Ponzi Schemes and the Financial Sector: DMG and DRFE in Colombia[*]

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Abstract

We use a novel dataset to estimate, for the first time in the literature, the effects of Ponzi schemes on the formal financial sector. DMG and DRFE, two Ponzi schemes that were shut down by the Colombian government in November 2008, had over half a million customers, who invested funds corresponding to 1.2% of Colombia's annual GDP. We find that pyramid customers obtained more loans from the financial sector, and their credit standings were better than those in the respective control groups while the schemes were operating. Afterwards, their loan stocks started to decrease and their ratings with the banking sector deteriorated. Prior to November 2008, deposits in the financial sector fell more in the municipalities more affected by the schemes.

Keywords: Ponzi Schemes, Pyramids, Colombia, Banking, Savings and Loans, Loan Ratings

JEL Codes: E21, E44, G11

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1 Introduction

In November 2008, the Colombian government closed down two firms, DMG and DRFE, accused of running Ponzi schemes. By the time these firms were put out of business, they had over half a million customers and the investments in the firms reached 1.2% of Colombia's annual GDP. This amount corresponds to 3.9% of total deposits in the financial sector, or 22% of the total deposits reported in 2008 by Bancolombia—the largest bank in the country. 80% of investors lost at least part of their deposits. The average investment was slightly below the annual per capita GDP for 2008.

While a few infamous schemes—like the Madoff fraud in the U.S. or the schemes in Albania that collapsed in the late-90s, sending the country into chaos and bringing down its government (Jarvis, 2000)—have drawn the concentrated attention of the media, Ponzi schemes are more common than is generally recognized. Deason, Rajgopal, and Waymire (2015) describe 376 Ponzi schemes prosecuted by the SEC (Securities & Exchange Commission) between 1988 and 2012 in the U.S. A study conducted by the Caribbean Policy Research Institute (CaPRI) (2008), identifies 21 schemes operating in Jamaica as of January 2008. Carvajal, Monroe, Wynter, and Pattillo (2009) report that in 2008, over 200 schemes operated in Colombia. In 2017, Germán Cardona—also known as the Spanish Madoff—was sentenced to 13 years in prison for leading a pyramid scheme that defrauded more than 180,000 people. While the scheme was initiated in Spain, it attracted investors from over 100 countries.

The literature on unregulated investment schemes has identified several of their negative consequences. Carvajal et al. (2009) summarize them in seven points: (i) they divert deposits from banks and increase non-performing loans if loan proceeds are diverted to these schemes; (ii) they divert savings from productive to unproductive uses and, in some cases, from the domestic economy to foreign destinations; (iii) they cause swings in consumption driven by paper profits or early withdrawals; (iv) they undermine confidence in financial markets; (v) they imply fiscal costs if bailouts occur; (vi) they cause socio-economic strife if a sufficiently large number of households are suddenly exposed to losses; and (vii) they undermine the reputation of political authorities, regulators, and law enforcers on account of their failure to prevent the fraud. More recently, Cortés, Santamaría, and Vargas (2016) found that the breakdown of Ponzi Schemes also increases shoplifting and robbery in places with weak law enforcement institutions and lower access to credit.

Despite the long list of negative consequences, the nature of the schemes and the lack of systematic data have precluded researchers from pinning down the size and scope of some of these consequences. What we find in the literature on Ponzi schemes remains, to a large extent, anecdotal.[1] Hence, Deason et al. (2015) claim that the "[*e*]*xtant knowledge of Ponzi schemes in the ... literature is mainly anecdotal*". Similarly, Jarvis (2000), in his study of the infamous Albanian schemes, acknowledges that, when assessing the impact of their collapse on the economy, the evidence is mostly anecdotal. Finally, and arguably more relevant to the focus of our paper, Carvajal et al. (2009)—who describe several Ponzi schemes in the Caribbean, Colombia, the U.S. and Africa—point out that there is "*anecdotal evidence that some of the schemes ... diverted deposits and increased NPLs* [*nonperforming loans*]".

There is also anecdotal evidence specifically on the impact of DMG and DRFE on the financial sector. David Murcia—the founder of DMG—repeatedly claimed that his business was legal and that the attacks on his firm were led by the banking sector because the high yields offered by his company diverted deposits from the formal banking sector to his firm.[2] In fact, as reported by Carvajal et al. (2009) "*commercial banks had expressed concerns that their depositors were withdrawing funds to invest them in these schemes.*" Other anecdotal evidence suggests that investors in Ponzi schemes often obtained loans from the formal financial sector to invest in these scams.

To the best of our knowledge, ours is the first paper in the literature to estimate the impact of Ponzi schemes on the formal banking system. We do so by using a novel dataset containing the universe of individual investments and profits or losses in these two Ponzi schemes, merged with individual loans and municipal deposits in the banking sector in Colombia. More precisely, we estimate the extent to which deposits fell in the banking system while the schemes were operating, and how persistent this effect was after the schemes were shut down by the government. On the loans' side, we estimate by how much the individuals that participated in the schemes increased their loans in the banking sector prior to these schemes being shut down, and the effect on nonperforming loans, both during the life-cycle of the schemes and after they were put out of business.

Our findings show that individuals that invested in the Ponzi schemes had (just before the schemes went out of business) 39% more loans with the formal financial sector than similar individuals who did not invest in pyramids. We also find that, prior to DMG and DRFE being shut down, the proportion of loans within the best rated tiers was 32% higher for investors in the pyramids: while they were making money, they maintained better ex-post loan ratings than similar individuals who did not participate in DMG or DRFE. However, once the schemes were no longer operating, the proportion of nonperforming loans was as much as 36% higher for individuals that invested, relative to those who did

[1] There are also some theoretical papers studying Ponzi schemes, e.g., Artzrouni (2009) and Bhattacharya (2003).

[2] In this video for instance, he accuses Luis Carlos Sarmiento, the largest bank owner in Colombia, of conspiring against his firm: `https://www.youtube.com/watch?v=LdWdgjnbFeE`.

not invest in DMG or DRFE.

We also show that deposits in the financial sector were affected by DMG and DRFE. While the Financial Supervisory Agency of Colombia (*Superfinanciera*) has no information on deposits at the individual level, it does record data on deposits at the municipal level. By exploiting the variation across municipalities for the presence of Ponzi schemes, as well as the information on deposits at the municipal level, we are able to estimate the effects of the pyramids on deposits. We find that a one standard deviation increase in the presence of pyramids (as defined below) at the municipal level reduces total deposits in the financial sector by between 2.4% and 2.7%. The effect is much greater on certificate deposits (CDs): they fell between 9.2% and 10.2%. Moreover, the latter effect was long-lived, as two years after the government put the schemes out of business, CDs had not fully recovered.

The rest of the paper is organized as follows. Section 2 describes the two Ponzi schemes. Section 3 complements this information by reporting some stylized facts and describing the datasets. In Sections 4 and 5, we explore the impact of these schemes on loans and deposits, respectively. Section 6 concludes.

2 DMG and DRFE

2.1 Pyramids or Ponzi schemes?

In the local jargon used by Colombia's media and government agencies, and even in judiciary instances, DMG and DRFE are referred to as "pyramids" as opposed to "Ponzi schemes." In the economic literature, there are some differences between Ponzi schemes and pyramids. According to Carvajal et al. (2009), "[*p*]*yramids are a form of fraud where the expected benefit to members depends primarily on the number of individuals they recruit which is not necessarily the case in a Ponzi scheme.*" The latter "*often grow larger than pyramid schemes as they can take in unlimited amounts from a single individual and can continue to operate indefinitely, as long as payments demanded by investors from the scheme do not exceed payments by investors into the scheme.*"

DRFE's modus operandi complies with this definition of a Ponzi scheme. DMG has elements of a Ponzi scheme in the sense that individuals were able to invest in the company without necessarily bringing in more customers (as in a standard Ponzi scheme), but, at times, the returns were enhanced if they recruited more investors (as in a pyramid scheme). The latter is consistent with the case studies reported by Carvajal et al. (2009), who find that many such schemes in the Caribbean have characteristics of both types of schemes. Correspondingly, throughout the paper, we use the terms "pyramid" and "Ponzi

Scheme" interchangeably.

2.2 Modus operandi[3]

DMG sold prepaid cards that promised high yields or granted the right to buy appliances and other goods and services at below market prices in the future. The high returns were paid via the deposits of new customers. The promised yields varied between 50% and 300% over a six-month period, and at times the returns could be enhanced by bringing in more customers. These rates of return were highly attractive: for similar maturities, formal financial institutions were offering nominal annual interest rates of 8% to 10% during the period of our analysis. The prepaid cards became key to masking the deposits (which a non-financially supervised firm is not allowed to collect), by making them appear as in-advance payments.

DRFE (*Dinero Rápido, Fácil y Efectivo*—Money in Cash, Fast and Easy) did not sell goods or prepaid cards. Instead, it offered monthly returns between 80% and 150%. In municipalities where the two companies competed, DMG offered higher interest rates, and emphasized in its advertisements that, unlike DRFE, its business model was not a pyramid (to use the local jargon).

The promised returns were high but not even close to the highest offered by other schemes described in the literature. Charles Ponzi's infamous scam in the 1920s in Boston offered returns of 30% a month, according to Kindleberger and Aliber (2005). Carvajal et al. (2009) report that the Madoff scam offered much lower returns, between 10% and 17% per year; the infamous schemes during the mid-90s in Romania, offered returns of 800%, while the Russian MMM scheme (also around that time) offered 7,000% rates, both over six months.

In November 2008, the Colombian government shut down both DMG and DRFE, using the legal authority of a decree declaring a State of Social Emergency that extended the powers of the *Supersociedades* (supervisory agency of large businesses). As in many other similar episodes around the world, a series of protests and riots followed, with crowds expressing support for David Murcia Guzmán and Carlos Suárez—the owners of the schemes. Shareholders and legal representatives received arrest orders. Prison sentences were awarded to the leaders of DMG and DRFE: David Murcia Guzmán, arrested in Panama City in 2009 and extradited to the U.S., was given a nine-year sentence in the U.S. and has a sentence pending in Colombia. Carlos Alfredo Suárez, head of DRFE, was

[3] Based on newspaper reports and judiciary sentences. The working paper version of this document (Hofstetter, Mejía, Rosas, & Urrutia, 2017) describes in greater detail the rise and fall of the schemes and the government's attempts to shut them down.

sentenced to seven years in jail and ordered to pay a large fine.

Regarding the reimbursing of funds to investors, the government appointed legal auditors to liquidate the assets seized from DMG and DRFE. Customers got back less than 5% of the average investment.

We provide further details and stylized facts of the pyramids in the next section based on the dataset of the customers' investments in the schemes.

3 Data and stylized facts

The main database contains a list of DMG and DRFE's investors, along with the amounts invested by each individual in each pyramid and the profits or losses they made at the time the two schemes were shut down by the Colombian government. The dataset was put together by the legal auditor's office—established after the government closed the firms—in charge of returning to investors the money recovered after the liquidation of seized assets. The information does not tell us anything about the timing of the investments: we do not know when customers deposited money or when they received the proceeds of their investments. We only know the final balance at the moment the government shut down the two firms by the end of 2008, along with how much each individual invested in the firms. If an individual invested multiple times, what we observe is the sum of his or her investments. Additionally, the dataset does not provide any information regarding the characteristics of the investors.

In Table 1, we describe the main stylized facts from this dataset. Over half a million people participated in the pyramids, and 80% lost some or all of the money they invested (we define losers as customers whose investments were larger than the amount they got back from the pyramids).

The anecdotal evidence suggests that, as time passed and the offices of the schemes expanded to dozens of municipalities, customers came to include all income groups, and even high-profile business persons and politicians (DRFE even offered special rates to government employees). The figures reported in Table 1 confirm the great heterogeneity of investors. While the mean investment was over US$4,600 (close to the per capita annual GDP of 2008) there is great variation across investors: investors in the 10th percentile invested, on average, just over US$400, while those in the 90th percentile invested more than US$12,000. The average loss was US$2,570, while the average net profit (of the winners) reached US$3,417. These figures are reported in dollars, using the average exchange rate for November 2008, when the government shut down the two firms.

Table 1: Descriptive statistics, DMG and DRFE's customers

	DMG	DRFE	Both	Total
Number of investors	356,631	153,878	23,051	533,560
% of losers	79%	83%	78%	80%
Deposits				
Total	$1,191,261,625	$865,592,979	$340,238,032	$2,395,378,591
Mean	$3,559	$5,656	$14,741	$4,671
Median	$1,714	$3,514	$10,284	$2,143
10th percentile	$321	$557	$2,485	$429
90th percentile	$9,170	$13,155	$32,096	$12,213
Winners' profits				
Total	$192,401,608	$72,418,423	$35,052,231	$299,957,963
Mean	$3,356	$2,825	$6,813	$3,417
Median	$1,276	$1,500	$3,447	$1,474
10th percentile	$93	$159	$433	$122
90th percentile	$9,213	$6,042	$15,341	$8,399
Losers' losses				
Total	$677,047,974	$312,813,304	$105,413,798	$1,096,989,122
Mean	$2,414	$2,449	$5,871	$2,570
Median	$1,071	$1,713	$4,028	$1,286
10th percentile	$96	$381	$888	$150
90th percentile	$6,256	$5,228	$13,027	$6,299

Notes: $ corresponds to figures in US$ dollars converted from Colombian pesos at the average exchange rate for November 2008.

3.1 Investors: who and where

To gain some insight into the socioeconomic characteristics of investors and their geographic locations, we match the DMG/DRFE dataset with the SISBEN survey—run by the Colombian government and used to target the recipients of many of its social programs. We use the second wave of SISBEN, conducted between 2003 and 2007, which collected information on 32.5 million individuals nationwide (the total population in 2007 was 43.9 million). This allows us to obtain socioeconomic characteristics of investors prior to the end of the pyramids.

For the most part, the SISBEN does not include individuals from the richest quartile of the population. Using the IDs in both datasets, we were able to match 51% (269,855 individuals) of all investors in DMG and DRFE with individuals in the SISBEN. Beyond the fact that the SISBEN database is not a Census, it is possible that for some individuals we could not find a match because there could be typos in the IDs in either the SISBEN or the DRFE/DMG datasets.

The fact that the merged sample excludes, by construction, the most affluent quartile of the population has consequences for interpreting our results. On the one hand, the right way to interpret the baseline findings in Sections 4 and 5, and the descriptive statistics reported below, is precisely by keeping in mind that they exclude the richest quartile of the population. Yet, besides being cautious in our interpretation, we go one step further and use the income variations within the sample that we have in order to check (in Section 4.4) how the effects of the pyramids on the financial sector change as we move along the income distribution. Beyond being interesting per se, these results provide some clues regarding the likely direction the results would move in if we had access to data on the richest quartile.

In Table 2, we report the descriptive statistics of the matched individuals. The sample is almost evenly split between males and females, with the latter holding a slight advantage. More than a third of investors were over 44 years old, while less than 8% were under the age of 25. They had on average 8 years of education. Almost 13% had an education beyond high school and 40% had at least a high school diploma. This figure, to put it in perspective, is comparable to that at the national level in 2008, when 38.5% of the population of 25+ years had attained an upper secondary educational level. As in other pyramid cases (Madoff, Spain, Albania) the customers were not necessarily uneducated or financially illiterate individuals. Moreover, 56% were married or living with a partner. Investors reported an average income of $82 per month, with a large standard deviation ($443) (to compare this with the general population, the unconditional mean income in the complete SISBEN survey is $33, while the mean income for individuals between 25 and 64—the age range of almost 90% of investors—is $59).

The two pyramids had customers with different profiles. Those in DRFE were poorer—their average income was less than half of those that invested in DMG. They were also less educated, with only about 5% of them having studied beyond high school, compared to almost 17% for customers of DMG. Those in DRFE were also part of larger households and had lower SISBEN scores.[4]

Finally, the mean investments in the schemes in this merged sample are close to 10% lower than for the universe of investors reported in Table 1. This is consistent with the observation that the merged sample does not include the richest quartile of the population, which presumably had more resources to invest in the pyramids.

What about their location? We proxy for location by assigning each investor the location reported in the SISBEN survey. Then, for each municipality, we calculate the ratio of investors to the population with 14+ years (taken from *DANE*, Colombia's statistical

[4]Eligibility to many social assistance programs depends on a household's SISBEN score. The cut-off point depends on the specific program and on whether a household is rural or urban. The main national program, *Familias en Acción*, a conditional cash transfer program, had cut-off points of 11 for urban households, and 17.5 for rural ones. Almost three quarters of the population is urban.

Table 2: Socioeconomic characteristics of matched investors

Invested in $\longrightarrow$	DMG or DRFE		DRFE		DMG		DMG and DRFE	
VARIABLES	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Demographics & income, investors								
Male	47.8%	0.50	51.2%	0.50	46.5%	0.50	48.5%	0.50
Income (monthly)	$82	$443	$43	$102	$104	$542	$50	$108
Age $<$ 18	5.1%	0.22	8.0%	0.27	3.9%	0.19	8.9%	0.28
Age 18–24	2.5%	0.16	1.8%	0.13	1.4%	0.12	2.2%	0.15
Age 25–34	26.8%	0.44	27.9%	0.45	27.0%	0.44	22.6%	0.42
Age 35–44	28.3%	0.45	28.5%	0.45	29.3%	0.46	30.0%	0.46
Age 45–54	20.7%	0.41	18.4%	0.38	21.5%	0.41	21.0%	0.41
Age 55–64	10.6%	0.31	9.8%	0.29	11.4%	0.31	10.4%	0.30
Age $>$64	4.7%	0.22	5.6%	0.22	5.4%	0.22	4.6%	0.21
Education, investors								
Years of education	8.0	5.0	6.4	4.5	8.8	5.2	6.3	4.6
Marital status, investors								
Cohabitation	23.7%	0.43	22.1%	0.42	24.8%	0.43	24.9%	0.43
Married	32.1%	0.47	31.9%	0.47	33.3%	0.47	32.8%	0.47
Widowed	2.5%	0.15	2.1%	0.14	2.7%	0.16	2.6%	0.16
Single/divorced	41.7%	0.49	43.9%	0.50	39.1%	0.49	39.7%	0.49
Household variables								
Household size	3.8	1.74	4.0	1.89	3.7	1.66	4.0	1.87
Kids' proportion	13.4%	0.18	15.0%	0.19	12.6%	0.18	15.0%	0.19
Household head's years of education	5.8	1.8	4.7	1.3	6.4	2.0	4.6	1.3
Household head's earnings	$126	$182	$74	$123	$151	$211	$86	$126
Household's per capita income	$58	$372	$29	$52	$71	$527	$34	$60
Sisben score	18.9	11.4	14.0	9.0	21.2	12.5	14.3	9.3
Ponzi schemes								
Deposits	$4,206	$6,428	$5,271	$6,471	$3,168	$4,928	$13,841	$14,098
Observations	269,855		76,827		181,360		11,668	

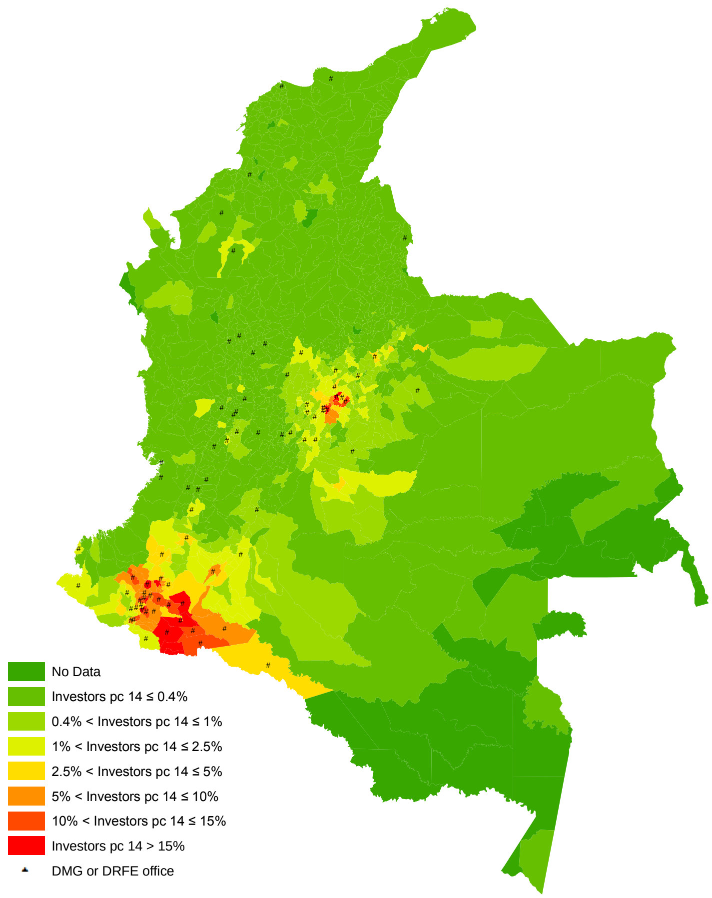
Notes: $ corresponds to US$ dollars at the average exchange rate as of November 2008.

agency). Of course, the ratios are underestimated given that we did not find a match for all of the investors.[5]

We report the distribution of per capita investors in Map 1, along with markers indicating municipalities where the pyramids had at least one office. Reassuringly, the municipalities that the anecdotal evidence suggests were heavily affected by the pyramids show

[5]It is also possible that the investors we could not match due to the fact that they belong to the richest quartile are not evenly distributed across the municipalities. If that is the case, they are mostly likely concentrated in the larger cities. The fact that they are concentrated in larger cities actually attenuates the errors. For instance, if we missed the actual figure of investors in Bogotá by 35,000, that city's ratio of investors to the 14+ population would only increase by 0.7 percentage points.

Map 1: Investors per capita (14+). DMG + DRFE



up as such in our maps.

Both pyramids were particularly strong in the southwest of the country, in municipalities belonging to the states of Nariño and Putumayo, where they were born. Out of the top 100 municipalities in terms of per capita investors, 55 belong to these two states. Cundinamarca—a state in the middle of the country, where Bogotá is located—was also hit hard, with 21 of its municipalities making it into the top 100. The five municipalities with larger numbers of per capita (14+) investors—all located in Nariño and Putumayo—have figures between 18% and 21%.[6]

Considering that our count of investors (that is, as matched with SISBEN) underestimates the actual figures, and that conceivably only one individual per household invested resources in the pyramids, these figures imply that virtually all households in these municipalities invested in DMG or DRFE. While the pyramids' stronghold was in the southwest,

[6]The top five municipalities are Valle del Guamuez, Nariño, Orito, Mocoa, and Sibundoy.

they also prospered in other parts of the country. For instance, in Bogotá, our matching strategy identifies close to 70,000 investors in the pyramids, the vast majority of them in DMG. Other smaller municipalities, like Suesca, Sopó and Tocancipá—all in Cundinamarca and near Bogotá—made it into the top twenty, with per capita investors above 10%.

We also calculate the losses and revenues in each municipality by adding all resources invested by individuals matched to the municipality and subtracting the sum of the resources they received back from the pyramids. We express the outcome as a percentage of annual municipal public expenditures (taken from *DNP*, the National Planning Department).

The list of municipalities with heavy losses is long. There are 110 municipalities where losses were above 10% of the corresponding annual municipal expenditures. Six of them had aggregate losses (again, likely underestimated, as we could not match all investors to a municipality) larger than the annual municipal public expenditures. Five out of these six are located in Nariño. Aggregate net revenues are only positive in a few municipalities. Expressed as a percentage of municipal annual expenditures, five municipalities had positive net balances above 10%. With the exception of Zipaquirá (located near Bogotá, in the middle of the country), the top five winners are also located in the southwest of the country, where the two pyramids were born.

4 Impact on loans

In this section, we test whether the individuals who invested in the pyramids obtained more loans in the financial sector, presumably to leverage their investments. Moreover, we also test whether they were paying their loans back on time and whether this changed after the shutdown of the pyramids. Our conjecture is that they should have paid the loans back on time while the pyramids were functioning, but afterwards, once the pyramids were shut down, they may have had trouble paying them back.

To address these questions, we first build a control group by identifying individuals in the SISBEN who did not participate in the pyramids, but who shared similar socioeconomic characteristics with the investors in the merged datasets of DMG/DRFE and SISBEN. We do this by using a propensity score matching technique (the details of which are presented in Appendix A) aimed at providing us with one similar individual surveyed by the SISBEN for each investor in the matched SISBEN/Pyramids sample. Then, for all individuals in the treatment and control groups, the *Superfinanciera* provided us with individual semiannual loan stocks and (ex-post) loan ratings from 2006 until 2010.

Since the two datasets were merged by staff from the *Superfinanciera*, we agreed with them to have only one control individual per investor. The controls were chosen with a matching algorithm (nearest neighbor) according to the PSM described in Appendix A. The anonymized sample[7], returned to us by the *Superfinanciera*, contained information on the treatment (investors) and control groups and comprised 269,855 investors and the same number of control individuals. The descriptive statistics are also provided in the Appendix, in Table A.1.[8]

Using this sample, we begin our empirical analysis by looking at the impact the pyramids had on loans and on ex-post loan ratings. We estimate the following panel data fixed effects equation, with standard errors clustered at the municipal level:

$$y_{it} = \gamma_t + \alpha T + \sum_{t=1}^{10} \beta_t \cdot Treat_i \cdot \gamma_t + e_{it} \tag{1}$$

where y_{it} is the variable of interest—for instance, consumer loans for individual i in semester t. The regression has time effects, γ_t, and a time trend, T. The latter controls for growth over time of the variables, while the former captures the remaining period specific shocks. The data is semiannual from 2006 through 2010. To avoid collinearity, we drop the 2006-1 coefficients. The fixed effects deal with time-invariant unobservable characteristics of investors. $Treat_i$ is a dummy variable that takes the value of 1 if the individual participated in the pyramids, and 0 otherwise. The coefficient of interest is β_t, which captures whether respective variables differ between the treatment and control groups over time. Finally, e_{it} corresponds to the idiosyncratic error term.

At about the same time that the pyramids were shut down, the global financial crisis (GFC) erupted. One concern one might have is that the GFC affected credit in Colombia, and that this might influence our results. Nevertheless, (i) our identification strategy relies not on the evolution of the financial variables of investors over time, but rather on their comparison relative to similar individuals that did not invest; (ii) there are no reasons to believe that the control group nor the treatment group were systematically affected in different ways by the GFC; (iii) the individual characteristics used to identify the control group were collected prior to the crisis; (iv) the time effects in the regressions should pick up any temporary systematic shocks such as the GFC.

[7]The *Superfinanciera* suppressed the IDs and replaced them with fictitious ones. In addition, they rounded some of the variables to avoid re-identification of the individuals.

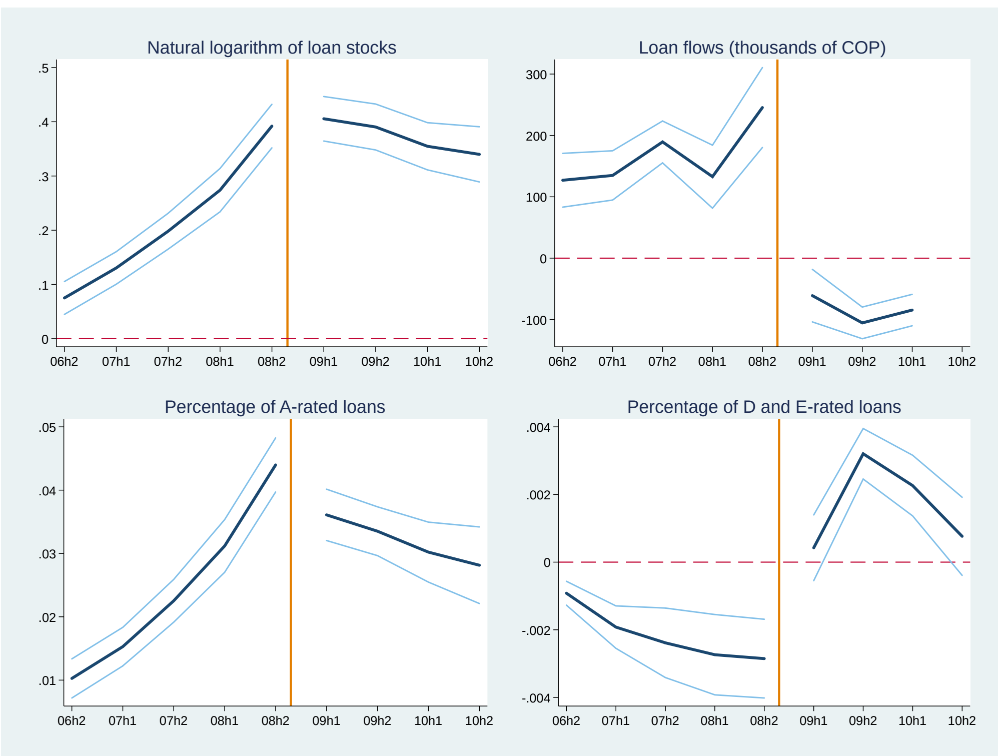
[8]The SISBEN surveys were carried out between 2002 and 2007. The merged dataset produced by the *Superfinanciera* does not include the date when each SISBEN survey was administered. In the original universe of SISBEN surveys, 93% were administered prior to 2007. We do not know the date at which investors became members of the Ponzi schemes, but the evidence suggests—and our results are consistent with—that most of the investors of the schemes entered in 2007 and 2008. Thus, by and large, the information in the SISBEN was collected prior to investments in the pyramids.

4.1 Baseline results

To summarize the results, we report plots of β_t over time with 90% confidence intervals. Figure 1 reports four subplots. The top left one reports the coefficients when y_{it} is the stock (in logs) of consumer loans (including credit cards); the top right one looks at the flow of consumer loans, that is, the change in the stock of loans for each individual from one semester to the next. At the bottom, the variable of interest is either the proportion of ex-post good quality consumer loans (the left hand, labeled "A rated loans") and non-performing loans (the right hand, labeled "D and E rated loans"). The *Superfinanciera* classifies consumer loans as belonging in category A (good loans) if they are not overdue or they are overdue by less than a month. Nonperforming loans, that is, loans in categories D or E, are overdue by more than three months.

We begin the analysis by looking first at the results *before* the pyramids were shut down, that is, to the left of the vertical line. The top panels show that while the schemes were operating, the loans acquired by investors from the formal financial sector were significantly and increasingly higher than for non-investors. The size of the effects is considerable. For instance, by the end of 2008, the loans (stocks) of investors were 39.2% higher than for

Figure 1: β_t for consumer loans – Complete sample



Notes: Fixed-effects panel data regression results with 90% confidence bands with errors clustered at municipal level. The vertical lines indicate when the pyramids were shut down.

non-investors. Consistent with the timing of the history of the pyramids described in Hofstetter et al. (2017), at the beginning of our sample, in 2006-2, investors already had higher credit stocks than the control group, though certainly by a much smaller magnitude: the size of the difference is 7.5%.

The bottom panels show that, relative to non-investors, the loan ratings of investors improved steadily while the pyramids were operating: the proportion of investors' A-rated loans rose while that of D- and E-rated loans fell. Regarding the size of the coefficient, for good quality loans—prior to November 2008—the largest coefficient is 4.4%. This is a large effect: in our control group, 13.6% of credits are A-rated.[9] The coefficient in the regression therefore implies that for investors, the proportion of good quality loans rose by close to 32% while the pyramids were functioning. As for bad quality loans (D and E rated loans), the last coefficient while the firms were still operating is 0.285%. Since the stock of bad quality consumer loans for the control group is 0.9%, the proportion of bad quality loans fell by 32% for the treatment group prior to the pyramids being shut down. Moreover, the fact that the coefficients are statistically different from zero at the beginning of the sample (2006-2) suggests that by that time, the pyramids had already affected loans' ratings.

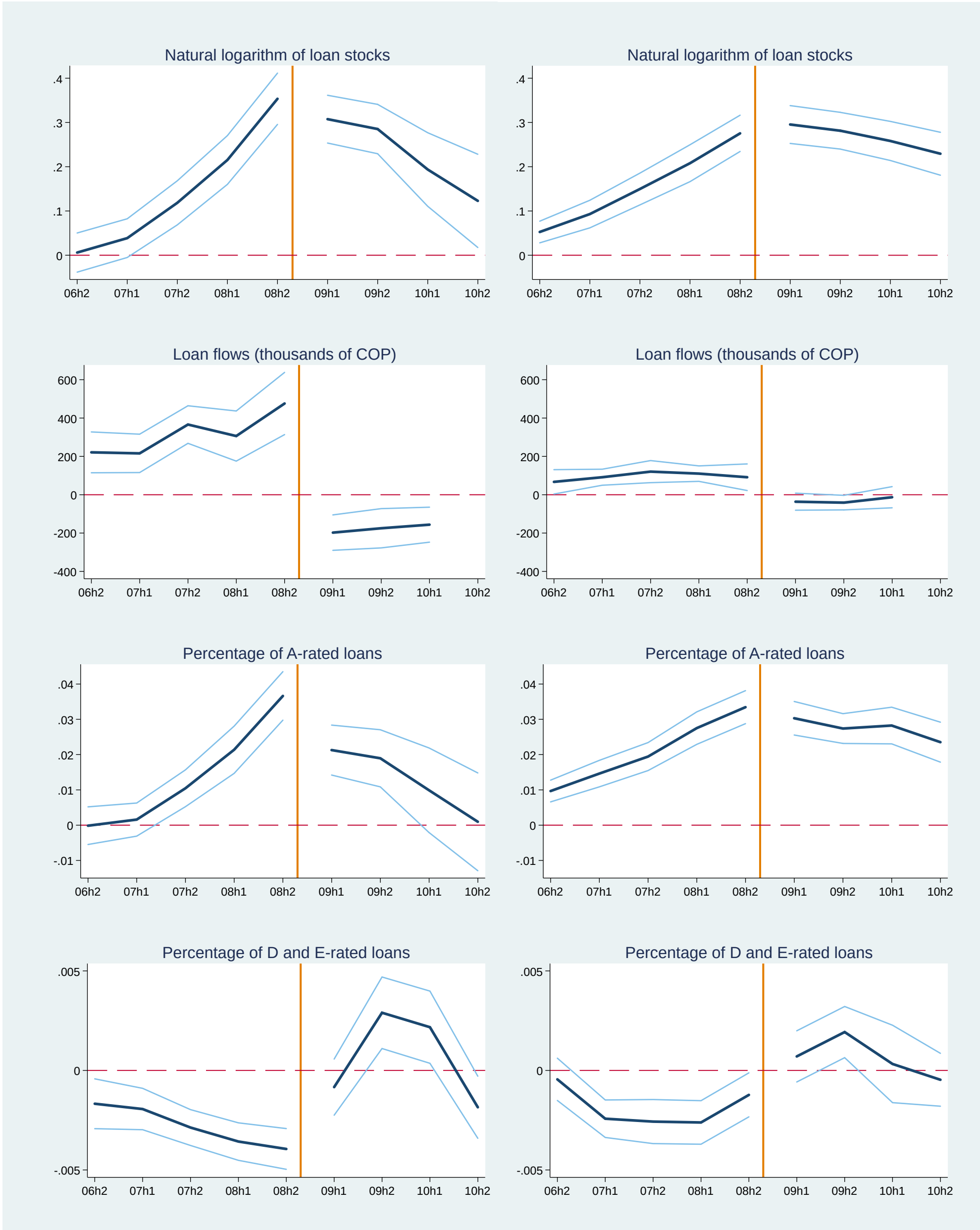
After the government shut down DMG and DRFE, the flow of loans and their ex-post ratings declined. As for the flow, it fell immediately to negative figures after the pyramids were shut down, by approximately COP 100,000 (US$43) per loan and period. In terms of bad loans (D- and E-rated) the largest coefficient after the pyramids ended is 0.32 percentage points—that is, an increase in bad loans of about 36% relative to the control group. Consistent with the latter, the proportion of investors' good quality loans began a steady decline after the pyramids were shut down.

4.2 Large and small investors

Are these results different if we focus on large compared to small investors? To address this question, we estimate Equation 1 for the highest and lowest quintiles in terms of the amounts invested in the pyramids. In each case, we use the individuals in the respective quintile as the treatment, with individuals sharing similar characteristics according to the PSM constituting the corresponding control group. We expect larger effects for those in the highest quintile of investments. The results are reported in Figure 2. The panels on the left hand side of this figure focus on the highest quintile, and those on the right hand, on the lowest. The scales on the axes are identical.

[9] We code the credit ratings of individuals without credit in the financial sector with zeros.

Figure 2: β_t for consumer loans – Large and small investors



Notes: Left column: highest quintile of investments; right column: lowest quintile of investments. Fixed-effects panel data regression results with 90% confidence bands and clustered standard errors (municipalities). The vertical line indicates when the pyramids were shut down.

In both cases, we still find that pyramid customers obtained more loans from the financial sector and their credit standings were better than those in the respective control groups while the schemes were operating—that is, to the left of the vertical lines. Afterwards, once the schemes were shut down, their loan stocks started to decrease and their ratings with the banking sector deteriorated.

In spite of the qualitative similarities in the results of the two quintiles, there are important quantitative differences. Prior to the pyramids being shut down—and relative to their respective control groups—the increase in the loan *stocks* of those in the highest quintile of investments is almost 8 percentage points higher than for those in the lowest quintile. Once the two schemes were put out of business, the loan *flows* fell 5.4 times more in the highest quintile than in the lowest. The non-performing loans increased by 36% for the highest quintile at their peak after the pyramids were shut down, compared to 18% for the lowest quintile (relative to the respective control groups).

Beyond the quantitative comparison across quintiles, a remarkable result of these estimations is that even for those individuals in the lowest quintile of investments, we detect sizeable and statistically relevant effects on their financial behavior as a consequence of having invested in the pyramids, both before and after they were shut down.

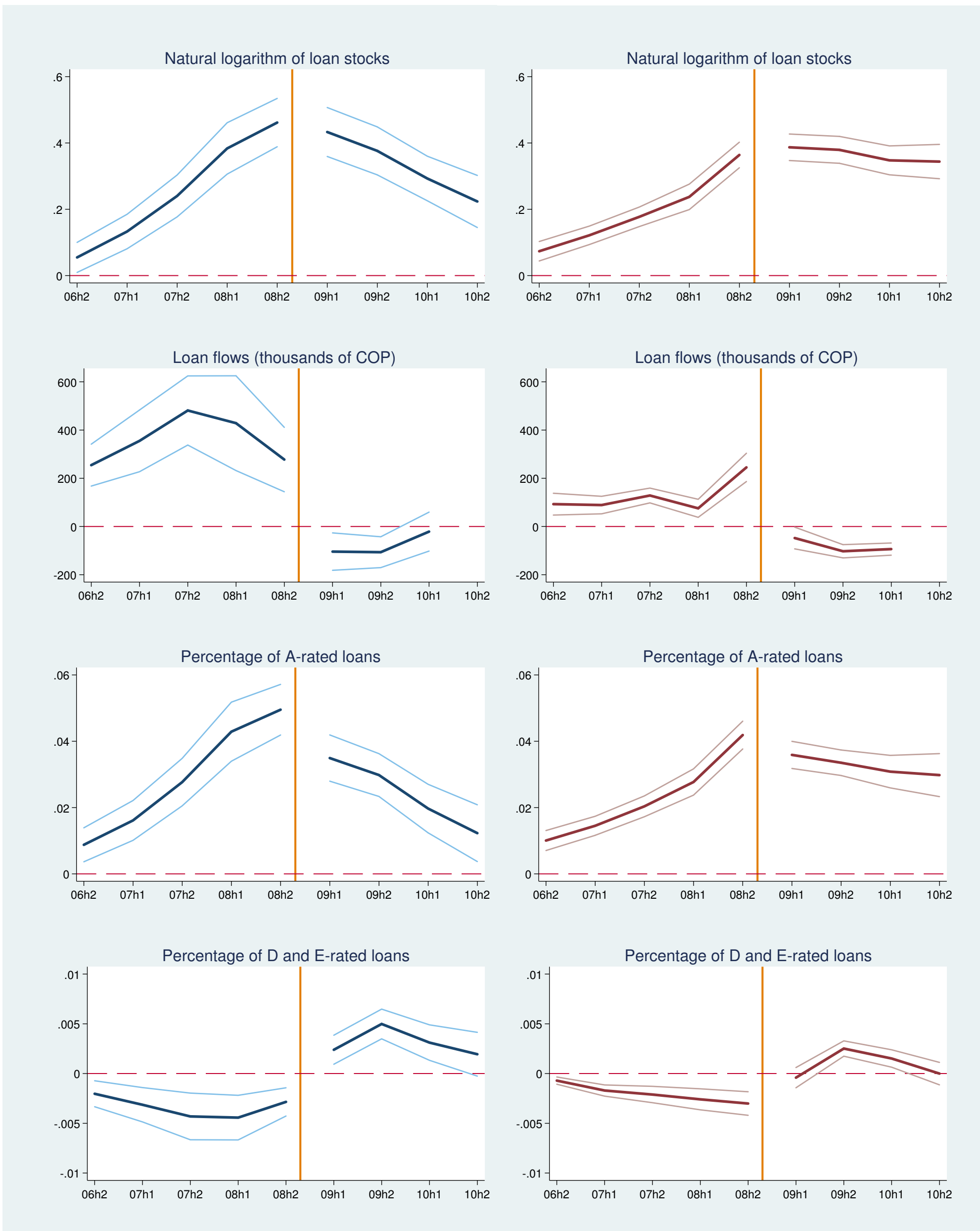
4.3 Winners vs. losers

We now study the financial behavior after the pyramids were shut down of investors who lost money and those who made a profit. Our prior hypothesis is that, once the pyramids were gone, winners used the proceeds of their investments to reduce the extra debt they acquired to invest in the pyramids. We thus expect their loan stocks to fall at a faster rate. We also expect better ex-post credit ratings for the winners after the pyramids were shut down.

As for differences *prior* to November 2008, it is unclear in what direction the results should go. 80% of investors lost money. It seems reasonable then to suspect that they did not know the government would shut them down. As for the 20% that made a profit, it is unclear whether they were lucky—simply happening to withdraw on time by chance—or whether they had more serious reasons for doing so. The latter could be the case if some of them withdrew from the schemes anticipating their collapse. Indeed, the government had been unsuccessfully trying to shut down the schemes for over a year. Some of the winners might have read these signals correctly. If this is the case, this should make us cautious about how we interpret these results, especially those corresponding to the winners' side. The reason is that the winners who read the signals correctly could be those with a higher level of education and greater financial literacy. This makes this group more likely to belong to the richest quartile, which was left out of the merged sample. We have one indication that this is the case: in the universe of investors (the original DMG/DRFE sample), 20% made money; in the merged sample (with SISBEN), this figure is 17%. In any case, for those investors in the merged sample, their respective control group takes into account the investors' income and education.

The results are reported in Figure 3, with plots on the left for the winners and on the right for the losers. We observe that the winners' *stock* of loans decreased at a faster pace after the pyramids were shut down, as expected. We also find that the ex-post loan ratings deteriorated faster for the winners, a result that is at odds with our prior assumptions: we

Figure 3: β_t for consumer loans – Winners and losers



Notes: Left column: winners; right column: losers. Fixed-effects panel data regression results with 90% confidence bands and clustered standard errors (municipalities). The vertical line indicates when the pyramids were shut down.

were expecting that once the pyramids were shut down, the winners' loan ratings would improve relative to that of the losers. Nevertheless, this latter result should be taken with a grain of salt. The sample gets significantly smaller on the winners side, inasmuch as only 17% of the investors actually made a profit (in the merged sample) and, out of the ones that made a profit, less than a quarter actually had loan ratings in the dataset.

4.4 Effects along the income distribution

As we emphasized earlier, the SISBEN survey does not collect information for the richest quartile of the population, therefore, the matched datasets do not include individuals in the higher brackets of the income distribution. Thus, the baseline results must be interpreted accordingly. Nevertheless, within the matched sample, we have an important variation in income across investors that we exploit to shed some light on how our results change along the income distribution. This analysis will also give us clues as to whether having the richest quartile in our sample would attenuate or amplify our findings.

Our conjecture is that not having the richest quartile attenuates our baseline estimates. The reason is that individuals in the highest brackets of the income distribution have greater access to financial services than those in the lowest brackets. For instance, according to the 2010 ELCA (Colombian Longitudinal Survey), more than 80% of individuals with outstanding loans and belonging to the highest quintile of the income distribution obtained their respective loans from the formal banking sector. This proportion is less than 40% for individuals in the lowest quintile. Thus, the potential for individuals in the highest brackets of the income distribution to impact the financial sector by withdrawing deposits or by obtaining loans to invest in the pyramids, is greater than for poorer individuals with less access (in each case relative to their respective control groups).

In Figure 4, we re-estimate the baseline models, splitting the sample along the income distribution. In particular, the plots on the left focus on the estimates for the richest 30% (measured using households' per capita income), while those on the right hand side reflect estimates for the poorest 30%. In both cases, the results are relative to their respective control groups.

The general trends in the figure are coherent with those using the whole sample: loans to investors increased and their ratings improved prior to the shutdown of the schemes; afterwards, loans decreased and the ratings deteriorated. Turning to the comparison between rich and poor investors, wherever differences are apparent, they go in the expected direction. More precisely, if the size of the effects is different, it is greater for the rich portion; where there are differences in the statistical relevance of the effects between rich and

Figure 4: β_t for consumer loans – Top and bottom 30% of the income distribution

Notes: Left column: top 30%; right column: bottom 30%. Fixed-effects panel data regression results with 90% confidence bands and clustered standard errors (municipalities). The vertical line indicates when the pyramids were shut down.

poor, the higher statistical relevance also corresponds to the richest portion.

Two important conclusions emerge from this analysis. First, the general findings regarding the impact of the pyramids on financial behavior also hold true when studied along the income distribution. Second, the effects tend to be stronger for the richest portions of the population. If the latter trend also holds for the richest quartile of the population (which our sample does not include), then the results based on the merged sample should be interpreted as the lower bound of the actual effects.

5 Impact on deposits

One popular story told by the founder of DMG around the time the government shut down his firm was that the higher yields he offered diverted the deposits that banks were able to attract from the public to his firm. Consistent with this claim, Carvajal et al. (2009) argue that there is anecdotal evidence that some of the schemes they analyzed diverted deposits from the financial sector. We estimate—again as far as can tell, for the first time in the literature—whether and by how much the pyramids impacted deposits.

The *Superfinanciera* does not record data on deposits at the individual level. To study the pyramids' impact on deposits, we exploit the variation in deposits across municipalities (which the *Superfinanciera* does report) and the intensity of the pyramids' presence in municipalities (we build proxies of the relative importance of the pyramids in each municipality).

We use two definitions of the municipal intensity of the pyramids. First, using the location of investors based on the data matched with the SISBEN survey, we calculate the number of investors per capita (14+) across municipalities. We call this variable I_{pc}. Second, we sum the total amount invested by individuals matched to each municipality, and express this figure relative to the respective municipal government's total annual expenditures. We label this variable K/E. In Table 3, we report the summary statistics of these ratios.

Table 3: Pyramid intensity in municipalities

Variables	Obs.	Mean	SD	Min	Max	p10	Median	p90
I_{pc}	1089	0.0100	0.0247	0	0.2074	0.0009	0.0026	0.0196
K/E	1082	0.1555	0.4810	0	5.4565	0.0079	0.0381	0.2087

Notes: I_{pc}: Investors per capita, 14+; K/E: Total municipal investments/municipal expenditures.

Finally, we estimate the pyramids' effect on municipal deposits in the formal financial sector by running regressions of the following form:

$$y_{ijt} = c_j + \alpha_j T + \sum_{t=1}^{T} \lambda_t + \sum_{t=1}^{T} \beta_{jt} \cdot X_i \cdot \lambda_t + \phi_i + e_{ijt} \tag{2}$$

where X_i is either I_{pc} or K/E in municipality i. y_{ijt} refers to the deposits of type j at time

t in municipality i in constant COP and expressed in logs. We estimate this for three types of deposits: total deposits, deposits in savings accounts, and certificate deposits (CDs), which the *Superfinanciera* records at a quarterly frequency at the municipality level.[10] c_j is a constant, T is a time trend, and λ_t are quarterly time effects.[11] ϕ_i is a municipal fixed effect and e_{ijt} is the random error term. We report the results with errors clustered at the municipal level. The results without clusters or with clusters at the state (*departamento*) level yield similar conclusions.[12]

In earlier versions of the paper, rather than the continuous version of X_i described above, we estimated the model with a dummy variable equal to 1 for the municipalities in the upper portions in terms of the intensity of the pyramids based on I_{pc} or K/E. The advantage of that specification is that it alleviates concerns about measurement error in X_i caused by the fact that the richest quartile of the population—which does not show up in the merged sample we use to identify the location of investors—might be unevenly distributed across municipalities (that is, municipalities with richer investors would be more likely to have more individuals not counted in these statistics).[13] The advantage of the continuous specification in Equation 2 is that it allows for a precise interpretation of the coefficients. The results are qualitatively very similar with either way of measuring the pyramids' intensity at the municipality level.

The parameters of interest, β_{jt}, represent the differences over time in deposits of type j if the "intensity" of the pyramids is marginally increased in a municipality. If the pyramids happened to have shifted deposits away from the financial sector, β_{jt} should be negative. To summarize our findings, we plot β_{jt} with 90% confidence bands in Figure 5 for three types of deposits (j) and two proxies of the intensity of Ponzi schemes in the municipalities (X_i). The left columns use I_{pc}, and the right ones K/E to identify the effects.

The two top plots—those illustrating the effects on total deposits—show that during the last quarter of 2006, two years prior to the pyramids being shut down, the coefficients become negative; that is, deposits in municipalities most affected by the pyramids fell relative to those least affected (or not affected at all). This downward trend reaches a trough during the second quarter of 2008—that is, a quarter and a half prior to the pyramids being shut down. At that point, the gap between the two series is statistically significant. After

[10] Total deposits are the sum of CDs, saving accounts, and current accounts. In 2006, 51% of total deposits were savings accounts and 29% were CDs. We do not focus on current accounts, as their balances are mostly driven by corporate and government transactions.

[11] We drop the interaction of 2006-I to avoid multicollinearity.

[12] Available from the authors upon request.

[13] Given that the measurement error is likely concentrated in larger cities, it is likely to be quantitatively small: suppose we missed 35,000 investors in Bogota (that is, we missed close to 50% of them). Then the per capita presence of investors in the city would only change by 0.7 percentage points.

Figure 5: β_{jt} for municipal deposits

Notes: Left column: $X = I_{pc}$; right column: $X = K/E$. Fixed-effects panel data regression results with 90% confidence bands and clustered standard errors (municipalities). The vertical line indicates when the pyramids were shut down.

the pyramids were shut down, the coefficients again become insignificant.

What does the size of the coefficients tell us? At the trough in the top left plot, the coefficient is -1.08. That means that a 1% increase in the ratio of the population investing in the pyramids reduces total deposits in the banking sector by 1.08%. To give further intuition to the size of the effects, we report in Table 4 two additional results for each case. On the one hand, we report by how much deposits j fell if I_{pc} or K/E change by one standard deviation; on the other hand, the table reports the predicted effect on deposits in the top five municipalities with a stronger average presence of pyramids in terms of I_{pc}

or K/E, respectively. These effects are reported for the respective troughs identified in Figure 5—that is, for either the second or third quarters of 2008, the quarters immediately prior to the pyramids being shut down.

Table 4: The effects on total deposits, saving accounts and CDs of changes in I_{pc} and K/E

Total deposits			
$\beta_{08Q2} \times$ SD	-2.7%	$\beta_{08Q2} \times$ SD	-2.4%
$\beta_{08Q2} \times$ mean top 5	-20.4%	$\beta_{08Q2} \times$ mean top 5	-22.3%
Savings' accounts			
$\beta_{08Q2} \times$ SD	-2.9%	$\beta_{08Q3} \times$ SD	-2.9%
$\beta_{08Q2} \times$ mean top 5	-22.3%	$\beta_{08Q3} \times$ mean top 5	-26.8%
CDs			
$\beta_{08Q3} \times$ SD	-9.2%	$\beta_{08Q3} \times$ SD	-10.2%
$\beta_{08Q3} \times$ mean top 5	-70.1%	$\beta_{08Q3} \times$ mean top 5	-94.6%

Notes: The effects in the left panel are identified with I_{pc}, those in the right panel, with K/E. The numbers reported correspond to the effects at the respective troughs (see Figure 5).

As reported in Table 4, a one standard deviation increase in I_{pc} reduces total deposits in a municipality by 2.7%. In the five municipalities with more per capita investors, total deposits fell on average by 20% (relative to municipalities without pyramids). Reassuringly, if we use K/E to identify the effects, the interpretation of the coefficients yields similar results—see the right hand panels: a one standard deviation increase in K/E reduces total deposits by 2.4%, and the predicted reduction in deposits in the five municipalities with the highest K/E is 22%.

In the middle panels of Figure 5, which report the pyramids' impact on savings accounts, we see a significant drop in the coefficients, especially during the final two quarters prior to the end of the pyramids. According to Table 4, the size of these coefficients at the trough indicate that a one standard deviation increase in either I_{pc} or K/E reduced deposits in savings accounts by 2.9%. Moreover, the pyramids caused a decrease of 22% to 27% in savings accounts in the top five most affected municipalities.

The bottom panels in both Figure 5 and Table 4 show the evolution of certificate deposits, CDs, a popular financial vehicle for saving money (almost a third of deposits in the banking sector consist of CDs). CDs pay higher interest rates than savings accounts, but are also less liquid and thus are a better substitute for investments in pyramids. This is indeed what the results suggest. Both the size and the persistence of the effects are large. In terms of persistence—unlike with savings and total deposits—the decline in the value of CDs continued well beyond the end of DMG and DRFE. Even by the end of 2010, they had not recovered completely. The size is also very large. A one standard deviation increase in I_{pc} reduced CDs in a municipality (at the trough) by 9.2%; using K/E to identify the effect indicates a reduction of 10.2% in CDs. In the five most affected municipalities, CDs are predicted to have fallen between 70% and 95%.

If we extrapolate the figures using investors per capita at a *national* scale to get back-of-the-envelope estimates of the pyramids' impact on nationwide deposits in the formal financial sector, we find that they caused total deposits to fall by 0.6% and CDs by 2%. The impact of DMG and DRFE on deposits in the financial sector is thus significant and economically relevant.

6 Conclusions

DMG and DRFE, two Ponzi schemes that operated in Colombia through 2008, attracted over half a million customers who invested resources equivalent to 1.2% of the country's GDP.

While Ponzi schemes are more common than normally thought, our understanding of their consequences is mostly anecdotal. Using a dataset merging the universe of investors in the two pyramids with their loan records in the formal financial sector and their socioeconomic characteristics, we show that *before* the government shut down these firms, the individuals who invested in DMG and DRFE acquired close to 40% more loans in the financial sector compared to similar individuals who did not invest in the pyramids.

Moreover, we also find that deposits in the formal financial sector fell in municipalities heavily affected by these two pyramids: individuals pulled resources away from the financial sector in order to invest in Ponzi schemes. We estimate that a one standard deviation increase in the municipal presence of the pyramids—measured as the number of investors per capita or their total investments as a proportion of municipal expenditures—reduced deposits in saving accounts by 2.9% and in CDs by more than 9%.

After the pyramids were shut down, the ex-post loan ratings of investors deteriorated: nonperforming loans increased by 36% compared to similar individuals who did not participate in the schemes. Moreover, we show that their loan stocks started falling and that, two years later, deposits had not yet fully recovered.

We believe the scope of our paper goes beyond being able to estimate, for the first time in the literature, the effects of Ponzi schemes on the financial behavior of households. Indeed, some of the effects we are able to estimate may have a parallel in episodes we generically call "bubbles." Samuelson (1957) used "Ponzi schemes" interchangeably with "chain letters" and "bubbles." Charles Kindleberger, in his comprehensive history of financial crises (Kindleberger & Aliber, 2005), describes bubbles as euphoric periods during which "*an increasing number of investors seek short-term capital gains from the increases in the prices of real estate and of stocks rather than from the* (...) *income based on the productive use of these assets.*"

This is analogous to what people seem to be doing when investing in Ponzi schemes. Thus, our results might hint at how financial consumers behave during episodes we identify as bubbles. This opens up interesting avenues of research. For instance, now that many believe that cryptocurrencies are bubbles (e.g., Nouriel Roubini, 2018, in an interview with Bloomberg) or a giant pyramid scheme (as former Wells Fargo CEO, Dick Kovacevich, defined Bitcoin in an interview with CNBC in January 2018), our paper sheds light on the consequences they might have on the formal banking sector.

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Appendices

A Propensity Score Matching

One of the uses of the merged dataset was to obtain a control group for the investors, by identifying individuals in the SISBEN who did not participate in the pyramids but who shared similar characteristics with those who did. For that purpose, we implemented a propensity score-matching technique, which estimated a propensity score for each individual in the sample, and paired individuals in the control and treatment groups following the nearest neighbor algorithm.

The main purpose of propensity score matching is to balance the distribution of observed covariates (Lee, 2013), so that there are no systematic differences in the distribution of covariates between the two groups. In this work, the equality of means of observed characteristics in the treatment and control groups was examined using the Imbens Statistic, which controls by the size of the sample. The last column displays stars at 99% (***), 95% (**), and 90% (*) confidence levels for the significance of the mean difference among the different variables for the treatment and control groups. The absence of stars in the last column in all the displayed rows leads us to conclude that, controlling for the size of the sample, there are no significant differences in the observable characteristics between the treatment and control groups. Table A.1 summarizes the results of this analysis.

The propensity score is estimated using a probit model, which defines the probability of investing in Ponzi schemes as a function of individual characteristics such as age, income, years of education, gender, marital status, location and SISBEN score, as well as household characteristics, like the proportion of kids in a household, household size, the household head's years of education, and the household's per capita income. All these variables were measured during the second wave of SISBEN, conducted between 2003 and 2007. This allows us to obtain investors' socioeconomic characteristics prior to the end of the pyramids. Estimates of the probit model are given in Table A.2.

The estimation results in Table A.2 indicate that, according to our model, the probability of investing in Ponzi schemes negatively correlates with age, being married, being male, and household size. Larger households with larger proportions of kids and lower per capita incomes probably can not spare any money to invest in Ponzi schemes, and thus are less likely to invest. On the other hand, the probability of investing positively correlates with being widowed, single or divorced. Likewise, it seems to relate positively to individual earnings and household per capita income, and with being located in the states of Putumayo (State dummy 27), Cundinamarca (State dummy 11) and Nariño (State dummy

Table A.1: Treatment and control groups, descriptive statistics

VARIABLES	Mean control	Mean treatment	Difference	Imbens statistic	Significance Imbens
Invested in DRFE					
Male	0.529	0.513	0.016	0.032	
Age	39.565	39.675	-0.110	-0.008	
Income	$93,767	$99,846	$-\$6,079$	-0.026	
No education	0.072	0.078	-0.007	-0.025	
Incomplete elementary	0.339	0.283	0.056	0.122	
Complete elementary	0.216	0.229	-0.013	-0.032	
Incomplete high school	0.132	0.138	-0.006	-0.018	
Complete high school	0.181	0.218	-0.037	-0.092	
Secondary/post education	0.060	0.053	0.007	0.030	
Cohabitation	0.213	0.224	-0.010	-0.025	
Married	0.333	0.321	0.012	0.025	
Widowed	0.021	0.021	0.000	0.001	
Single/divorced	0.432	0.434	-0.002	-0.003	
Household size	4.253	4.048	0.204	0.107	
Proportion of kids	0.145	0.149	-0.004	-0.024	
Household head's years of education	4.716	4.676	0.039	0.027	
Household's per capita income	$64,334	$68,106	$-\$3,772$	-0.028	
SISBEN score	13.987	14.079	-0.092	-0.010	
Invested in DMG					
Male	0.474	0.465	0.009	0.018	
Age	41.765	41.405	0.360	0.027	
Income	$179,992	$242,996	$-\$63,004$	-0.069	
No education	0.048	0.040	0.008	0.039	
Incomplete elementary	0.215	0.159	0.055	0.142	
Complete elementary	0.211	0.171	0.040	0.102	
Incomplete high school	0.200	0.166	0.033	0.086	
Complete high school	0.223	0.295	-0.072	-0.165	
Secondary/post education	0.104	0.168	-0.064	-0.189	
Cohabitation	0.280	0.248	0.032	0.072	
Married	0.307	0.333	-0.026	-0.057	
Widowed	0.029	0.027	0.002	0.015	
Single/divorced	0.384	0.391	-0.008	-0.016	
Household size	3.947	3.723	0.224	0.132	
Proportion of kids	0.128	0.126	0.002	0.011	
Household head's years of education	6.333	6.377	-0.045	-0.021	
Household's per capita income	$124,556	$166,102	$-\$41,546$	-0.047	
SISBEN score	18.348	21.212	-2.864	-0.240	

Table A.1: Treatment and control groups, descriptive statistics (continued)

VARIABLES	Mean control	Mean treatment	Difference	Imbens statistic	Significance Imbens
Invested in DRFE & DMG					
Male	0.502	0.490	0.011	0.023	
Age	39.755	40.114	-0.359	-0.025	
Income	$113,774	$120,852	$-\$7,078$	-0.025	
No education	0.076	0.090	-0.014	-0.050	
Incomplete elementary	0.336	0.288	0.047	0.103	
Complete elementary	0.205	0.221	-0.017	-0.041	
Incomplete high school	0.138	0.134	0.004	0.010	
Complete high school	0.174	0.213	-0.039	-0.100	
Secondary/post education	0.057	0.053	0.013	0.078	
Cohabitation	0.246	0.255	-0.009	-0.021	
Married	0.332	0.327	0.005	0.011	
Widowed	0.026	0.028	-0.002	-0.013	
Single/divorced	0.397	0.391	0.006	0.012	
Household size	4.190	3.997	0.193	0.101	
Proportion of kids	0.145	0.149	-0.004	-0.023	
Household head's years of education	4.711	4.644	0.067	0.048	
Household's per capita income	$76,675	$80,887	$-\$4,212$	-0.029	
SISBEN score	14.676	14.453	0.223	0.023	

17), something corroborated by our results in the previous sections.

The probit estimates are used to calculate the propensity score for all individuals. It is crucial for the validity of the matching that there is a common support. Figure A.1 depicts the kernel densities of the propensity scores for both investors (treated) and non-investors (control) in the SISBEN survey. The results allow us to conclude that there is sufficient overlap between the propensity scores of the treatment and control group.

The purpose of this propensity score matching is to obtain a control group of investors by identifying individuals in the SISBEN who did not participate in the pyramids, but shared similar characteristics with those who did. For this we finally implement a matching algorithm of nearest neighbor with no replacement, in order to ensure that there is one control for each individual in the treatment group. The nearest neighbor matching matches a subject from the control group to a subject in the treatment group based on the closest propensity score. With the no replacement property, if for a treated unit, forward and backward matches happen to be equally good, the program randomly draws either the forward or backward match (Cox-Edwards & Rodríguez-Oreggia, 2009). This leaves us with 269,855 investors and the same number of controls.

Table A.2: Probit estimates

VARIABLES	Coefficient	Std. Errors
Age	-0.003^{***}	0.000
log(Income)	0.001^{***}	0.000
Sisben score	0.004^{***}	0.000
Years of education	0.030^{***}	0.001
Married	-0.013^{***}	0.002
Widowed	0.056^{***}	0.002
Single/divorced	0.040^{***}	0.005
Male	-0.012^{***}	0.001
Household head's years of education	0.013^{***}	0.001
Household size	-0.005^{***}	0.001
Proportion of kids	0.002	0.011
log(Household's per capita income)	0.004^{***}	0.000
State dummy 1	0.233^{***}	0.046
State dummy 2	0.261^{***}	0.045
State dummy 3	0.304^{***}	0.045
State dummy 4	0.291^{***}	0.043
State dummy 5	0.312^{***}	0.042
State dummy 6	0.163^{***}	0.048
State dummy 7	0.267^{***}	0.044
State dummy 8	0.327^{***}	0.041
State dummy 9	0.230^{***}	0.047
State dummy 10	0.364^{***}	0.037
State dummy 11	0.362^{***}	0.041
State dummy 12	0.270^{***}	0.045
State dummy 13	0.330^{***}	0.041
State dummy 14	0.243^{***}	0.047
State dummy 15	0.338^{***}	0.039
State dummy 16	0.344^{***}	0.039
State dummy 17	0.344^{***}	0.044
State dummy 18	0.182^{***}	0.048
State dummy 19	0.195^{***}	0.047
State dummy 20	0.248^{***}	0.045
State dummy 21	0.169^{**}	0.048
State dummy 22	0.264^{***}	0.046
State dummy 23	0.152^{***}	0.048
State dummy 24	0.070	0.049
State dummy 25	0.185^{**}	0.050
State dummy 26	0.275^{***}	0.044
State dummy 27	0.465^{***}	0.031
State dummy 29	0.075	0.060
State dummy 30	0.095	0.068
State dummy 31	0.113^{**}	0.053
State dummy 32	0.184^{*}	0.101
State dummy 33	0.197^{**}	0.059

Notes: The dependent variable takes the value of 1 if the individual invested in Ponzi schemes, and 0 otherwise. The dummy variable for state 28 (*San Andrés*) is dropped to avoid collinearity. Likewise, the comparison category for marital status is *Cohabitation*. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Figure A.1: Kernel densities of propensity scores for investors and non-investors in the SISBEN survey