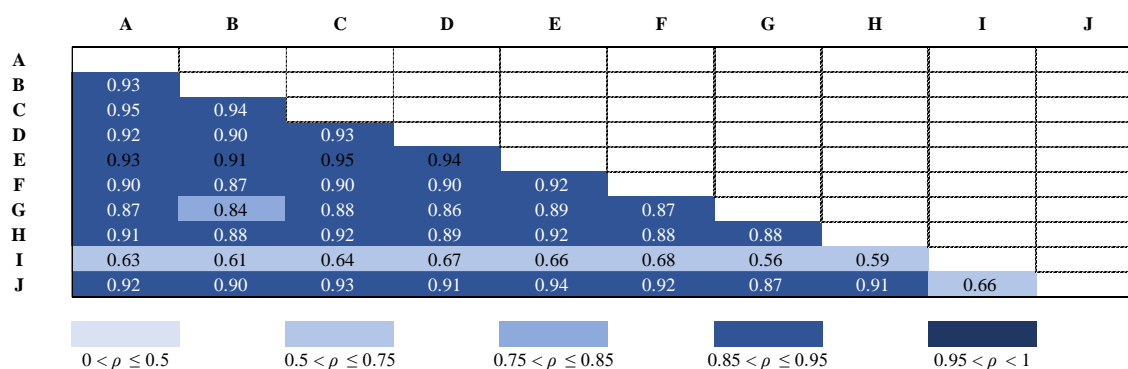
10. Annex B. Correlation Matrices

Table 1: Daily return correlation matrix among SB1 AFORE
(January 2005-September 2019)



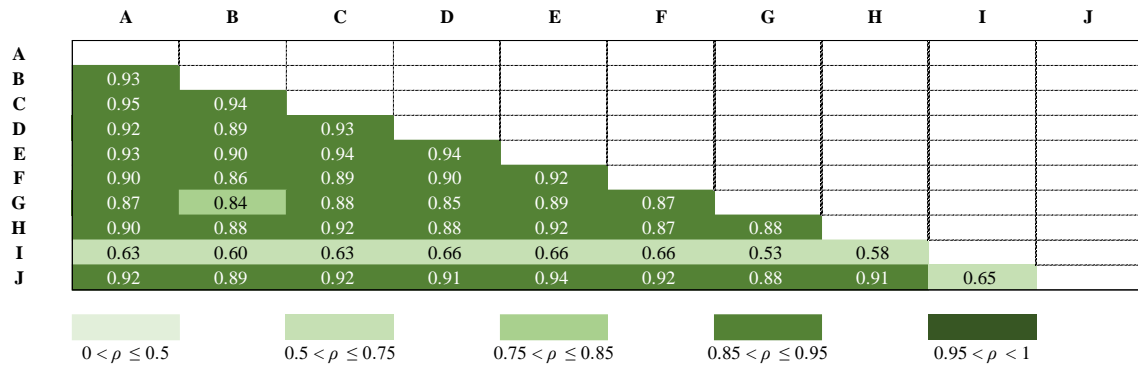
Source: Own elaboration with data from CONSAR.

Table 2: Daily return correlation matrix among SB2 AFORE
(July 1997-September 2019)



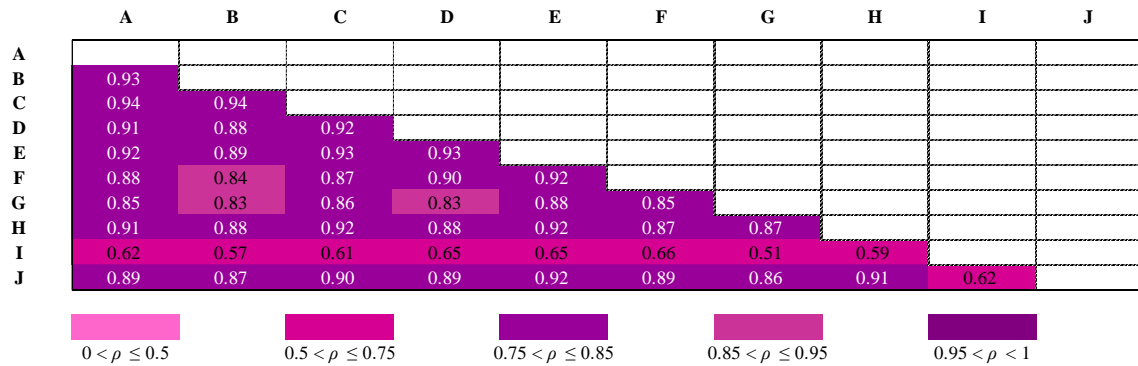
Source: Own elaboration with data from CONSAR.

Table 3: Daily return correlation matrix among SB3 AFORE
(March 2008-September 2019)



Source: Own elaboration with data from CONSAR.

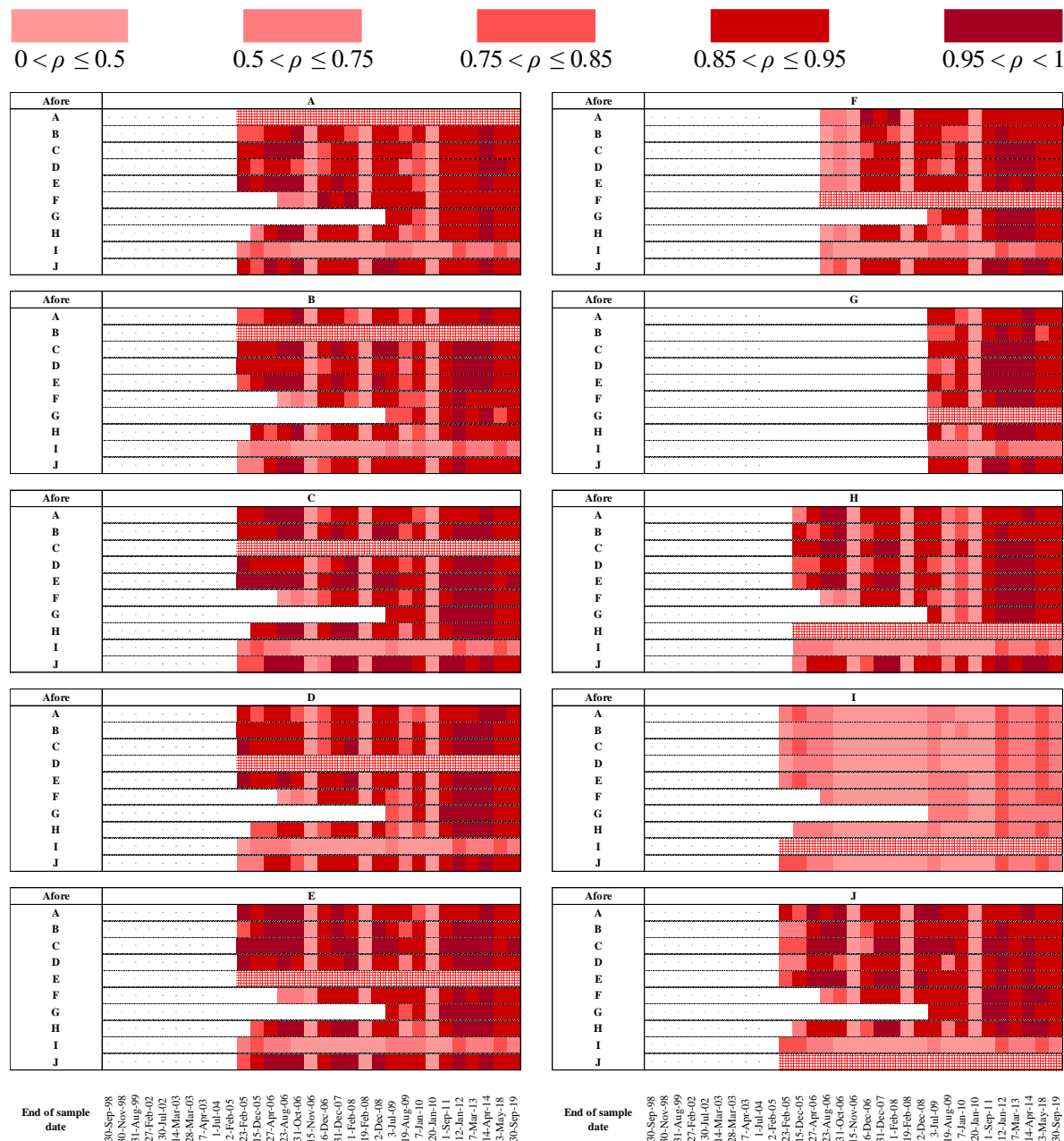
Table 4: Daily return correlation matrix among SB4 AFORE
(March 2008-September 2019)



Source: Own elaboration with data from CONSAR.

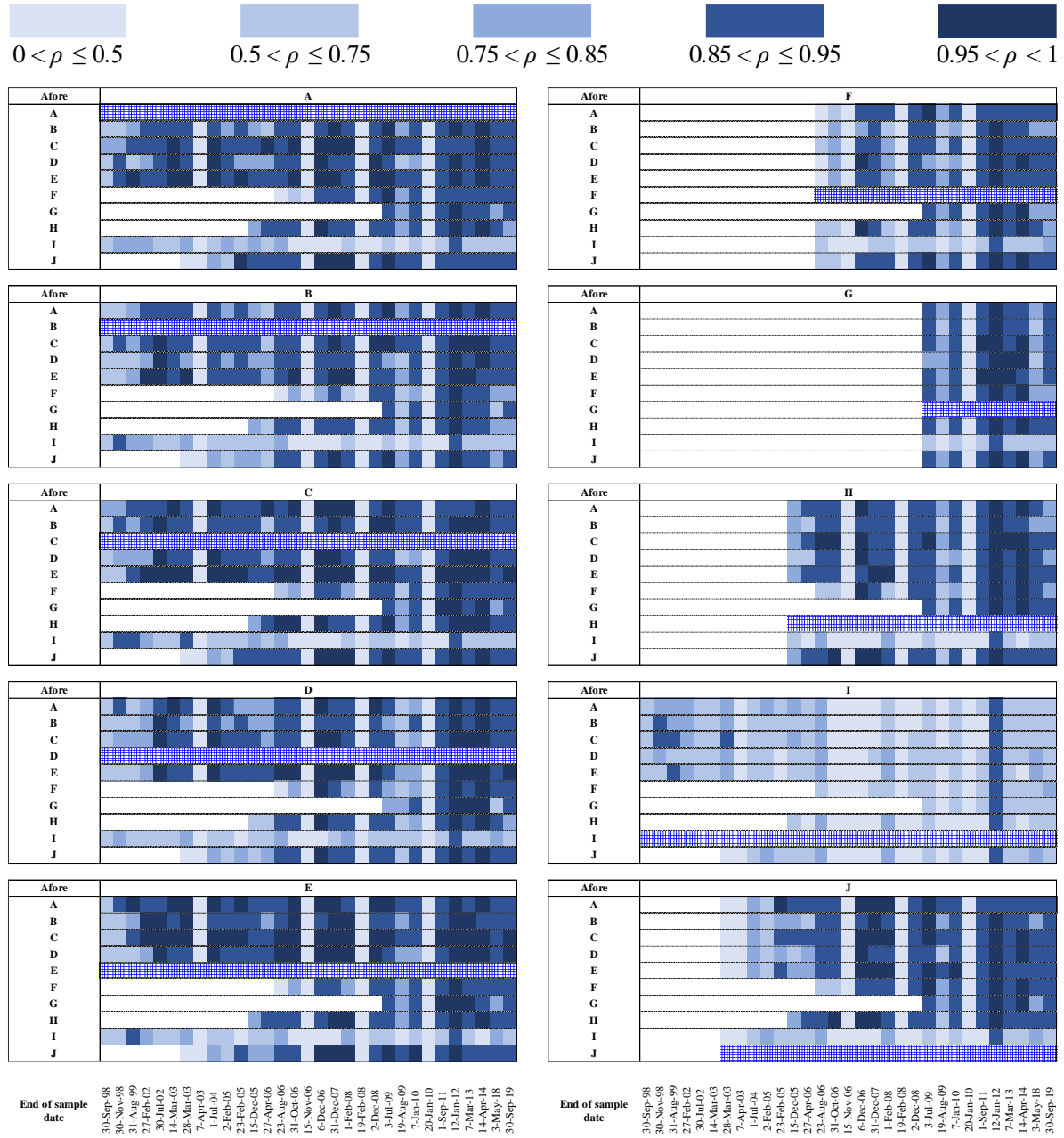
11. Annex C. Daily Correlation across Time

Table 1: SB1 Daily returns correlation across time
(January 2005-September 2019)



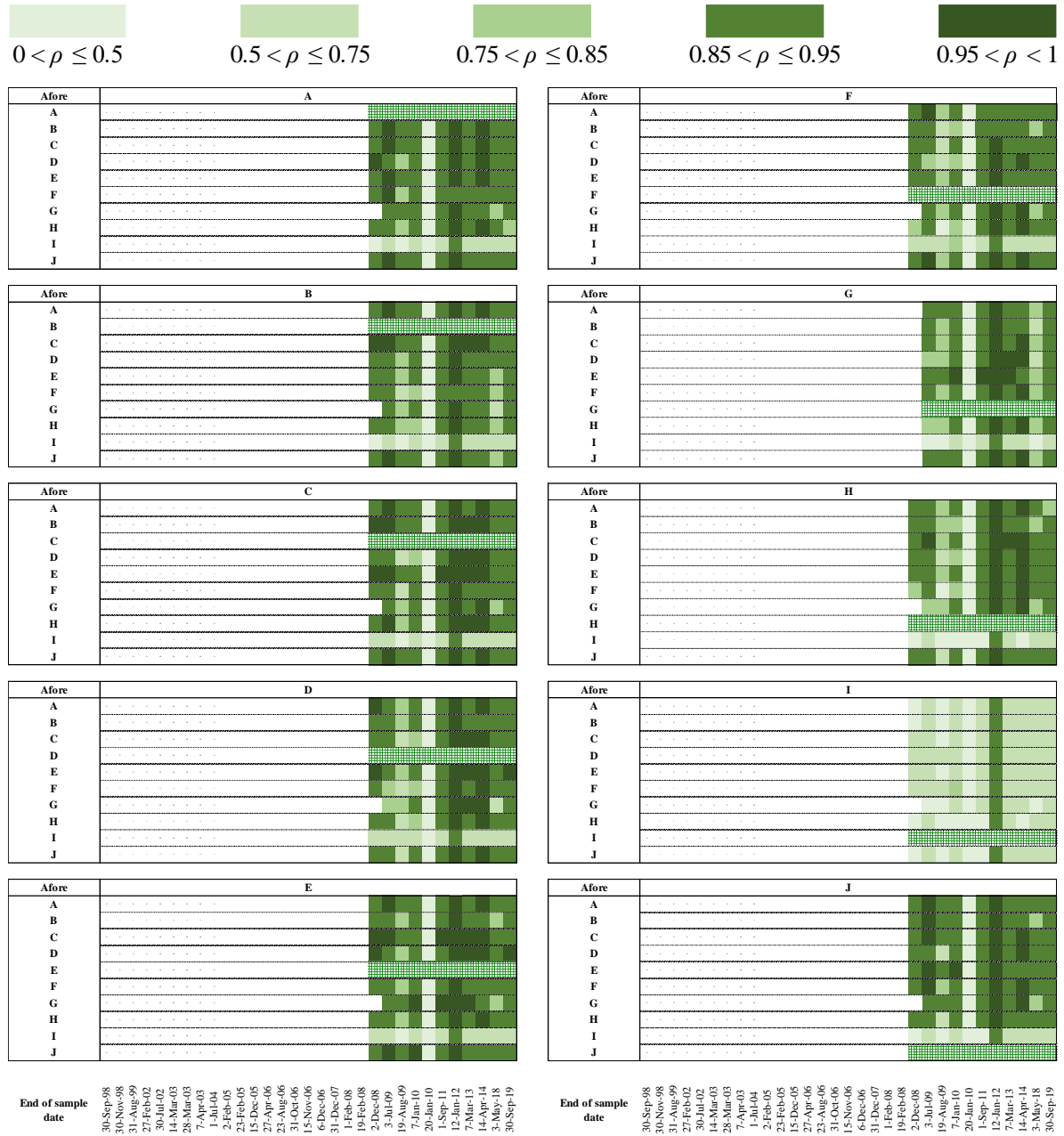
Source: Own elaboration with data from CONSAR.

Table 2: SB2 Daily returns correlation across time
(July 1997-September 2019)



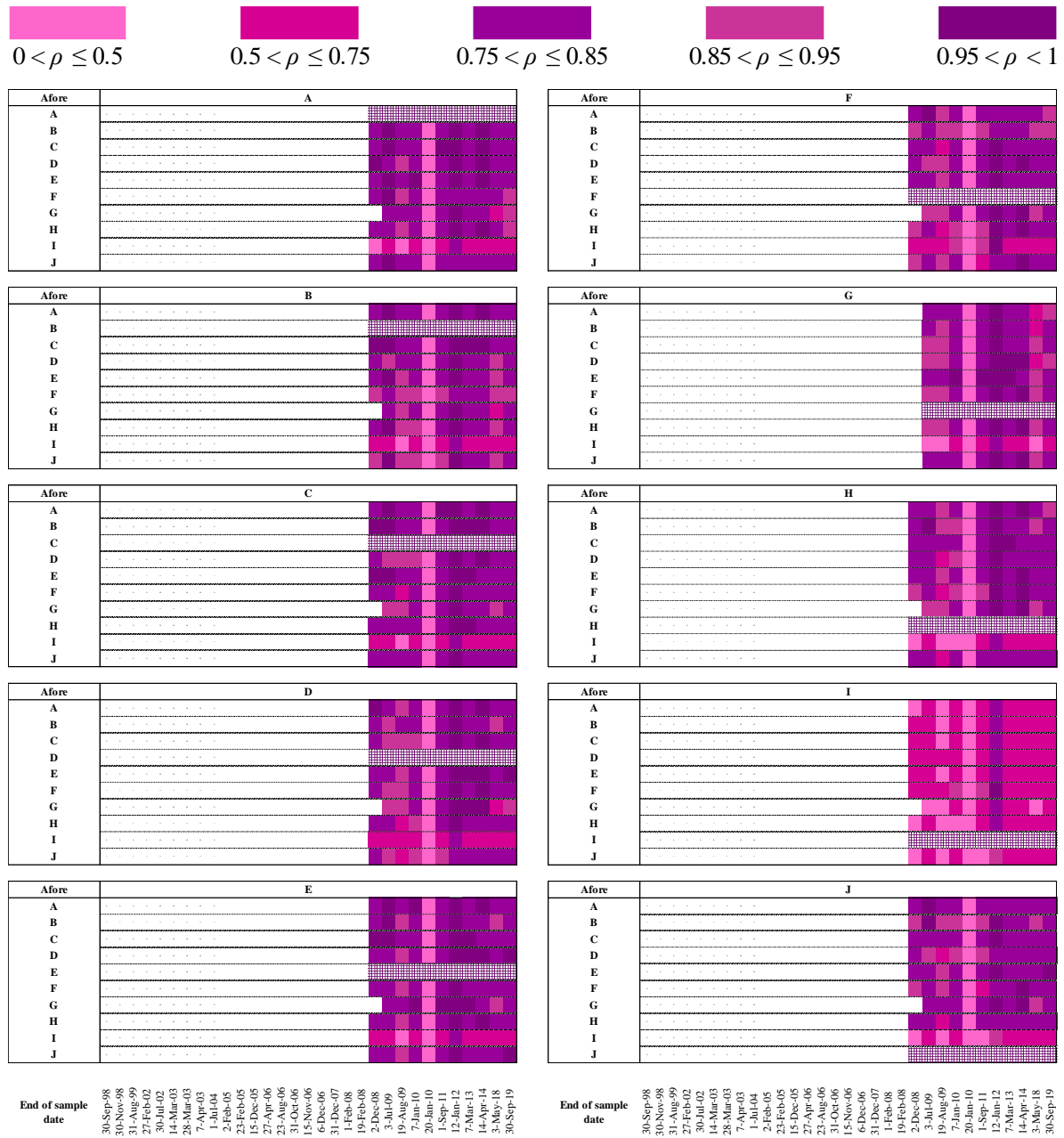
Source: Own elaboration with data from CONSAR.

Table 3: SB3 Daily returns correlation across time
(March 2008-September 2019)



Source: Own elaboration with data from CONSAR.

Table 4: SB4 Daily returns correlation across time
(March 2008-September 2019)



Source: Own elaboration with data from CONSAR.

12. Annex D. Impulse – Response Functions

A vector auto regressive (VAR) is defined as a set of variables $R_t = (R_{1,t}, R_{2,t}, \dots, R_{k,t})$ where in each moment t , each $R_{i,t}$ can be estimated from its own lagged information and the lags of the other variables.

A VAR looks like:

$$\begin{aligned}
 R_{1,t} &= c_1 + \sum_{i=1}^T \phi_{1,1}^i R_{1,t-i} + \sum_{i=1}^T \phi_{1,2}^i R_{2,t-i} + \dots + \sum_{i=1}^T \phi_{1,k}^i R_{k,t-i} + u_{1,t} \\
 R_{2,t} &= c_2 + \sum_{i=1}^T \phi_{2,1}^i R_{1,t-i} + \sum_{i=1}^T \phi_{2,2}^i R_{2,t-i} + \dots + \sum_{i=1}^T \phi_{2,k}^i R_{k,t-i} + u_{2,t} \\
 &\vdots \\
 R_{k,t} &= c_k + \sum_{i=1}^T \phi_{k,1}^i R_{1,t-i} + \sum_{i=1}^T \phi_{k,2}^i R_{2,t-i} + \dots + \sum_{i=1}^T \phi_{k,k}^i R_{k,t-i} + u_{k,t}
 \end{aligned}$$

Or:

$$R_t = c + \Phi^1 R_{t-1} + \Phi^2 R_{t-2} + \dots + \Phi^T R_{t-T} + u_t$$

where $c = (c_1, c_2, \dots, c_k)$ are the constants of each regression, $u_t = (u_{1,t}, u_{2,t}, \dots, u_{k,t})$ is a innovations vector and:

$$\Phi^i = \begin{bmatrix} \phi_{1,1}^i & \phi_{1,2}^i & \dots & \phi_{1,k}^i \\ \phi_{2,1}^i & \phi_{2,2}^i & \dots & \phi_{2,k}^i \\ \vdots & \vdots & \ddots & \vdots \\ \phi_{k,1}^i & \phi_{k,2}^i & \dots & \phi_{k,k}^i \end{bmatrix}$$

contains the coefficients of the regressions.

Assuming that the process is non – explosive, it is possible to write R as an infinite moving average:

$$R_t = \sum_{i=0}^{\infty} A_i u_{t-i}, t = 1, 2, \dots, T$$

where matrices A_i can be obtained recursively as follows:

$$A_0 = I_k$$

$$\begin{aligned}
A_1 &= \Phi_1 \\
A_2 &= \Phi_1 A_1 + \Phi_2 \\
A_3 &= \Phi_1 A_2 + \Phi_2 A_1 + \Phi_3 \\
&\dots \\
A_i &= \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \dots + \Phi_p A_{i-p}
\end{aligned}$$

Potter (1999) defines the Impulse – Response Function in a system like the difference of the expected value in the system with the impulse and the expected value in the system without the impulse.

It is possible to write the last definition as:

$$FIR_R(h, \delta, \Omega_{t-1}) = \mathbb{E}[R_{t+h} | u_t = \delta, \Omega_{t-1}] - \mathbb{E}[R_{t+h} | \Omega_{t-1}]$$

where:

- FIR_R denotes the value of the impulse – response function in the system R
- h is the time horizon evaluated in the function
- δ denotes the size of the impulse and
- Ω_{t-1} is the set with historical information of system R

The manner in which the impulse δ is applied in the system R produces different responses. The Cholesky's method decomposes the vector u in a product of triangular matrices and a ε structural innovations vector that receives the orthogonal impulse δ . Given the construction of this method, the response in R to the impulse δ is not immediate and depends on the order in which the triangular matrices are generated.

On the other hand, Pesaran and Shin (1997) propose to apply the impulse δ to original innovations u . So, the response to the generalized impulse is:

$$\begin{aligned}
GI_R(h, \delta, \Omega_{t-1}) &= \mathbb{E}[R_{t+h} | u_t = \delta, \Omega_{t-1}] - \mathbb{E}[R_{t+h} | \Omega_{t-1}] \\
&= \mathbb{E} \left[\sum_{i=0}^{\infty} A_i u_{t+h-i} \mid u_t = \delta, \Omega_{t-1} \right] - \mathbb{E} \left[\sum_{i=0}^{\infty} A_i u_{t+h-i} \mid \Omega_{t-1} \right] \\
&= \mathbb{E} \left[\sum_{i=0}^{\infty} A_i u_{t+h-i} \mid u_t = \delta \right] - \mathbb{E} \left[\sum_{i=0}^{\infty} A_i u_{t+h-i} \right] \\
&= A_h \delta
\end{aligned}$$

While:

$$\mathbb{E}[u_t | u_{j,t} = \delta] = \begin{bmatrix} \sigma_{1,j} \\ \sigma_{2,j} \\ \vdots \\ \sigma_{k,j} \end{bmatrix} \frac{\delta_j}{\sigma_{j,j}} = \Sigma \cdot e_j \cdot \frac{\delta_j}{\sigma_{j,j}}$$

where Σ is the variance and covariance matrix of the system R , and the vector e_j is such that $e_{i,j} = 0 \ \forall i \neq j, e_{j,j} = 1, i = 1, 2, \dots k$.

If the impulse is equal to a standard deviation, then $\delta_j = \sqrt{\sigma_{j,j}}$, so:

$$\begin{aligned} GI_R(h, \delta, \Omega_{t-1}) &= A_h \cdot \Sigma \cdot e_j \cdot \frac{\delta_j}{\sigma_{j,j}} \\ &= A_h \cdot \Sigma \cdot e_j \cdot \frac{\sqrt{\sigma_{j,j}}}{\sigma_{j,j}} \\ &= \frac{1}{\sqrt{\sigma_{j,j}}} \cdot A_h \cdot \Sigma \cdot e_j \end{aligned}$$

13. Annex E. Vector Auto Regression

Table 1: SB1 Vector Auto Regression

	A_SB1	B_SB1	C_SB1	D_SB1	E_SB1	F_SB1	G_SB1	H_SB1	I_SB1	J_SB1
A_SB1(-1)	-0.030286 (0.0736) [-0.41173]	0.064552 (0.0678) [0.95287]	0.017483 (0.0730) [0.23952]	0.027854 (0.0718) [0.38792]	0.016669 (0.0674) [0.24716]	0.033123 (0.0602) [0.54983]	0.005771 (0.0682) [0.08462]	-0.097121 (0.0996) [-0.97556]	0.026274 (0.0213) [1.23153]	-0.00744 (0.0654) [-0.11385]
A_SB1(-2)	-0.04192 (0.0735) [-0.57008]	-0.021083 (0.0677) [-0.31132]	-0.034592 (0.0730) [-0.47407]	-0.065736 (0.0718) [-0.91580]	-0.037232 (0.0674) [-0.55224]	-0.024013 (0.0602) [-0.39875]	-0.034676 (0.0682) [-0.50861]	-0.154526 (0.0995) [-1.55270]	0.006457 (0.0213) [0.30277]	-0.045835 (0.0653) [-0.70164]
B_SB1(-1)	0.095721 (0.0748) [1.27925]	0.070788 (0.0689) [1.02719]	0.127367 (0.0743) [1.71539]	0.122281 (0.0730) [1.67410]	0.061694 (0.0686) [0.89923]	0.055138 (0.0613) [0.89976]	0.04948 (0.0694) [0.71319]	0.093557 (0.1013) [0.92383]	0.024661 (0.0217) [1.13631]	0.068538 (0.0665) [1.03104]
B_SB1(-2)	0.175669 (0.0746) [2.35479]	0.165625 (0.0687) [2.41062]	0.202501 (0.0740) [2.73552]	0.190268 (0.0728) [2.61276]	0.181607 (0.0684) [2.65506]	0.144589 (0.0611) [2.36659]	0.182345 (0.0692) [2.63625]	0.321174 (0.1010) [3.18101]	0.034014 (0.0216) [1.57202]	0.159286 (0.0663) [2.40341]
C_SB1(-1)	0.048173 (0.0793) [0.60779]	0.012266 (0.0730) [0.16803]	-0.081208 (0.0787) [-1.03255]	0.121484 (0.0774) [1.57019]	0.040285 (0.0727) [0.55435]	0.051372 (0.0649) [0.79143]	0.121077 (0.0735) [1.64760]	0.087809 (0.1073) [0.81858]	-0.004854 (0.0230) [-0.21114]	0.078119 (0.0704) [1.10944]
C_SB1(-2)	-0.143322 (0.0794) [-1.80437]	-0.13503 (0.0732) [-1.84582]	-0.129906 (0.0788) [-1.64816]	-0.080223 (0.0775) [-1.03465]	-0.11322 (0.0728) [-1.55461]	-0.075458 (0.0651) [-1.15998]	-0.097412 (0.0737) [-1.32270]	-0.107318 (0.1075) [-0.99828]	0.000505 (0.0230) [0.02192]	-0.064601 (0.0706) [-0.91548]
D_SB1(-1)	-0.016864 (0.0693) [-0.24320]	0.007949 (0.0639) [0.12448]	-0.02985 (0.0688) [-0.43381]	-0.264204 (0.0677) [-3.90315]	-0.01381 (0.0636) [-0.21720]	-0.055146 (0.0568) [-0.97105]	-0.029318 (0.0643) [-0.45601]	0.096301 (0.0939) [1.02612]	-0.029331 (0.0201) [-1.45840]	0.001073 (0.0616) [0.01741]
D_SB1(-2)	-0.087885 (0.0693) [-1.26744]	-0.061684 (0.0639) [-0.96590]	-0.088248 (0.0688) [-1.28255]	-0.161269 (0.0677) [-2.38254]	-0.068616 (0.0636) [-1.07926]	-0.06184 (0.0568) [-1.08896]	-0.115481 (0.0643) [-1.79621]	-0.062475 (0.0939) [-0.66571]	0.007915 (0.0201) [0.39355]	-0.070196 (0.0616) [-1.13952]
E_SB1(-1)	-0.065704 (0.0894) [-0.73458]	-0.143238 (0.0824) [-1.73881]	-0.116073 (0.0888) [-1.30779]	-0.078091 (0.0873) [-0.89439]	-0.110279 (0.0820) [-1.34471]	-0.070747 (0.0733) [-0.96580]	-0.096717 (0.0829) [-1.16624]	-0.03617 (0.1211) [-0.29879]	-0.001777 (0.0259) [-0.06850]	-0.059452 (0.0795) [-0.74818]
E_SB1(-2)	0.355626 (0.0895) [3.97484]	0.341247 (0.0824) [4.14134]	0.348943 (0.0888) [3.93041]	0.34895 (0.0873) [3.99547]	0.307686 (0.0820) [3.75076]	0.279631 (0.0733) [3.81630]	0.24272 (0.0830) [2.92595]	0.386074 (0.1211) [3.18834]	0.052426 (0.0260) [2.20232]	0.279722 (0.0795) [3.51923]
F_SB1(-1)	0.036945 (0.0851) [0.43410]	0.075478 (0.0784) [0.96294]	0.06622 (0.0845) [0.78411]	0.034525 (0.0831) [0.41557]	0.076404 (0.0780) [0.97911]	0.158777 (0.0697) [2.27797]	0.004043 (0.0789) [0.05124]	-0.102272 (0.1152) [-0.88789]	0.01329 (0.0247) [0.53838]	0.028874 (0.0756) [0.38189]
F_SB1(-2)	-0.087872 (0.0850) [-1.03335]	-0.092167 (0.0783) [-1.17686]	-0.084423 (0.0844) [-1.00050]	-0.098697 (0.0830) [-1.18900]	-0.089623 (0.0780) [-1.14949]	-0.158028 (0.0696) [-2.26915]	-0.072275 (0.0788) [-0.91669]	-0.031705 (0.1151) [-0.27548]	-0.067615 (0.0247) [-2.74149]	-0.075887 (0.0587) [-1.00453]
G_SB1(-1)	0.118696 (0.0661) [1.79515]	0.052053 (0.0609) [0.85479]	0.151494 (0.0656) [2.30897]	0.158077 (0.0645) [2.44913]	0.122473 (0.0606) [2.02018]	0.05945 (0.0542) [1.09787]	0.237884 (0.0613) [3.88031]	-0.101237 (0.0895) [-1.13128]	0.040933 (0.0192) [2.13444]	0.069086 (0.0587) [1.17611]
G_SB1(-2)	-0.035551 (0.0662) [-0.53724]	-0.05966 (0.0609) [-0.97893]	-0.096213 (0.0657) [-1.46525]	-0.050106 (0.0607) [-0.77569]	-0.071653 (0.0646) [-1.18096]	-0.050699 (0.0542) [-0.93552]	-0.052391 (0.0614) [-0.85392]	-0.020579 (0.0896) [-0.22978]	-0.025135 (0.0192) [-1.30963]	-0.053265 (0.0588) [-0.90606]
H_SB1(-1)	0.097773 (0.0336) [2.91187]	0.095068 (0.0309) [3.07420]	0.120169 (0.0333) [3.60664]	0.088314 (0.0328) [2.69440]	0.086864 (0.0308) [2.82148]	0.048124 (0.0275) [1.75003]	0.037128 (0.0311) [1.19257]	0.267058 (0.0454) [5.87658]	0.008399 (0.0097) [0.86243]	0.055721 (0.0298) [1.86796]
H_SB1(-2)	-0.126317 (0.0334) [-3.77995]	-0.106495 (0.0308) [-3.46018]	-0.098946 (0.0332) [-2.98386]	-0.064137 (0.0326) [-1.96612]	-0.084354 (0.0306) [-2.75306]	-0.068748 (0.0274) [-2.51196]	-0.051364 (0.0310) [-1.65773]	-0.206685 (0.0452) [-4.56983]	-0.010962 (0.0097) [-1.13097]	-0.078638 (0.0297) [-2.64881]
I_SB1(-1)	-0.188285 (0.0872) [-2.15887]	-0.138269 (0.0803) [-1.72140]	-0.170582 (0.0865) [-1.97106]	-0.181934 (0.0851) [-2.13699]	-0.19612 (0.0800) [-2.45255]	-0.156314 (0.0714) [-2.18846]	-0.219995 (0.0809) [-2.72056]	-0.17757 (0.1180) [-1.50435]	0.037862 (0.0253) [1.49679]	-0.133607 (0.0775) [-1.72438]
I_SB1(-2)	0.020645 (0.0873) [0.23661]	0.033977 (0.0804) [0.42280]	0.055741 (0.0866) [0.64378]	0.023414 (0.0852) [0.27489]	0.009494 (0.0800) [0.11867]	0.065868 (0.0715) [0.92175]	0.023325 (0.0809) [0.28831]	0.016364 (0.1181) [0.13857]	0.026754 (0.0253) [1.05714]	0.035419 (0.0775) [0.45691]
J_SB1(-1)	-0.037453 (0.0956) [-0.39175]	-0.02572 (0.0881) [-0.29210]	-0.021559 (0.0949) [-0.22725]	0.007389 (0.0933) [0.07917]	-0.056536 (0.0877) [-0.64495]	-0.079109 (0.0783) [-1.01035]	-0.106723 (0.0886) [-1.20395]	0.013019 (0.1294) [0.10061]	-0.043004 (0.0277) [-1.55084]	-0.037906 (0.0849) [-0.44629]
J_SB1(-2)	-0.03538 (0.0951) [-0.37199]	-0.073254 (0.0876) [-0.83626]	-0.049714 (0.0944) [-0.52674]	-0.058026 (0.0928) [-0.62498]	-0.056785 (0.0872) [-0.65116]	-0.048658 (0.0779) [-0.62467]	-0.037643 (0.0882) [-0.42686]	-0.137954 (0.1287) [-1.07168]	-0.019865 (0.0276) [-0.72009]	-0.103123 (0.0845) [-1.22043]
C	0.000265 (0.0001) [4.97897]	0.000285 (0.0001) [5.80880]	0.000288 (0.0001) [5.45232]	0.000307 (0.0001) [5.89406]	0.000282 (0.0000) [5.76807]	0.000263 (0.0000) [6.03315]	0.000298 (0.0000) [6.02282]	0.00029 (0.0001) [4.02307]	0.000235 (0.0000) [15.2126]	0.000268 (0.0000) [5.64979]

Source: Own elaboration with data from CONSAR.

Table 2: Vector Auto Regression SB2

	A_SB2	B_SB2	C_SB2	D_SB2	E_SB2	F_SB2	G_SB2	H_SB2	I_SB2	J_SB2
A_SB2(-1)	0.000752 (0.0852) [0.0088]	0.126593 (0.0859) [1.4736]	0.143368 (0.0899) [1.5943]	0.140529 (0.0904) [1.5543]	0.121952 (0.0837) [1.4563]	0.055082 (0.0663) [0.8313]	0.050554 (0.0806) [0.6273]	0.057353 (0.1223) [0.4691]	0.008345 (0.0244) [0.3415]	0.114396 (0.0745) [1.5361]
A_SB2(-2)	-0.009559 (0.0853) [-0.1121]	0.029239 (0.0860) [0.3401]	-0.002797 (0.0900) [-0.0311]	-0.021745 (0.0905) [-0.2403]	-0.002837 (0.0838) [-0.0339]	-0.010097 (0.0663) [-0.1523]	0.001394 (0.0807) [0.0173]	0.054653 (0.1224) [0.4467]	-0.025863 (0.0245) [-1.0575]	0.017977 (0.0745) [0.2412]
B_SB2(-1)	0.007848 (0.0702) [0.1118]	-0.129208 (0.0708) [-1.8246]	0.020686 (0.0741) [0.2791]	-0.049048 (0.0745) [-0.6581]	0.011763 (0.0690) [0.1704]	0.044221 (0.0546) [0.8096]	0.059342 (0.0664) [0.8933]	0.058975 (0.1008) [0.5852]	0.033645 (0.0202) [1.6701]	0.026935 (0.0614) [0.4388]
B_SB2(-2)	0.111603 (0.0694) [1.6091]	0.102538 (0.0700) [1.4659]	0.154934 (0.0732) [2.1161]	0.104182 (0.0736) [1.4152]	0.09531 (0.0682) [1.3978]	0.086997 (0.0540) [1.6125]	0.100141 (0.0656) [1.5261]	0.174336 (0.0996) [1.7513]	0.043834 (0.0199) [2.2028]	0.106189 (0.0606) [1.7513]
C_SB2(-1)	0.214534 (0.0881) [2.4342]	0.273526 (0.0889) [3.0774]	0.176971 (0.0930) [1.9022]	0.203024 (0.0935) [2.1704]	0.125612 (0.0866) [1.4498]	0.094291 (0.0686) [1.3754]	0.183211 (0.0834) [2.1973]	0.236061 (0.1265) [1.8662]	-0.007364 (0.0253) [-0.2913]	0.105185 (0.0771) [1.3652]
C_SB2(-2)	-0.160158 (0.0881) [-1.8187]	-0.198333 (0.0888) [-2.2333]	-0.198674 (0.0930) [-2.1372]	-0.095375 (0.0935) [-1.0205]	-0.141796 (0.0866) [-1.638]	-0.1489 (0.0685) [-2.1738]	-0.154328 (0.0833) [-1.8524]	-0.201305 (0.1264) [-1.5928]	-0.036548 (0.0253) [-1.4467]	-0.132136 (0.0770) [-1.7164]
D_SB2(-1)	-0.061991 (0.0540) [-1.148]	-0.014577 (0.0545) [-0.2677]	-0.09105 (0.0570) [-1.5973]	-0.190425 (0.0573) [-3.3225]	-0.092327 (0.0531) [-1.7393]	-0.093622 (0.0420) [-2.2288]	-0.106954 (0.0511) [-2.0935]	-0.185683 (0.0775) [-2.3958]	-0.023433 (0.0155) [-1.5126]	-0.071439 (0.0472) [-1.5133]
D_SB2(-2)	-0.110174 (0.0541) [-2.0358]	-0.081003 (0.0546) [-1.4842]	-0.10173 (0.0571) [-1.7807]	-0.103373 (0.0574) [-1.7997]	-0.096539 (0.0532) [-1.8146]	-0.049853 (0.0421) [-1.1842]	-0.118601 (0.0512) [-2.3164]	-0.22178 (0.0777) [-2.8553]	0.014048 (0.0155) [0.9048]	-0.106208 (0.0473) [-2.2449]
E_SB2(-1)	0.042237 (0.0867) [0.4874]	0.011517 (0.0874) [0.1318]	-0.049863 (0.0915) [-0.5451]	0.074538 (0.0920) [0.8104]	-0.024557 (0.0852) [-0.2883]	-0.00696 (0.0674) [-0.1033]	0.030041 (0.0820) [0.3664]	0.052497 (0.1244) [0.4221]	-0.013366 (0.0249) [-0.5376]	-0.022275 (0.0758) [-0.294]
E_SB2(-2)	0.37889 (0.0864) [4.3833]	0.407115 (0.0872) [4.6702]	0.385263 (0.0913) [4.2221]	0.324408 (0.0917) [3.536]	0.388152 (0.0850) [4.5679]	0.329527 (0.0672) [4.9009]	0.29811 (0.0818) [3.6453]	0.520562 (0.1241) [4.196]	0.06109 (0.0248) [2.4634]	0.317931 (0.0756) [4.2072]
F_SB2(-1)	-0.084967 (0.0757) [-1.1231]	-0.054727 (0.0763) [-0.7173]	-0.106067 (0.0799) [-1.3281]	-0.108659 (0.0803) [-1.3532]	-0.061308 (0.0744) [-0.8244]	0.002967 (0.0589) [0.0504]	-0.17399 (0.0716) [-2.4309]	-0.191306 (0.1086) [-1.7619]	-0.020883 (0.0217) [-0.9622]	-0.079348 (0.0661) [-1.1997]
F_SB2(-2)	0.07748 (0.0758) [1.0229]	0.020734 (0.0764) [0.2714]	0.068456 (0.0800) [0.8561]	0.077882 (0.0804) [0.9688]	0.043003 (0.0745) [0.5775]	-0.009773 (0.0589) [-0.1659]	0.03693 (0.0717) [0.5153]	0.117258 (0.1087) [1.0786]	0.015654 (0.0217) [0.7204]	0.055574 (0.0662) [0.8393]
G_SB2(-1)	0.044216 (0.0460) [0.9608]	-0.030759 (0.0464) [-0.6628]	0.070926 (0.0486) [1.46]	0.0442 (0.0488) [0.9049]	0.073122 (0.0452) [1.6163]	0.046695 (0.0358) [1.3044]	0.230791 (0.0435) [5.3008]	-0.046419 (0.0661) [-0.7028]	0.016987 (0.0132) [1.2866]	0.034763 (0.0402) [0.8641]
G_SB2(-2)	-0.117672 (0.0463) [-2.5436]	-0.116479 (0.0467) [-2.4966]	-0.134947 (0.0488) [-2.7632]	-0.104806 (0.0491) [-2.1345]	-0.119943 (0.0455) [-2.6374]	-0.083718 (0.0360) [-2.3264]	-0.100717 (0.0438) [-2.3011]	-0.126929 (0.0664) [-1.9116]	-0.030607 (0.0133) [-2.306]	-0.096759 (0.0404) [-2.3924]
H_SB2(-1)	0.067274 (0.0342) [1.9664]	0.072878 (0.0345) [2.1123]	0.090555 (0.0361) [2.5075]	0.066518 (0.0363) [1.832]	0.089325 (0.0336) [2.6561]	0.043722 (0.0266) [1.643]	0.026231 (0.0324) [0.8104]	0.265841 (0.0491) [5.4141]	0.010632 (0.0098) [1.0832]	0.070163 (0.0299) [2.346]
H_SB2(-2)	-0.129277 (0.0341) [-3.7965]	-0.151438 (0.0343) [-4.4099]	-0.117614 (0.0360) [-3.272]	-0.097001 (0.0361) [-2.684]	-0.108401 (0.0335) [-3.2384]	-0.077548 (0.0265) [-2.9277]	-0.055228 (0.0322) [-1.7143]	-0.228181 (0.0489) [-4.6689]	-0.022481 (0.0098) [-2.3012]	-0.116133 (0.0298) [-3.9012]
I_SB2(-1)	-0.153398 (0.0957) [-1.6034]	-0.090359 (0.0965) [-0.9365]	-0.183361 (0.1010) [-1.8155]	-0.163521 (0.1015) [-1.6104]	-0.269205 (0.0941) [-2.8623]	-0.185079 (0.0744) [-2.4869]	-0.228606 (0.0905) [-2.5256]	-0.212678 (0.1373) [-1.5488]	-0.000842 (0.0275) [-0.0307]	-0.107785 (0.0836) [-1.2887]
I_SB2(-2)	-0.063738 (0.0961) [-0.6632]	-0.091265 (0.0969) [-0.9416]	-0.068837 (0.1015) [-0.6785]	-0.099806 (0.1020) [-0.9784]	-0.048041 (0.0945) [-0.5085]	0.0215 (0.0748) [0.2876]	-0.009705 (0.0909) [-0.1067]	-0.038298 (0.1379) [-0.2776]	-0.004398 (0.0276) [-0.1595]	-0.076472 (0.0840) [-0.9101]
J_SB2(-1)	-0.06646 (0.0814) [-0.8164]	-0.091027 (0.0821) [-1.1087]	-0.088371 (0.0859) [-1.0283]	-0.051683 (0.0864) [-0.5981]	-0.071573 (0.0800) [-0.8943]	-0.049185 (0.0633) [-0.7767]	-0.150675 (0.0770) [-1.9563]	-0.111353 (0.1169) [-0.953]	0.015936 (0.0234) [0.6823]	-0.055681 (0.0712) [-0.7823]
J_SB2(-2)	-0.052313 (0.0813) [-0.6435]	-0.006441 (0.0820) [-0.0786]	-0.062784 (0.0858) [-0.7316]	-0.089579 (0.0863) [-1.0382]	-0.085556 (0.0799) [-1.0706]	-0.08364 (0.0632) [-1.3226]	-0.04284 (0.0769) [-0.557]	-0.091024 (0.1167) [-0.7801]	-0.019377 (0.0233) [-0.8308]	-0.06151 (0.0711) [-0.8655]
C	0.000311 (0.0001) [4.676]	0.000346 (0.0001) [5.1587]	0.000388 (0.0001) [5.5224]	0.000411 (0.0001) [5.8213]	0.000374 (0.0001) [5.7207]	0.000345 (0.0001) [6.6662]	0.000353 (0.0001) [5.6055]	0.000359 (0.0001) [3.7638]	0.000254 (0.0000) [13.334]	0.00035 (0.0001) [6.0127]

Source: Own elaboration with data from CONSAR.

Table 3: Vector Auto Regression SB3

	A_SB3	B_SB3	C_SB3	D_SB3	E_SB3	F_SB3	G_SB3	H_SB3	I_SB3	J_SB3
A_SB3(-1)	-0.010754 (0.0847) [-0.1269]	0.165817 (0.0875) [1.895]	0.151822 (0.0916) [1.6583]	0.133936 (0.0916) [1.4622]	0.143893 (0.0813) [1.7697]	0.059664 (0.0639) [0.9335]	0.015088 (0.0787) [0.1918]	0.090487 (0.1217) [0.7434]	0.017691 (0.0289) [0.6132]	0.087247 (0.0738) [1.1831]
A_SB3(-2)	0.053092 (0.0848) [0.6259]	0.100839 (0.0876) [1.151]	0.072673 (0.0917) [0.7928]	0.074407 (0.0917) [0.8113]	0.072538 (0.0814) [0.891]	0.060138 (0.0640) [0.9397]	0.078179 (0.0788) [0.9925]	0.166773 (0.1219) [1.3683]	-0.00664 (0.0289) [-0.2299]	0.066653 (0.0738) [0.9027]
B_SB3(-1)	-0.051204 (0.0715) [-0.7163]	-0.235623 (0.0738) [-3.1914]	-0.051063 (0.0773) [-0.661]	-0.104372 (0.0773) [-1.3505]	-0.038957 (0.0686) [-0.5679]	0.008035 (0.0539) [0.149]	0.008167 (0.0664) [0.123]	-0.028037 (0.1027) [-0.273]	0.016747 (0.0243) [0.688]	-0.011501 (0.0622) [-0.1848]
B_SB3(-2)	0.042024 (0.0700) [0.6]	0.024724 (0.0723) [0.3418]	0.086382 (0.0757) [1.1412]	0.028615 (0.0757) [0.3779]	0.023575 (0.0672) [0.3507]	0.03475 (0.0528) [0.6576]	0.037723 (0.0650) [0.58]	0.077231 (0.1006) [0.7674]	0.026245 (0.0239) [1.1003]	0.058879 (0.0610) [0.9657]
C_SB3(-1)	0.274321 (0.0897) [3.0571]	0.322005 (0.0927) [3.4744]	0.252947 (0.0970) [2.6085]	0.286758 (0.0970) [2.9557]	0.16372 (0.0861) [1.9011]	0.124596 (0.0677) [1.8405]	0.239698 (0.0833) [2.8767]	0.286962 (0.1289) [2.2257]	0.007451 (0.0306) [0.2438]	0.161578 (0.0781) [2.0685]
C_SB3(-2)	-0.130811 (0.0896) [-1.4605]	-0.167551 (0.0925) [-1.8113]	-0.166783 (0.0968) [-1.7232]	-0.080122 (0.0968) [-0.8274]	-0.106024 (0.0860) [-1.2335]	-0.129088 (0.0676) [-1.9105]	-0.129664 (0.0832) [-1.5591]	-0.180239 (0.1287) [-1.4006]	-0.018413 (0.0305) [-0.6037]	-0.120069 (0.0780) [-1.5401]
D_SB3(-1)	-0.034373 (0.0505) [-0.6811]	0.009624 (0.0521) [0.1847]	-0.049857 (0.0545) [-0.9142]	-0.204789 (0.0546) [-3.7532]	-0.055765 (0.0485) [-1.1514]	-0.062316 (0.0381) [-1.6367]	-0.066867 (0.0469) [-1.4269]	-0.11534 (0.0725) [-1.5906]	-0.010502 (0.0172) [-0.6111]	-0.037056 (0.0439) [-0.8435]
D_SB3(-2)	-0.103389 (0.0505) [-2.0458]	-0.070567 (0.0522) [-1.352]	-0.099744 (0.0546) [-1.8264]	-0.094243 (0.0546) [-1.7248]	-0.090812 (0.0485) [-1.8724]	-0.059228 (0.0381) [-1.5535]	-0.108353 (0.0469) [-2.309]	-0.213266 (0.0726) [-2.937]	0.008408 (0.0172) [0.4886]	-0.094474 (0.0440) [-2.1476]
E_SB3(-1)	0.060163 (0.0895) [0.6724]	0.042024 (0.0924) [0.4547]	-0.045534 (0.0967) [-0.4709]	0.096769 (0.0968) [1.0002]	-0.030278 (0.0859) [-0.3526]	-0.02231 (0.0675) [-0.3305]	0.033694 (0.0831) [0.4055]	0.085114 (0.1286) [0.662]	-0.02446 (0.0305) [-0.8027]	0.000262 (0.0779) [0.0034]
E_SB3(-2)	0.356037 (0.0891) [3.994]	0.372444 (0.0921) [4.0453]	0.352932 (0.0963) [3.6637]	0.298805 (0.0964) [3.1003]	0.336191 (0.0856) [3.9296]	0.30216 (0.0673) [4.493]	0.245058 (0.0828) [2.9606]	0.469891 (0.1281) [3.6686]	0.063516 (0.0304) [2.0924]	0.282844 (0.0776) [3.645]
F_SB3(-1)	-0.113369 (0.0757) [-1.4973]	-0.091543 (0.0782) [-1.1706]	-0.120809 (0.0818) [-1.4765]	-0.106341 (0.0819) [-1.299]	-0.090279 (0.0727) [-1.2424]	-0.017913 (0.0571) [-0.3136]	-0.17806 (0.0703) [-2.5326]	-0.193999 (0.1088) [-1.7833]	-0.028246 (0.0258) [-1.0955]	-0.094543 (0.0659) [-1.4344]
F_SB3(-2)	0.112831 (0.0757) [1.4901]	0.043426 (0.0782) [0.5553]	0.098311 (0.0818) [1.2014]	0.101527 (0.0819) [1.2402]	0.075539 (0.0727) [1.0395]	0.009977 (0.0571) [0.1746]	0.052076 (0.0703) [0.7407]	0.146693 (0.1088) [1.3483]	0.037883 (0.0258) [1.4692]	0.067519 (0.0659) [1.0244]
G_SB3(-1)	0.028982 (0.0484) [0.5986]	-0.06097 (0.0500) [-1.2193]	0.041422 (0.0523) [0.7917]	-0.003972 (0.0524) [-0.0759]	0.043973 (0.0465) [0.9463]	0.037628 (0.0365) [1.0301]	0.205556 (0.0450) [4.5722]	-0.07682 (0.0696) [-1.1043]	0.002299 (0.0165) [0.1395]	0.026541 (0.0422) [0.6297]
G_SB3(-2)	-0.146923 (0.0487) [-3.0142]	-0.14101 (0.0503) [-2.801]	-0.162259 (0.0527) [-3.0804]	-0.137286 (0.0527) [-2.6051]	-0.133899 (0.0468) [-2.8623]	-0.094353 (0.0368) [-2.5658]	-0.099787 (0.0453) [-2.2047]	-0.168456 (0.0700) [-2.4053]	-0.033803 (0.0166) [-2.0365]	-0.111125 (0.0424) [-2.619]
H_SB3(-1)	0.043946 (0.0355) [1.2381]	0.075331 (0.0367) [2.0548]	0.073835 (0.0384) [1.9249]	0.060454 (0.0384) [1.5753]	0.075512 (0.0341) [2.2166]	0.026835 (0.0268) [1.0021]	0.011675 (0.0330) [0.3542]	0.238075 (0.0510) [4.6681]	0.008172 (0.0121) [0.6761]	0.049337 (0.0309) [1.5968]
H_SB3(-2)	-0.144887 (0.0354) [-4.0963]	-0.172564 (0.0365) [-4.7237]	-0.136974 (0.0382) [-3.5835]	-0.115454 (0.0382) [-3.0191]	-0.119963 (0.0340) [-3.5339]	-0.085722 (0.0267) [-3.2124]	-0.070197 (0.0328) [-2.1373]	-0.228581 (0.0508) [-4.4977]	-0.032315 (0.0120) [-2.6829]	-0.121319 (0.0308) [-3.9403]
I_SB3(-1)	-0.185683 (0.0798) [-2.3271]	-0.123637 (0.0824) [-1.5003]	-0.224692 (0.0862) [-2.6058]	-0.193321 (0.0863) [-2.2409]	-0.281383 (0.0766) [-3.6745]	-0.197022 (0.0602) [-3.273]	-0.240531 (0.0741) [-3.2464]	-0.298204 (0.1147) [-2.6011]	-0.022819 (0.0272) [-0.8398]	-0.167746 (0.0695) [-2.4151]
I_SB3(-2)	-0.07589 (0.0803) [-0.9452]	-0.071663 (0.0829) [-0.8642]	-0.079178 (0.0868) [-0.9126]	-0.111035 (0.0868) [-1.2792]	-0.053484 (0.0771) [-0.6941]	0.000163 (0.0606) [0.0027]	0.004655 (0.0746) [0.0624]	-0.032664 (0.1154) [-0.2832]	-0.008105 (0.0273) [-0.2964]	-0.090638 (0.0699) [-1.2969]
J_SB3(-1)	-0.037004 (0.0826) [-0.4481]	-0.057096 (0.0853) [-0.6694]	-0.08403 (0.0893) [-0.9415]	-0.027574 (0.0893) [-0.3088]	-0.056969 (0.0793) [-0.7188]	-0.022206 (0.0623) [-0.3564]	-0.131186 (0.0767) [-1.7107]	-0.149336 (0.1187) [-1.2585]	0.02883 (0.0281) [1.0251]	-0.057906 (0.0719) [-0.8055]
J_SB3(-2)	-0.015436 (0.0826) [-0.1868]	0.041935 (0.0853) [0.4914]	-0.026558 (0.0893) [-0.2974]	-0.047665 (0.0893) [-0.5335]	-0.057154 (0.0793) [-0.7207]	-0.059165 (0.0623) [-0.9491]	-0.019646 (0.0767) [-0.256]	-0.04134 (0.1187) [-0.3482]	-0.034028 (0.0281) [-1.2093]	-0.015446 (0.0719) [-0.2147]
C	0.000317 (0.0001) [4.3343]	0.000362 (0.0001) [4.797]	0.000422 (0.0001) [5.3428]	0.00044 (0.0001) [5.561]	0.000396 (0.0001) [5.6457]	0.000364 (0.0001) [6.6008]	0.000365 (0.0001) [5.3791]	0.000398 (0.0001) [3.7903]	0.000274 (0.0000) [10.9839]	0.000376 (0.0001) [5.9082]

Source: Own elaboration with data from CON SAR.

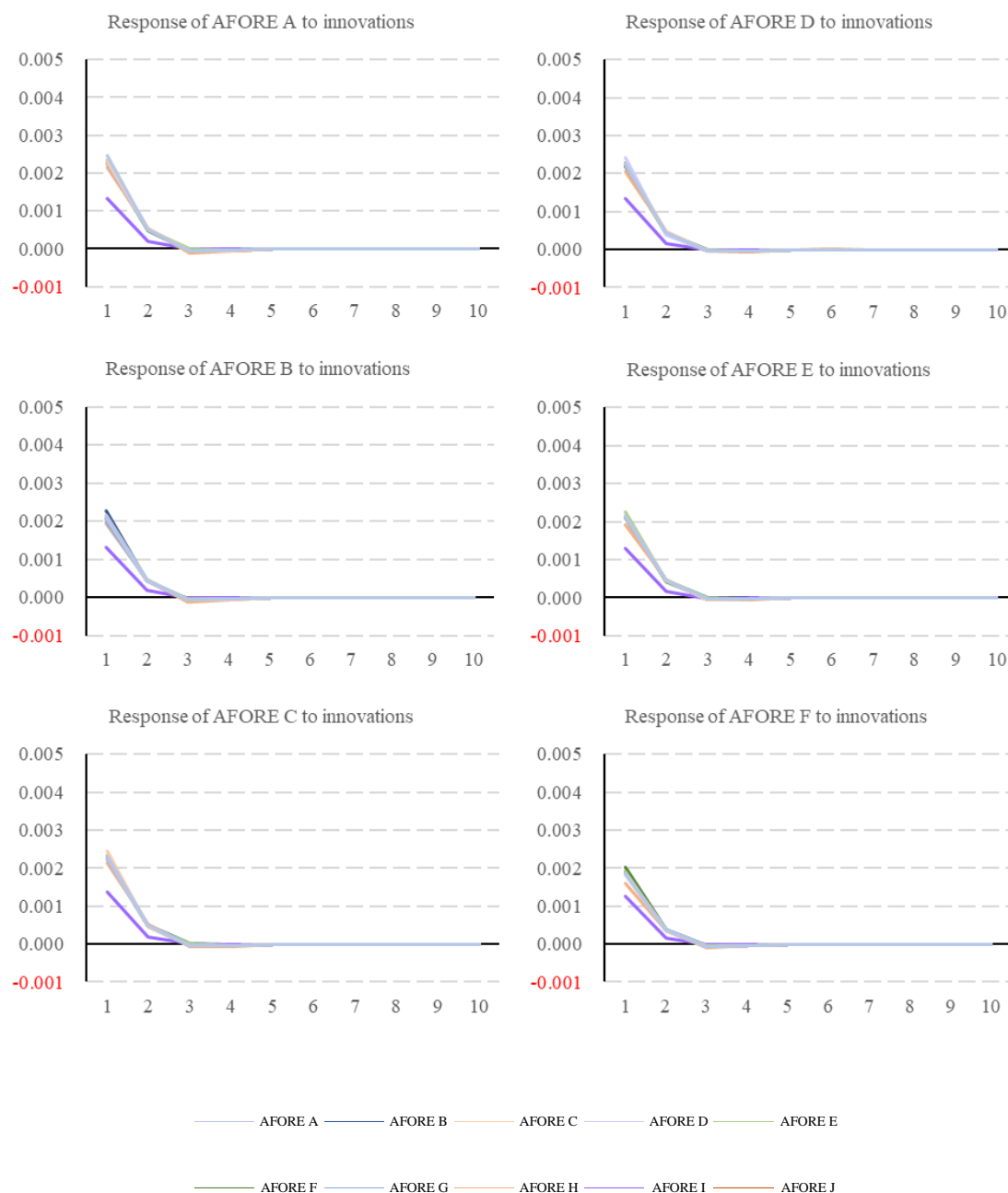
Table 4: Vector Auto Regression SB4

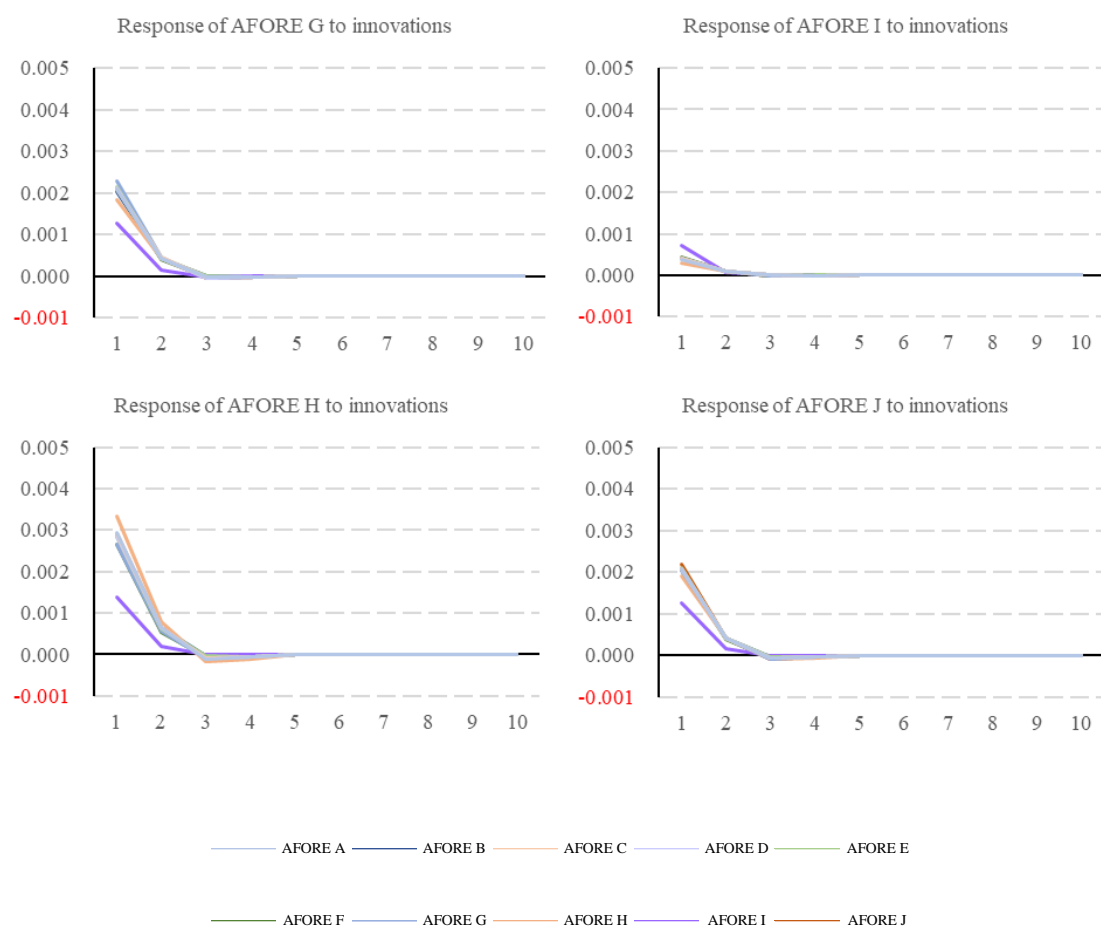
	A_SB4	B_SB4	C_SB4	D_SB4	E_SB4	F_SB4	G_SB4	H_SB4	I_SB4	J_SB4
A_SB4(-1)	0.05443 (0.0802) [0.6786]	0.206669 (0.0835) [2.4757]	0.189068 (0.0863) [2.1903]	0.184348 (0.0861) [2.142]	0.183518 (0.0738) [2.4876]	0.088932 (0.0571) [1.5578]	0.056762 (0.0678) [0.8376]	0.133039 (0.1089) [1.2219]	0.038193 (0.0292) [1.3082]	0.113444 (0.0620) [1.8308]
A_SB4(-2)	0.131691 (0.0802) [1.643]	0.198262 (0.0834) [2.3766]	0.16577 (0.0863) [1.9217]	0.173632 (0.0860) [2.0188]	0.137057 (0.0737) [1.8591]	0.099948 (0.0571) [1.7519]	0.140874 (0.0677) [2.0802]	0.272889 (0.1088) [2.508]	0.004608 (0.0292) [0.158]	0.149829 (0.0619) [2.4196]
B_SB4(-1)	-0.095592 (0.0664) [-1.4399]	-0.280951 (0.0691) [-4.0659]	-0.084222 (0.0715) [-1.1787]	-0.137534 (0.0712) [-1.9306]	-0.063529 (0.0611) [-1.0404]	-0.000365 (0.0473) [-0.0077]	-0.022145 (0.0561) [-0.3948]	-0.06814 (0.0901) [-0.7561]	-0.007753 (0.0242) [-0.3208]	-0.040811 (0.0513) [-0.7957]
B_SB4(-2)	-0.021485 (0.0651) [-0.3301]	-0.060478 (0.0678) [-0.8927]	0.010132 (0.0701) [0.1446]	-0.037267 (0.0699) [-0.5336]	-0.029229 (0.0599) [-0.4882]	0.000357 (0.0463) [0.0077]	-0.000284 (0.0550) [-0.0052]	-0.014772 (0.0884) [-0.1672]	0.0137 (0.0237) [0.5782]	0.002358 (0.0503) [0.0469]
C_SB4(-1)	0.195826 (0.0810) [2.4164]	0.238424 (0.0844) [2.8267]	0.176508 (0.0872) [2.0237]	0.225271 (0.0870) [2.5905]	0.079052 (0.0745) [1.0605]	0.068121 (0.0577) [1.181]	0.164269 (0.0685) [2.3991]	0.170465 (0.1100) [1.5495]	0.003575 (0.0295) [0.1212]	0.09281 (0.0626) [1.4824]
C_SB4(-2)	-0.108651 (0.0807) [-1.3463]	-0.141921 (0.0840) [-1.6896]	-0.15992 (0.0869) [-1.8412]	-0.082413 (0.0866) [-0.9517]	-0.089458 (0.0742) [-1.2051]	-0.103495 (0.0574) [-1.8017]	-0.126184 (0.0682) [-1.8505]	-0.192325 (0.1096) [-1.7554]	-0.003675 (0.0294) [-0.1251]	-0.118521 (0.0624) [-1.9009]
D_SB4(-1)	-0.02045 (0.0499) [-0.4102]	0.006006 (0.0519) [0.1157]	-0.017299 (0.0537) [-0.3224]	-0.205487 (0.0535) [-3.8409]	-0.036631 (0.0459) [-0.7988]	-0.048291 (0.0355) [-1.3608]	-0.056548 (0.0421) [-1.3423]	-0.08505 (0.0677) [-1.2566]	-0.001121 (0.0182) [-0.0618]	-0.022764 (0.0385) [-0.591]
D_SB4(-2)	-0.117136 (0.0498) [-2.3523]	-0.112621 (0.0518) [-2.1729]	-0.112461 (0.0536) [-2.0984]	-0.118422 (0.0534) [-2.2162]	-0.105962 (0.0458) [-2.3135]	-0.06949 (0.0354) [-1.9606]	-0.111253 (0.0421) [-2.6442]	-0.202941 (0.0676) [-3.0021]	0.003884 (0.0181) [0.2143]	-0.090178 (0.0385) [-2.344]
E_SB4(-1)	0.053851 (0.0911) [0.5913]	0.033392 (0.0948) [0.3523]	-0.085784 (0.0980) [-0.8752]	0.130093 (0.0977) [1.3312]	-0.029281 (0.0838) [-0.3495]	-0.061762 (0.0648) [-0.9527]	0.000134 (0.0770) [0.0018]	0.064865 (0.1236) [0.5246]	-0.031071 (0.0332) [-0.9372]	-0.005814 (0.0704) [-0.0826]
E_SB4(-2)	0.307847 (0.0908) [3.3895]	0.331311 (0.0945) [3.5048]	0.274073 (0.0978) [2.8039]	0.246115 (0.0975) [2.5254]	0.269661 (0.0835) [3.228]	0.251828 (0.0647) [3.8955]	0.185647 (0.0767) [2.4192]	0.354061 (0.1233) [2.8716]	0.059465 (0.0331) [1.7987]	0.201836 (0.0702) [2.8765]
F_SB4(-1)	-0.143711 (0.0755) [-1.9028]	-0.079105 (0.0786) [-1.0063]	-0.143294 (0.0813) [-1.7628]	-0.128161 (0.0810) [-1.5814]	-0.12107 (0.0695) [-1.7428]	-0.04683 (0.0538) [-0.8711]	-0.185923 (0.0638) [-2.9135]	-0.18187 (0.1025) [-1.7738]	-0.036578 (0.0275) [-1.3305]	-0.098578 (0.0584) [-1.6894]
F_SB4(-2)	0.170435 (0.0911) [2.2616]	0.109066 (0.0784) [1.3905]	0.167087 (0.0811) [2.0601]	0.153161 (0.0809) [1.894]	0.127741 (0.0693) [1.8429]	0.079033 (0.0536) [1.4734]	0.099231 (0.0637) [1.5584]	0.212647 (0.1023) [2.0786]	0.05397 (0.0274) [1.9674]	0.080231 (0.0582) [1.378]
G_SB4(-1)	0.000894 (0.0532) [0.0168]	-0.099503 (0.0554) [-1.7964]	0.013151 (0.0573) [0.2296]	-0.049881 (0.0571) [-0.8735]	0.010239 (0.0490) [0.2092]	0.025353 (0.0379) [0.6693]	0.171368 (0.0450) [3.8111]	-0.100368 (0.0723) [-1.3893]	-0.016988 (0.0194) [-0.8769]	0.018559 (0.0411) [0.4514]
G_SB4(-2)	-0.158234 (0.0536) [-2.9523]	-0.151541 (0.0558) [-2.7165]	-0.165354 (0.0577) [-2.8665]	-0.137128 (0.0575) [-2.3843]	-0.132537 (0.0493) [-2.6884]	-0.095014 (0.0382) [-2.4905]	-0.096983 (0.0453) [-2.1416]	-0.160683 (0.0728) [-2.2084]	-0.040006 (0.0195) [-2.0506]	-0.106531 (0.0414) [-2.5727]
H_SB4(-1)	0.03284 (0.0410) [0.8009]	0.093857 (0.0427) [2.1992]	0.081896 (0.0441) [1.8558]	0.051804 (0.0440) [1.1774]	0.064614 (0.0377) [1.7132]	0.008926 (0.0292) [0.3058]	0.007897 (0.0347) [0.2279]	0.2104 (0.0557) [3.7798]	0.002136 (0.0149) [0.1431]	0.043475 (0.0317) [1.3724]
H_SB4(-2)	-0.112106 (0.0409) [-2.7398]	-0.138704 (0.0426) [-3.2569]	-0.093332 (0.0440) [-2.1193]	-0.083476 (0.0439) [-1.9012]	-0.087612 (0.0376) [-2.3279]	-0.064299 (0.0291) [-2.2077]	-0.038667 (0.0346) [-1.1184]	-0.16539 (0.0556) [-2.9774]	-0.034831 (0.0149) [-2.3385]	-0.088079 (0.0316) [-2.7862]
I_SB4(-1)	-0.165662 (0.0756) [-2.1911]	-0.152308 (0.0787) [-1.9355]	-0.201382 (0.0814) [-2.4749]	-0.1927 (0.0811) [-2.3752]	-0.265906 (0.0695) [-3.8237]	-0.163455 (0.0538) [-3.0374]	-0.190463 (0.0639) [-2.9815]	-0.308974 (0.1026) [-3.0103]	-0.022573 (0.0275) [-0.8202]	-0.153625 (0.0584) [-2.6301]
I_SB4(-2)	-0.074832 (0.0760) [-0.9845]	-0.051075 (0.0791) [-0.6456]	-0.085104 (0.0818) [-1.0403]	-0.104094 (0.0816) [-1.2763]	-0.04008 (0.0699) [-0.5733]	-0.013635 (0.0541) [-0.252]	-0.010455 (0.0642) [-0.1628]	-0.024329 (0.1032) [-0.2358]	-0.008508 (0.0277) [-0.3075]	-0.065664 (0.0587) [-1.1182]
J_SB4(-1)	0.088429 (0.0778) [1.1367]	0.077664 (0.0810) [0.9592]	0.032917 (0.0837) [0.3931]	0.063161 (0.0835) [0.7566]	0.062919 (0.0716) [0.8793]	0.095007 (0.0554) [1.7157]	-0.013497 (0.0657) [-0.2053]	-0.006922 (0.1056) [-0.0655]	0.068192 (0.0283) [2.4081]	0.010525 (0.0601) [0.1751]
J_SB4(-2)	-0.068653 (0.0781) [-0.8787]	-0.004055 (0.0813) [-0.0499]	-0.069735 (0.0841) [-0.8293]	-0.088827 (0.0838) [-1.0595]	-0.097168 (0.0719) [-1.3521]	-0.118004 (0.0556) [-2.1219]	-0.059799 (0.0660) [-0.9059]	-0.071363 (0.1061) [-0.6728]	-0.044664 (0.0284) [-1.5705]	-0.026598 (0.0604) [-0.4406]
C	0.000338 (0.0001) [4.0032]	0.0004 (0.0001) [4.5609]	0.000463 (0.0001) [5.0988]	0.000492 (0.0001) [5.4432]	0.000424 (0.0001) [5.4634]	0.000376 (0.0001) [6.2672]	0.000369 (0.0001) [5.1804]	0.000428 (0.0001) [3.7424]	0.000283 (0.0001) [9.2322]	0.000392 (0.0001) [6.0133]

Source: Own elaboration with data from CONSAR.

14. Annex F. Impulse – Response Results

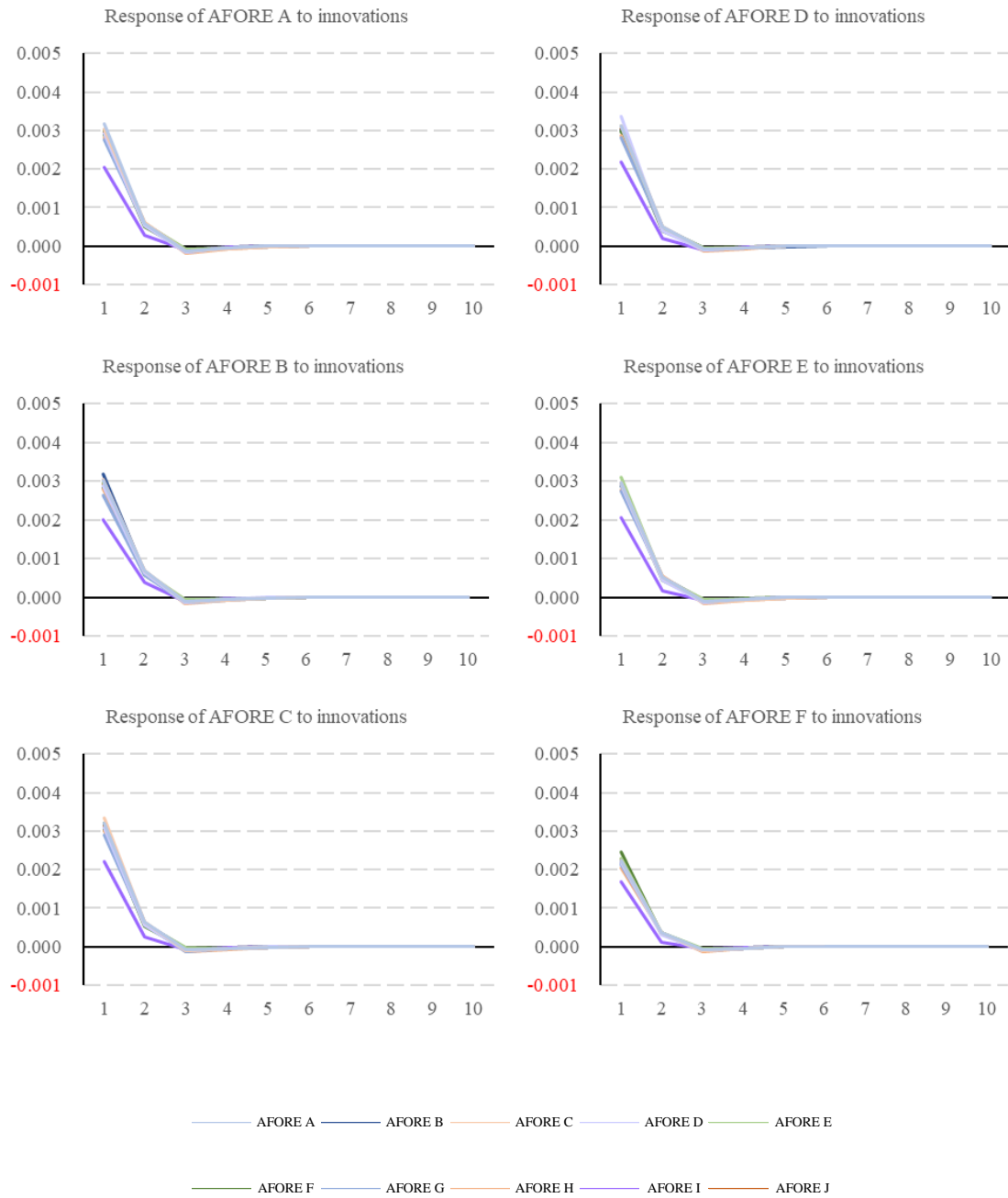
Figure 1: SB1 Impulse – Response Functions
(October 2008-September 2019)

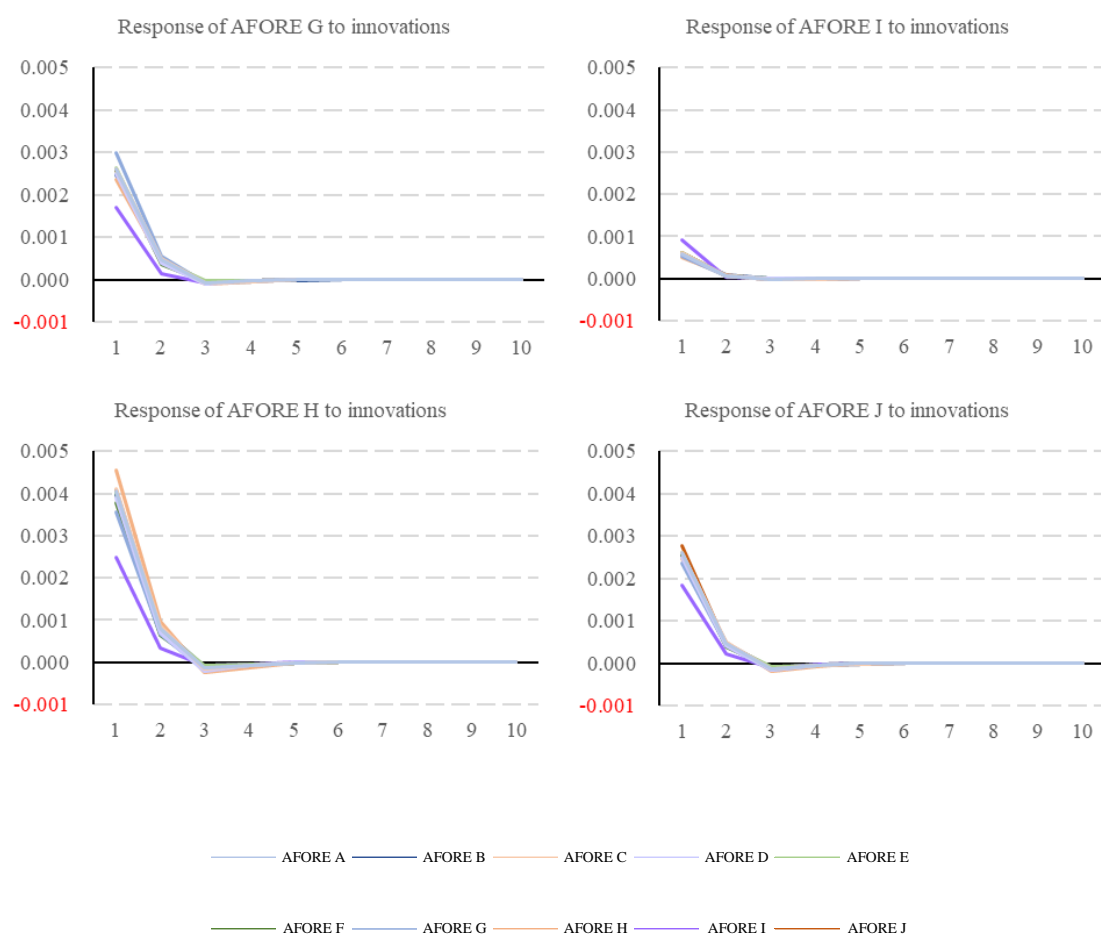




Source: Own elaboration with data from CONSAR.

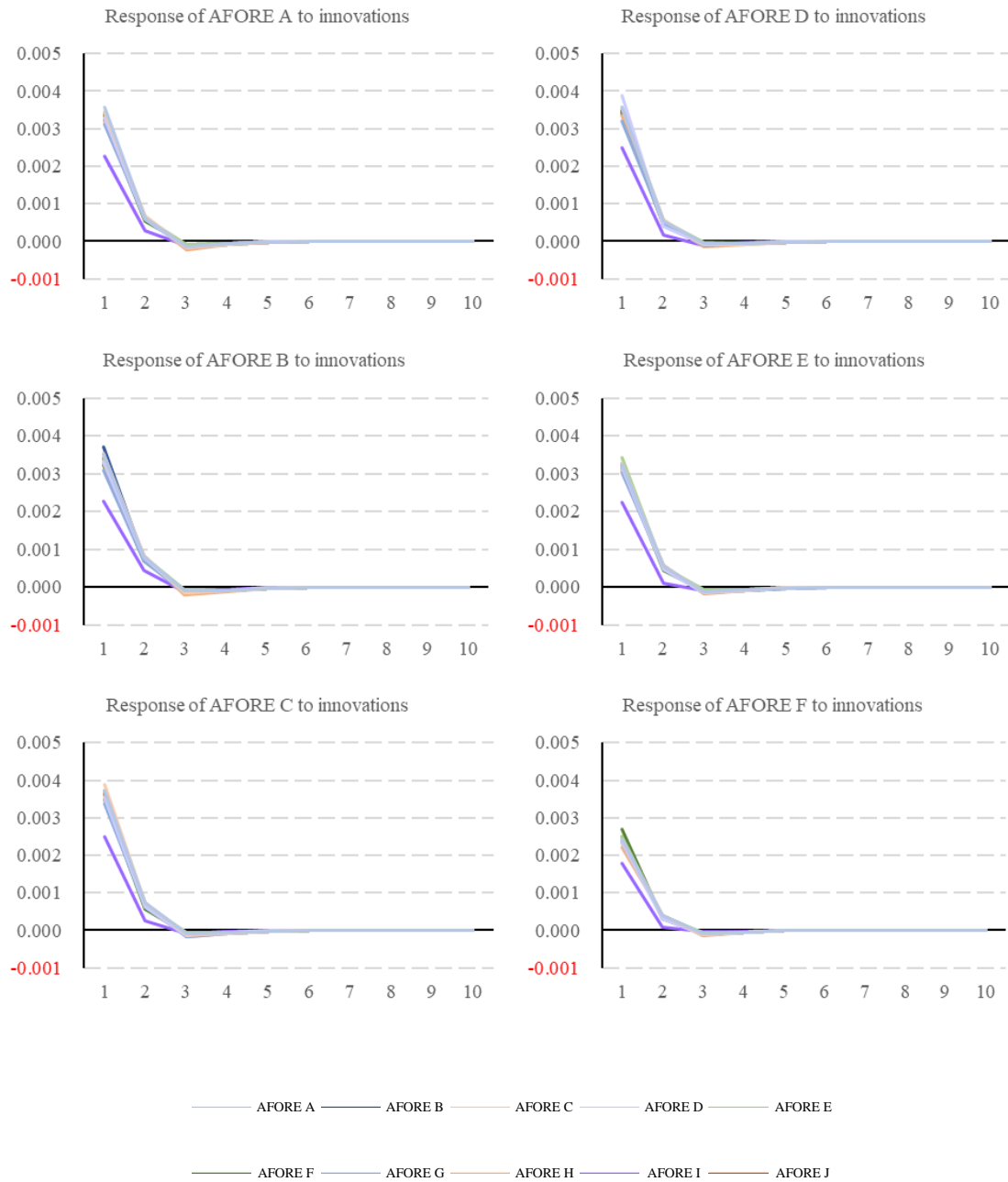
Figure 2: SB2 Impulse – Response Functions
(October 2008-September 2019)

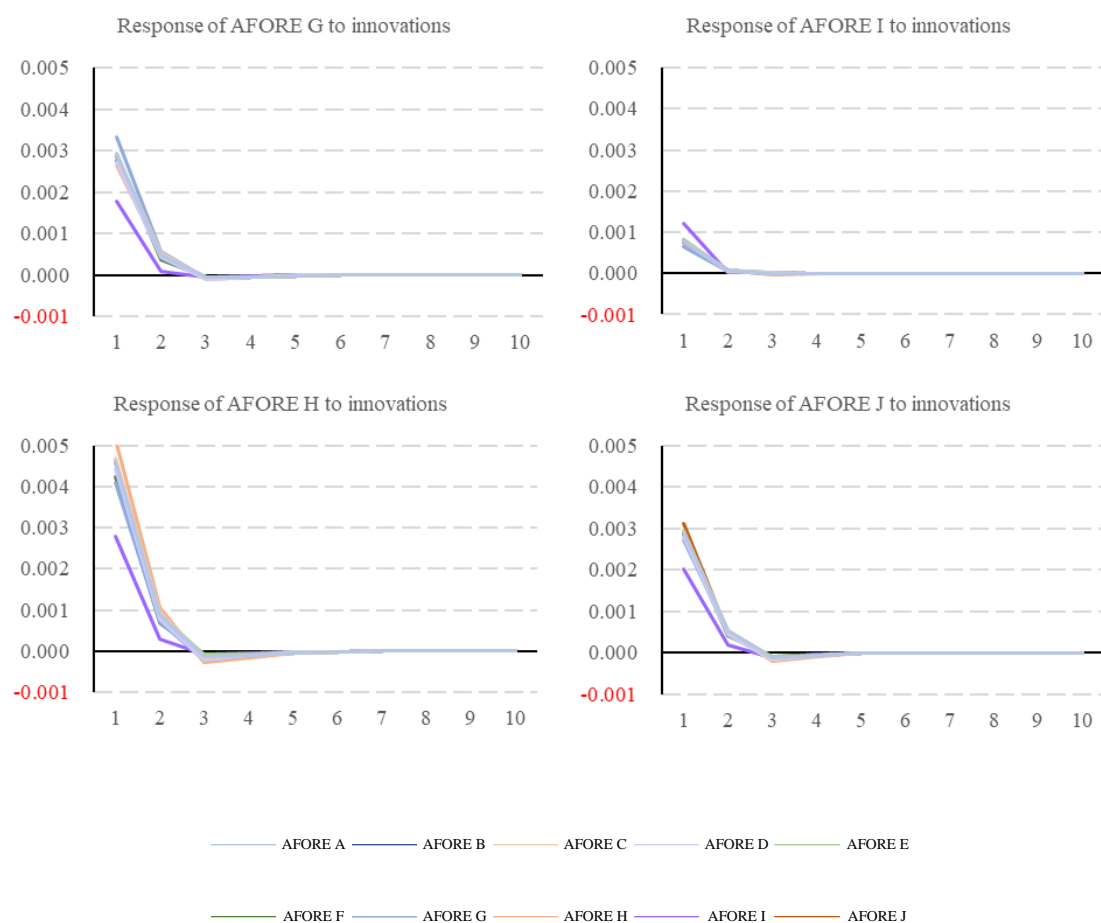




Source: Own elaboration with data from CONSAR.

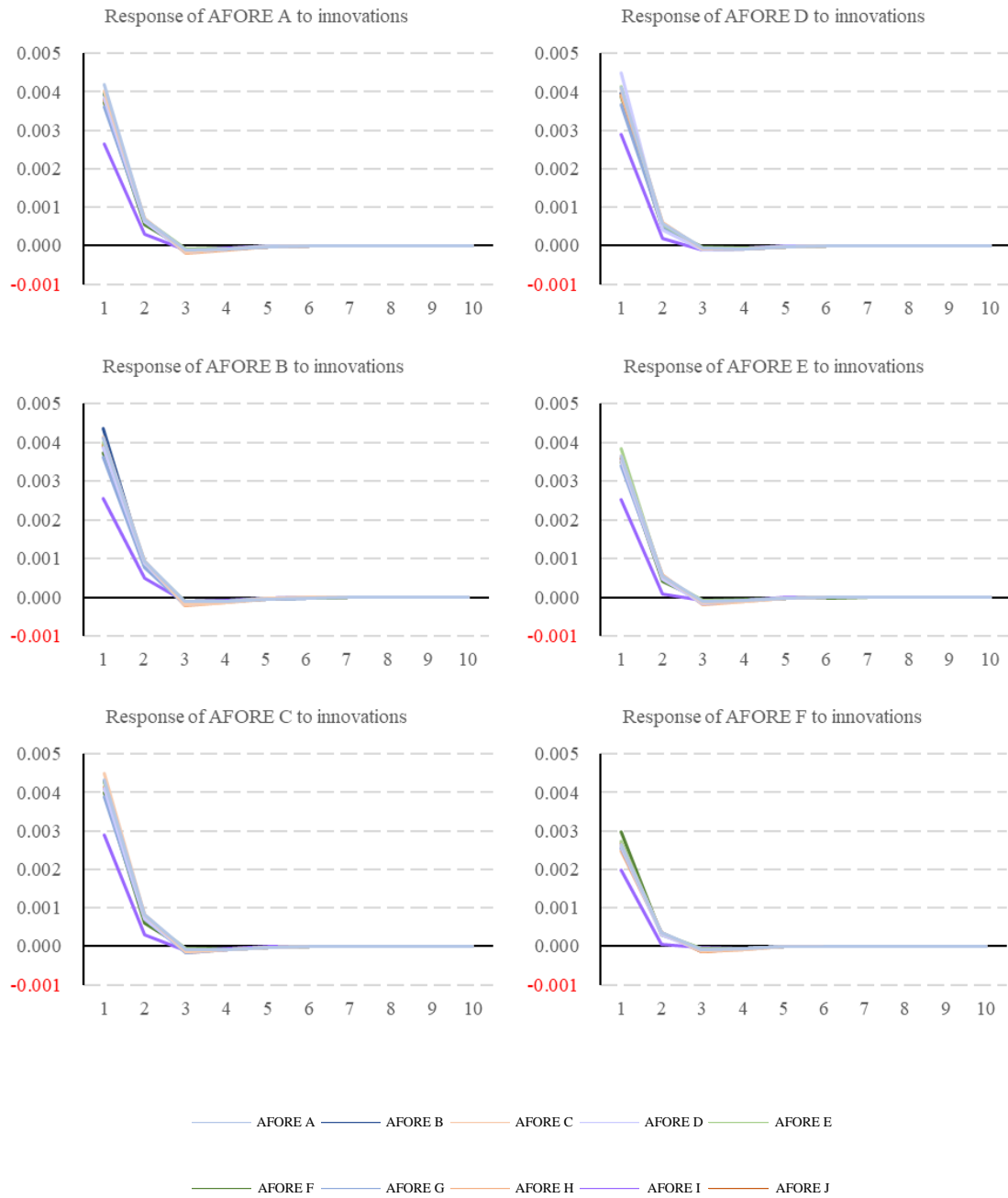
Figure 3: SB3 Impulse – Response Functions
(October 2008-September 2019)

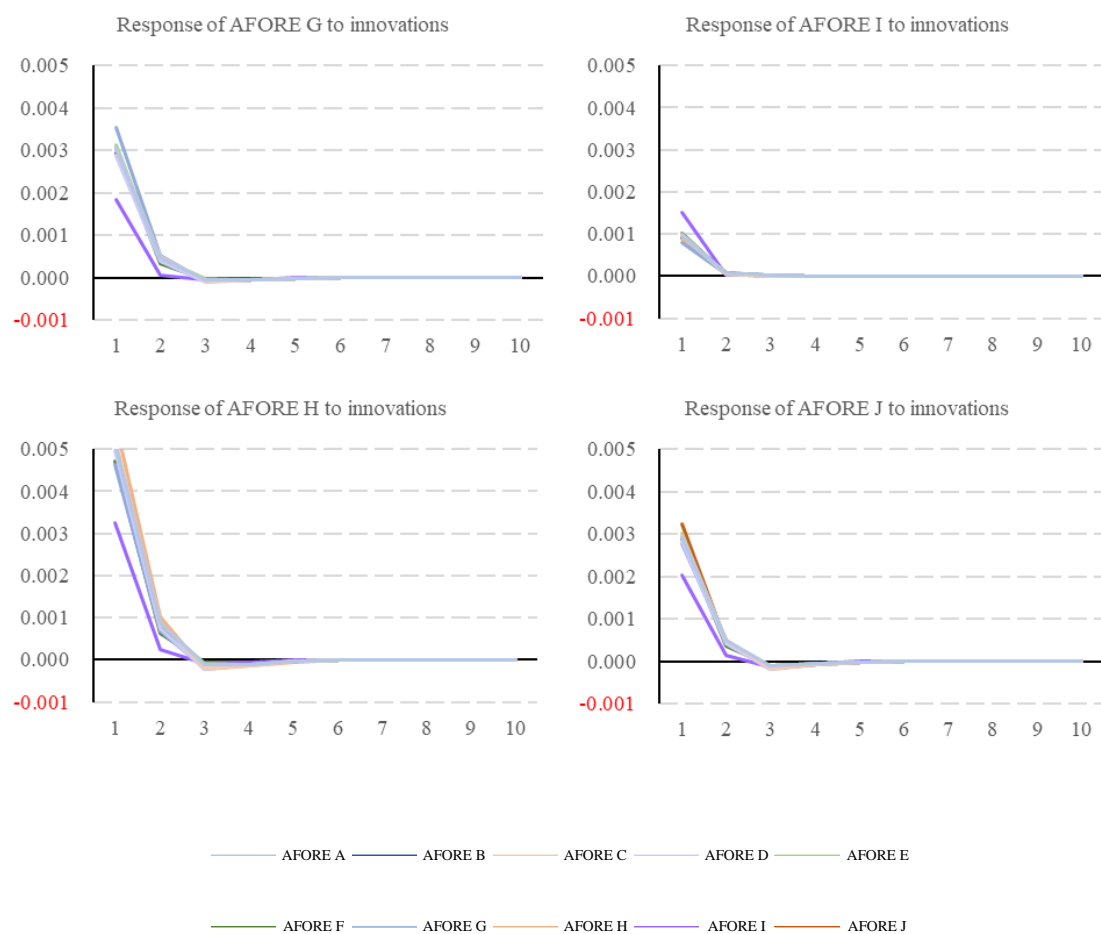




Source: Own elaboration with data from CONSAR.

Figure 4: SB4 Impulse – Response Functions
(October 2008-September 2019)





Source: Own elaboration with data from CONSAR.

15. Annex G. Connectedness Tables

Table 1: SB1 Connectedness Table

Shock on Impact on	A	B	C	D	E	F	G	H	I	J	From others
A	12.25	10.75	10.84	10.61	10.92	10.38	10.24	9.56	3.52	10.93	87.75
B	10.93	12.41	11.15	10.64	10.76	10.30	9.72	9.19	4.09	10.80	87.59
C	10.76	10.91	12.16	10.63	10.94	10.34	10.27	9.39	3.70	10.89	87.84
D	10.74	10.62	10.87	12.30	10.94	10.22	10.54	9.10	3.71	10.95	87.70
E	10.81	10.51	10.92	10.70	12.06	10.66	10.50	8.95	3.92	10.97	87.94
F	10.66	10.40	10.68	10.32	11.04	12.51	10.42	8.03	4.74	11.20	87.49
G	10.69	10.01	10.83	10.88	11.07	10.61	12.84	8.20	3.89	10.99	87.16
H	11.12	10.53	11.03	10.53	10.52	9.11	9.13	14.71	2.43	10.90	85.29
I	7.92	8.98	8.30	8.12	8.86	10.26	8.37	4.71	25.61	8.88	74.39
J	10.76	10.48	10.82	10.67	10.92	10.77	10.38	9.17	3.96	12.06	87.94
To others	94.39	93.20	95.44	93.10	95.98	92.64	89.57	76.30	33.97	96.50	86.11

Source: Own elaboration with data from CONSAR.

Table 2: SB2 Connectedness Table

Shock on Impact on	A	B	C	D	E	F	G	H	I	J	From others
A	12.06	10.86	11.19	10.36	10.95	10.01	9.21	9.76	4.93	10.66	87.94
B	11.32	12.48	11.52	10.16	10.78	9.77	8.61	9.76	4.92	10.70	87.52
C	11.13	10.99	12.07	10.25	10.97	9.78	9.15	9.92	5.11	10.62	87.93
D	10.97	10.28	10.92	12.63	11.02	9.95	8.96	9.45	5.34	10.47	87.37
E	10.96	10.35	11.05	10.39	12.01	10.38	9.37	9.65	5.18	10.67	87.99
F	10.68	10.02	10.50	9.99	11.05	12.70	9.47	8.96	5.81	10.81	87.30
G	10.75	9.70	10.73	9.86	10.91	10.31	14.18	8.78	4.46	10.33	85.82
H	10.92	10.50	11.19	10.00	10.78	9.38	8.42	13.81	4.04	10.95	86.19
I	8.98	8.59	9.37	9.14	9.48	9.97	7.03	6.59	21.36	9.50	78.64
J	10.87	10.48	10.89	10.07	10.85	10.30	9.05	9.97	5.30	12.22	87.78
To others	96.57	91.78	97.35	90.22	96.79	89.84	79.28	82.85	45.10	94.72	86.45

Source: Own elaboration with data from CONSAR.

Table 3: SB3 Connectedness Table

Shock on Impact on	A	B	C	D	E	F	G	H	I	J	From others
A	12.10	10.97	11.29	10.26	11.00	9.85	9.24	9.83	4.81	10.65	87.90
B	11.37	12.44	11.61	10.11	10.80	9.52	8.73	10.13	4.64	10.64	87.56
C	11.19	11.11	12.09	10.09	10.99	9.65	9.23	10.11	4.91	10.62	87.91
D	10.94	10.37	10.87	12.77	10.99	9.82	8.80	9.68	5.28	10.47	87.23
E	10.97	10.39	11.07	10.26	12.02	10.23	9.38	9.81	5.08	10.80	87.98
F	10.63	9.94	10.52	9.90	11.06	12.87	9.80	8.87	5.49	10.92	87.13
G	10.70	9.84	10.82	9.56	10.89	10.50	14.13	8.97	3.98	10.61	85.87
H	10.87	10.82	11.31	10.05	10.87	9.07	8.54	13.68	3.91	10.86	86.32
I	9.05	8.40	9.35	9.28	9.63	9.64	6.49	6.67	22.21	9.27	77.79
J	10.83	10.47	10.91	9.98	11.00	10.28	9.32	9.98	5.00	12.23	87.77
To others	96.56	92.30	97.75	89.49	97.24	88.55	79.53	84.06	43.12	94.85	86.35

Source: Own elaboration with data from CONSAR.

Table 4: SB4 Connectedness Table

Shock on Impact on	A	B	C	D	E	F	G	H	I	J	From others
A	12.27	10.91	11.34	10.27	11.04	9.67	9.20	10.23	4.84	10.23	87.73
B	11.39	12.65	11.65	10.08	10.83	9.35	8.76	10.57	4.37	10.36	87.35
C	11.30	11.13	12.27	10.11	10.96	9.52	9.11	10.40	4.90	10.31	87.73
D	10.96	10.27	10.83	12.95	11.06	9.78	8.66	10.02	5.39	10.08	87.05
E	10.95	10.30	10.92	10.26	12.11	10.08	9.45	10.27	5.14	10.52	87.89
F	10.50	9.76	10.40	9.92	11.02	13.12	9.76	9.15	5.73	10.64	86.88
G	10.66	9.81	10.63	9.40	11.04	10.39	14.28	9.52	3.74	10.54	85.72
H	10.94	10.83	11.17	10.05	11.06	9.00	8.77	13.29	4.25	10.64	86.71
I	9.04	7.78	9.22	9.43	9.72	9.92	6.04	7.44	22.51	8.89	77.49
J	10.61	10.32	10.76	9.81	10.99	10.13	9.45	10.34	4.92	12.67	87.33
To others	96.34	91.12	96.93	89.32	97.73	87.84	79.19	87.94	43.27	92.21	86.19

Source: Own elaboration with data from CONSAR.

16. Annex H. Net Connectedness Tables

Table 1: SB1 Net Connectedness Matrix

Shock on Impact on	A	B	C	D	E	F	G	H	I	J
A			0.08		0.11					0.17
B	0.18		0.23	0.02	0.25					0.32
C					0.02					0.07
D	0.13		0.24		0.24					0.29
E										0.05
F	0.28	0.10	0.35	0.10	0.38					0.43
G	0.45	0.29	0.55	0.34	0.57	0.19				0.61
H	1.56	1.34	1.64	1.43	1.58	1.07	0.93			1.73
I	4.40	4.89	4.60	4.41	4.94	5.51	4.48	2.28		4.91
J										
Net	6.64	5.61	7.59	5.40	8.04	5.15	2.42	-8.99	-40.42	8.56

Source: Own elaboration with data from CONSAR.

Table 2: SB2 Net Connectedness Matrix

Shock on Impact on	A	B	C	D	E	F	G	H	I	J
A			0.06							
B	0.45		0.52		0.43					0.21
C										
D	0.61	0.13	0.67		0.63					0.40
E	0.01		0.07							
F	0.67	0.25	0.72	0.05	0.68					0.51
G	1.53	1.09	1.58	0.89	1.53	0.84		0.36		1.28
H	1.16	0.74	1.26	0.55	1.13	0.42				0.99
I	4.05	3.67	4.26	3.80	4.30	4.16	2.57	2.55		4.20
J	0.21		0.26		0.18					
Net ²	8.63	4.26	9.41	2.85	8.79	2.54	-6.54	-3.34	-33.55	6.94

Source: Own elaboration with data from CONSAR.

Table 3: SB3 Net Connectedness Matrix

Shock on Impact on	A	B	C	D	E	F	G	H	I	J
A			0.10		0.03					
B	0.40		0.51		0.41					0.17
C										
D	0.68	0.26	0.78		0.74					0.49
E			0.08							
F	0.78	0.42	0.87	0.08	0.83					0.65
G	1.46	1.11	1.58	0.76	1.51	0.70		0.43		1.29
H	1.05	0.69	1.20	0.37	1.06	0.20				0.87
I	4.24	3.76	4.43	4.00	4.55	4.14	2.51	2.76		4.27
J	0.18		0.29		0.20					
Net	8.66	4.74	9.84	2.26	9.25	1.42	-6.33	-2.25	-34.67	7.08

Source: Own elaboration with data from CONSAR.

Table 4: SB4 Net Connectedness Matrix

Shock on Impact on	A	B	C	D	E	F	G	H	I	J
A			0.04		0.09					
B	0.48		0.52		0.53					0.04
C					0.03					
D	0.69	0.19	0.73		0.80					0.27
E										
F	0.83	0.41	0.88	0.14	0.95			0.15		0.51
G	1.46	1.06	1.52	0.74	1.59	0.63		0.76		1.08
H	0.71	0.26	0.77	0.03	0.80					0.30
I	4.20	3.41	4.32	4.04	4.59	4.20	2.30	3.19		3.97
J	0.37		0.45		0.47					
Net	8.61	3.77	9.20	2.27	9.84	0.96	-6.53	1.23	-34.22	4.88

Source: Own elaboration with data from CONSAR.