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Ponzi Schemes and the Financial Sector:
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Abstract

By the time the Colombian government closed DMG and DRFE, two Ponzi schemes that were operating in Colombia until 2008, over half a million customers had deposited funds corresponding to 1.2% of Colombia's annual GDP. We show that the individuals who invested in DMG and DRFE obtained close to 40% more loans in the formal financial sector prior to the government closing these firms, compared to similar individuals who did not invest in these pyramids. Moreover, deposits in the formal financial sector fell in those municipalities affected by these two pyramids: a one-standard deviation increase in the municipal presence of the pyramid schemes reduced municipal saving deposits by 2.9% and Certificate Deposits by close to 10%. After the firms were shut down, the proportion of nonperforming loans of investors rose 35% above non-investors' loans; two years later, investors' deposits had not yet fully recovered.

Keywords: Ponzi Schemes; Pyramids; Colombia; Financial Sector; Savings and Loans; Loan Ratings.
JEL codes: E 21, E 44, G 11.

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Las pirámides y el sector financiero:
DMG y DRFE en Colombia*

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Resumen

Para cuando el gobierno colombiano logró cerrar DMG y DRFE, dos pirámides que operaron en el país hasta finales de 2008, más de medio millón de personas habían depositado allí recursos equivalentes a 1.2% del PIB. Mostramos que los individuos que invirtieron en DMG y DRFE tenían 40% más créditos con el sector financiero formal justo antes del cierre de las pirámides, comparados con individuos similares pero que no invirtieron allí. Adicionalmente, en los municipios con mayor presencia de las pirámides, los depósitos en el sector financiero formal cayeron. Un aumento de una desviación estándar en la presencia municipal de las pirámides redujo los depósitos municipales en cuentas de ahorros en 2.9% y de los CDTs en casi 10%. Tras la desaparición de las firmas, la proporción de cartera mala de los inversionistas se incrementó en 35% en comparación a la de los que no invirtieron en pirámides.

Palabras Clave: Ponzi; Pirámides; Colombia; Sector financiero; Ahorro y crédito, Calificación crediticia.
Códigos JEL: E 21, E 44, G11.

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1. Introduction

As of the end of 2008, the Colombian government had closed two firms, DMG and DRFE, both of which were accused of running Ponzi schemes. By the time these firms where put out of business, over half a million people had invested in them. 533,560 costumers deposited resources equivalent to 1.2% of Colombia's GDP, an amount corresponding to 3.9% of total deposits in the financial sector in 2008, or 22% of the total deposits Bancolombia—the largest bank in the country—reported as of the end of that year. 80% of investors lost their deposits. The amount of the average deposit reached 93% of 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 that 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 et al. (2015) described 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), identified 21 schemes operating in Jamaica as of January 2008. Carvajal et al. (2009) reported that in 2008, over 200 schemes promising returns of up to 300 percent within 6 months were operating 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 open fraud and to address money laundering or the support of other illegal enterprises by the schemes' operators. More recently, Cortés et al. (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 grave consequences, the nature of the schemes and the lack of systematic data has 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.[5] 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 abundant anecdotal evidence 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 he was subjected to a conspiracy by the banking sector because the high yields offered by his company were diverting deposits from the formal banking sector to his firm.[6] In fact, as reported by Carvajal et al. "commercial banks had expressed concern that their depositors were withdrawing funds to invest in schemes." Other anecdotal evidence

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

[6] In this video for instance, he accuses Luis Carlos Sarmiento, the main banker in Colombia, of conspiring against his firm: http://www.youtube.com/watch?v=LdWdgjnbFeE

suggests that investors in pyramids often obtained loans from the formal financial sector to invest in these scams.

Using a unique dataset containing the universe of individual investments and profits or losses in these two schemes, we are able to estimate—for the first time, as far as we can tell, in the literature studying Ponzi schemes—the impact they had on the formal banking system. In particular, we are able to pinpoint by how much deposits fell in the banking system while the schemes were operating, and how persistent this effect was after the schemes were shut down. Moreover, on the loans' side, we estimate by how much the individuals that participated in the schemes increased their loans within the banking sector prior to the schemes ending, and the effect this had on non-performing loans both during the life-cycle of the pyramids 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 within the formal financial sector than similar individuals who did not invest in pyramids. We also find that, prior to DMG and DRFE ending, the proportion of loans within the tiers with the best ratings was 33% 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. Later, nevertheless, once the firms were no longer operating, the proportion of nonperforming loans was as much as 35% higher for individuals that had invested in the pyramids.

We also provide evidence showing that deposits in the financial sector were affected by DMG and DRFE. While the Financial Supervisory Agency of Colombia (Superfinanciera) has no information concerning 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 municipal deposits, 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 reduced total deposits in the financial sector by between 2.4% and 2.7%. The same effect is much greater on

certificate deposits (CDs): they fell by 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 summarizes the story of the two Ponzi schemes. Section 3 describes the datasets and stylized facts. In sections 4 and 5, we explore the impact of these schemes on loans and deposits, respectively. Section 6 concludes.

2. Some background: The Rise and fall of DMG and DRFE[7]

David Murcia Guzman, the founder of DMG, arrived to La Hormiga, Putumayo, a small town in the southwest of the country, in 2003. With a high school diploma and previous experience as a door-to-door salesman in a multi-level marketing company, he began DMG. A couple of years later, he opened offices in the states of Meta and Nariño. By the time his empire was put out of business in November 2008, DMG had expanded to 62 (out of 1103) municipalities in Colombia and had investments in Panama, Venezuela and Ecuador. Before being shut down by the government, the company had diversified into businesses ranging from freight companies to television channels.

The *modus operandi* was a masked Ponzi scheme where high returns were paid via the deposits of new customers. To avoid drawing the attention of the authorities for illegally taking deposits without being a financially supervised firm, it sold "prepaid cards" that promised high yields or granted the right to buy appliances and other goods at below-market prices in the future.

DRFE (Dinero Rápido, Fácil y Efectivo—Money in Cash, Fast and Easy) also attracted thousands of customers with similar strategies, although fewer than DMG, as is reported in the next section. The company was started by a Pastor, Carlos Alfredo Suarez, in San Juan de Pasto, capital of the state of Nariño, also in

[7] This section is based on newspaper reports, decrees by government agencies, and judiciary sentences.

the southwest of Colombia. By the end of 2008, when the authorities finally shut it down, it had offices in 69 municipalities.

An ostentatious ceremony of DMG's official launching of a television channel (called the Body Channel) in 2006—one attended by several celebrities—caught the attention of the national media and the authorities. Soon after, the Superfinanciera published a public warning in the newspapers explaining that DMG was not a financially supervised firm and was not authorized to take deposits from the public. Several government agencies began tracking the firm's activities. The Superfinanciera sent a commission to the south of the country to investigate DMG's operations, while the Intelligence and Financial Analysis Unit (UIAF)—a government agency that tracks money laundering activities—began investigating DMG's activities. The latter discovered suspicious transactions at the "Body Channel" company, and over the ensuing year, two additional visits by the Superfinanciera ended with a resolution in 2007, ordering DMG to cease taking deposits from the public and to return the COP $18,145 million (US$ 8 million) invested by nearly 12,000 people. After the ban was imposed by the Superintendent, David Murcia Guzmán began a public relations campaign, began financing various political campaigns for mayors and governors in the states of Putumayo and Nariño, and lobbied Congress to approve a law making his firm's activities legal. Further attempts by the Superfinanciera to close the company received harsh critiques by the House representative of Putumayo, Orlando Guerra. Another representative of the State, Guillermo Rivera, encouraged the government to intensify its investigation of the origins of the firm's wealth. A mob attacked Rivera's family business in Putumayo following his statements.

At the end of 2007, the Superfinanciera ordered the company's liquidation for the first time. Murcia and his lawyers appealed in small local courts and succeeded in reversing the decision. The operations resumed under a new company and some changes in the modus operandi so as to circumvent the Superfinanciera's orders. In February 2008, the DIAN (Colombia's tax agency) together with the

Superintendencia de Sociedades (the supervisor of large corporations) joined in the investigations against DMG. From June through November 2008, DMG continued to attract the money of thousands of Colombians and used the media attention and Murcia Guzman's extravagant lifestyle—inclusive of a private jet and a fleet of luxury cars—to promote the firm. Finally, 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 and extending the powers of the Supersociedades.

A series of protests and riots followed, with crowds expressing support for David Murcia Guzman and Carlos Suarez, but this time their luck had run out. Shareholders and legal representatives received arrest orders, and as investigations progressed, it turned out that several politicians including two governors and several congressmen, journalists and officials had been involved in the schemes. Additionally, the authorities also investigated the links these schemes had with guerrillas, paramilitaries and drug trafficking organizations. After all, DMG was born during the years of the coca boom in Putumayo.

Prison sentences were awarded to the leaders of DMG and DRFE: David Murcia Guzman, 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 pending 22 year long one in Colombia. Several other accomplices were also captured and sentenced in Colombia or extradited to the U.S. In 2011, Carlos Alfredo Suárez, head of DRFE, was sentenced to seven years in jail and ordered to pay a heavy fine.

Regarding the reimbursing of funds to investors, the government appointed legal auditors to liquidate the assets seized from DMG and DRFE. Reimbursement of the money from DMG began in July 2009, with each investor receiving COP $275,000 (US$118)—a fraction of their actual investments. In 2012, the US government returned USD $2'183,000 from Murcia´s confiscated bank accounts to be distributed among DMG's victims. The reimbursement of the money from DRFE began in 2009, with each investor receiving $350,000 (US$ 150)—again a fraction of their investments.

Since 2011, the Superfinanciera has given advice to citizens regarding the appearance of at least 100 new schemes similar to DMG and DRFE across the country. In September 2016, the Superfinanciera was investigating flyers announcing the return of DMG.

3. Data and stylized facts

The main database contains a list of DMG and DRFE's costumers, along with their investments in the firms and the profits or losses they made. The information does not, however, tell us anything about the timing of the investments: we do not know when costumers deposited money or when they received the proceeds, if any, of their investments. We only know the final balance at the moment the government shut the two firms down as of the end of 2008, along with total investments. Additionally, the dataset does not provide any information regarding the characteristics of the investors beyond their identification.

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. 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 10^{th} percentile invested, on average, just over US$400, while those in the 90^{th} 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 in November 2008, when the government seized the two businesses.

Table 1. Descriptive statistics, DMG and DRFE's costumers. $ corresponds to figures in US$ dollars converted from Colombian pesos at the exchange rate for November 2008.

	DMG	DRFE	Both	Total
Number of investors	356.631	153.878	23.051	533.560
% of losers	0,79	0,83	0,78	0,80
		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
		Winner's 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

Investors: who and where

The dataset just described provides no information on the characteristics of the investors. To gain some insight into who the investors were and their geographic locations, we match the DMG/DRFE dataset with the SISBEN survey run by the Colombian government to gather information on individuals' socioeconomic characteristics. 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 2008 was 44.5 million.) This allows us to obtain socioeconomic characteristics of investors prior to the end of the pyramids.

The government uses the SISBEN survey to target the recipients of many of its social programs. Thus, for the most part, it does not include individuals from the most affluent portions 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 is not a Census, typos in the IDs in either the SISBEN or the pyramids explain why the merged sample is not larger. As we emphasize in sections 4 and 5, the fact that the matched sample does not include individuals in the higher brackets of the income distribution, along with the observation that we did not find a match for roughly half the investors, imply that our estimates on the impact of the pyramids on loans and deposits should be interpreted as constituting the lower bound of their actual impact. There are two reasons for this: first, 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 survey in Colombia, more than 80% of individuals with outstanding loans and belonging to the highest quintile of the income distribution obtained their respective loans from the banking sector. This proportion is less than 40% for individuals in the lowest quintile. On the other hand, once we turn to econometric estimations, some individuals who invested in pyramids but who we were unable to match to the SISBEN due to typos in the IDs, could end up in our control groups, thus attenuating the effects.

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 and less that 8% were under the age of 25. 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 similar to that at the national level in 2008: 38.5% of the population of 25+ years had attained an upper secondary educational level. This supports the idea that, as in other pyramid cases (Madoff, Spain, Albania) the costumers were not necessarily uneducated or financially illiterate.

Moreover, 56% were married or living with a partner. Investors reported an average income of $82 per month, with a large standard deviation ($443). Recall,

however, that the SISBEN does not survey individuals in the highest deciles of the income distribution, so this figure should be read as a lower bound.

The two pyramids had costumers with different profiles. Those in DRFE were much poorer—their average income was less than half of those in DMG. They were also less educated, with only about 5% of them having studied beyond high school, a statistic that is almost 17% for customers of DMG. Those in DRFE were also part of larger households and had lower SISBEN scores (which are used by the government to prioritize subsidies).

Table 2. Socioeconomic characteristics of matched investors. $ corresponds to US$ dollars (at average exchange rate as of November 2008)

Invested in→	**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 (montlhy)	$ 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>44	36,0%	0,48	33,8%	0,47	38,3%	0,49	36,1%	0,48
Education, investors								
No education	5,3%	0,22	8,1%	0,27	4,0%	0,20	9,3%	0,29
Incomplete elementary	19,7%	0,40	28,1%	0,45	15,9%	0,37	28,3%	0,45
Complete elementary	18,9%	0,39	22,8%	0,42	17,1%	0,38	22,4%	0,42
Incomplete high school	16,2%	0,37	13,6%	0,34	16,6%	0,37	13,1%	0,34
Complete high school	27,0%	0,44	21,9%	0,41	29,5%	0,46	21,4%	0,41
More than complete high school	12,8%	0,33	5,5%	0,23	16,8%	0,37	5,6%	0,23
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	3,6	1,7	3,1	1,6	3,9	1,8	3,2	1,6
Household head's earnings (monthly)	$ 126	$ 182	$ 74	$ 123	$ 151	$ 211	$ 86	$ 126
Household's per capita income (monthly)	$ 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	269.885		76.827		181.360		11.668	

What about their location? We proxy for location by assigning to each investor the location reported in the SISBEN survey. Then, for each municipality, we

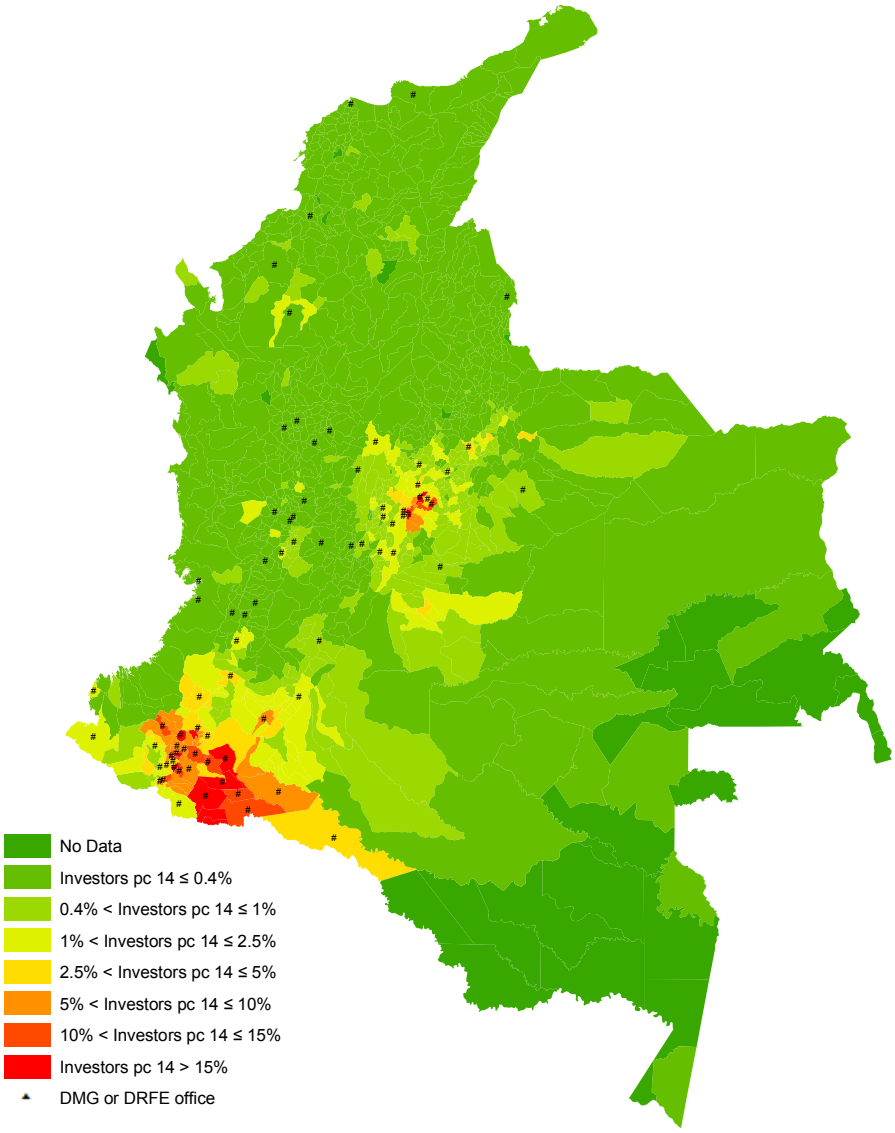
calculate the ratio of investors to the population with 14+ years.[8] Of course, the ratios are underestimated given that we did not find a match for 49% of investors. We report the distribution of per capita investors in Map 1, along with markers indicating municipalities where the pyramids had at least one office. Reassuringly, the municipalities that the anecdotal evidence suggests should be heavily affected by the pyramids show up as such on 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—the state in the middle of the country, where Bogota is located—was also hit hard, with 21 of its municipalities making it into the top 100. The five municipalities with large numbers of per capita (14+) investors—all in Nariño and Putumayo—have figures between 18% and 21%.[9] 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.

Only municipalities in the states of Amazonas, Guainia and Vaupes report zero investors. While the pyramids' stronghold was in the southwest, 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. As a matter of fact, out of the individuals investing in DMG whose origin we were able to proxy, close to a third were from Bogota. Other smaller municipalities like Suesca, Sopó and Tocancipá—all in Cundinamarca and near Bogotá—made it into the top twenty, with large numbers of per capita investors corresponding to figures above 10%.

[8] The population 14+ for each municipality is taken from the DANE, Colombia's statistical agency.
[9] The top five municipalities are Valle del Guamuez, Nariño, Orito, Mocoa, and Sibundoy.

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



We also use the location of investors and information on their investments and losses or profits to further explore the size and scope of the pyramids. In particular, we 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.[10]

[10] Annual municipal public expenditures are taken from DNP—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, in the southwest of the country. Aggregate net revenues are only positive in a few municipalities. Expressed as a percentage of municipal annual expenditures, five municipalities had in terms of profits a net balance above 10%. With the exception of Zipaquirá (which is located near Bogotá, in the center 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 within the financial sector, presumably to leverage their investments. Moreover, we would also like to know whether they were paying their loans back on time. Our prior assumption is that they should have paid the loans back on time while the pyramids were functioning, but afterwards, once the pyramids had been shut down, they may have had trouble paying them back.

To address these questions, we first built a control group of investors by identifying individuals in the SISBEN who did not participate in the pyramids, but who shared similar 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 in the appendix) 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 provides us with individual semiannual loan stocks and (ex-post) loan ratings from 2006 until 2010.

Since to comply with the habeas data regulation, the dataset had to be merged by staff from the Superfinanciera, we agreed with them that the dataset would only have one control individual per investor. The controls were chosen with a

matching algorithm of the nearest neighbor according to the PSM described in the appendix.[11] The anonymized sample returned to us by the Superfinanciera—which contained information on the treatment (investors) and control groups (similar individuals according to the propensity score)—comprised 269.855 investors and the same number of controls. The descriptive statistics of this sample are also provided in the appendix.

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 run panel data fixed effects regressions of the following kind, with standard errors clustered at the municipal level:

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

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 data is semiannual from 2006 through 2010.[12] $Treat_i$ 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 denotes whether respective variables differ between the treatment and control groups over time.

As mentioned in the previous section, the effects that we estimate should be interpreted as a lower bound of actual impacts for two reasons. First, the SISBEN sample does not survey individuals in the upper brackets of the income distribution, which also happen to comprise those with the greatest access to credit from the financial sector. Second, it is conceivable that a few of the investors we were unable to match due to errors in the ID ended up in our control group. This would also attenuate the size of our coefficients.

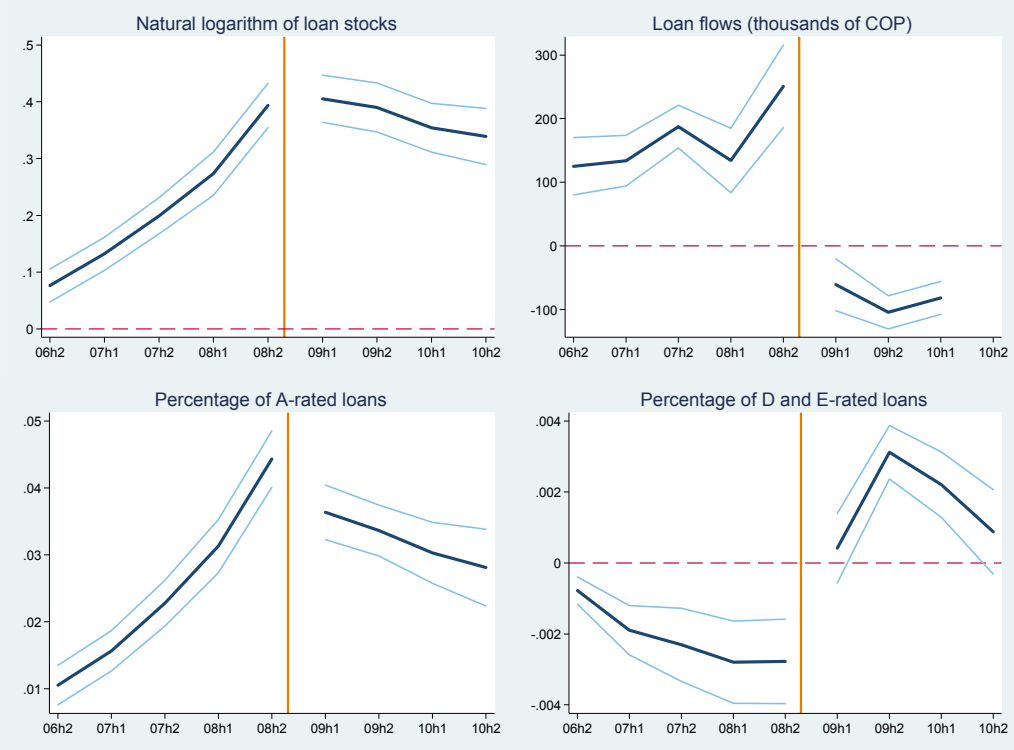
To summarize the results, we report plots of β_t over time with 90% confidence intervals. Figure 1 reports four subplots. The top left one reports the coefficients

[11] To comply with the habeas data regulation of Colombia, the Superfinanciera suppressed the IDs and replaced them with fictitious ones in the dataset they returned to us. In addition, they rounded some of the variables to avoid re-identification of the individuals.

[12] To avoid collinearity, we drop the 2006-1 coefficients.

when y_{it} is the stock (in logs) of consumer loans (including credit cards); the top right one looks at the flows of consumer loans, that is, the change in the stock of loans for each individual from one semester to the next. At the bottom, we look at the results when the variable of interest is either the proportion of ex-post good quality consumer loans (the left hand, labeled "A rated loans") and nonperforming 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—if they are—they are not overdue by more than a month. Nonperforming loans, that is, loans in categories D or E, are overdue by more than three months.

Figure 1. β_t for consumer loans - complete sample. 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.



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 where 39.3% higher than for non-investors. Consistent with the timing described when discussing the history of the pyramids, 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 7.6%.

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 DMG and DRFE being shut down—the largest coefficient is 4.43%. This is a large figure: in our control group, 13.6% of credits are A-rated.[13] The coefficient in the regression therefore implies that for investors, the proportion of good quality loans rose by close to 33% while the pyramids were functioning. As for bad quality loans, the last coefficient while the firms were still operating is 0.279%. Since the stock of bad quality consumer loans for the control group is 0.9%, the proportion of bad quality loans fell by 31% 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 after the pyramids ended to negative figures, close to 100,000 pesos (US$43) per loan and period: the increasing trend in the difference in loan stocks between investors and non-investors prior to the vertical line, therefore, was reversed. In terms of bad loans (D- and E-rated) the largest coefficient after the pyramids ended is 0.311 percentage points—that is, an increase in bad loans of 35% relative to the control

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

group. Consistent with the latter, the proportion of investors' good quality loans began a steady decline after the pyramids were shut down.

Further results-Loans

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 focus on the highest quintile, those on the right hand, on the lowest. The scales on the axes are identical in order to facilitate the comparison.

The qualitative patterns when we split the sample between high and low investment quintiles are very similar to those uncovered when looking at the whole sample. Pyramid costumers' obtained more loans from the financial sector and their credit standings where better than those in the respective control groups while the schemes were in business—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.

The qualitative similarities between the two quintiles hide important quantitative differences. Prior to the pyramids being shut down—and relative to the respective control groups—the increase in the loan *stocks* of those in the highest quintile of investments is almost 11 percentage points above those in the lowest quintile. Once they were put out of business, the loan *flows* fell by 360,000 pesos (US$ 162) in the highest quintile, 20 times more than in the lowest. The non-performing loans increased by 38% for the highest quintile at their peak after the pyramids were shut down, compared to 21% for the lowest quintile (relative to the respective control groups).

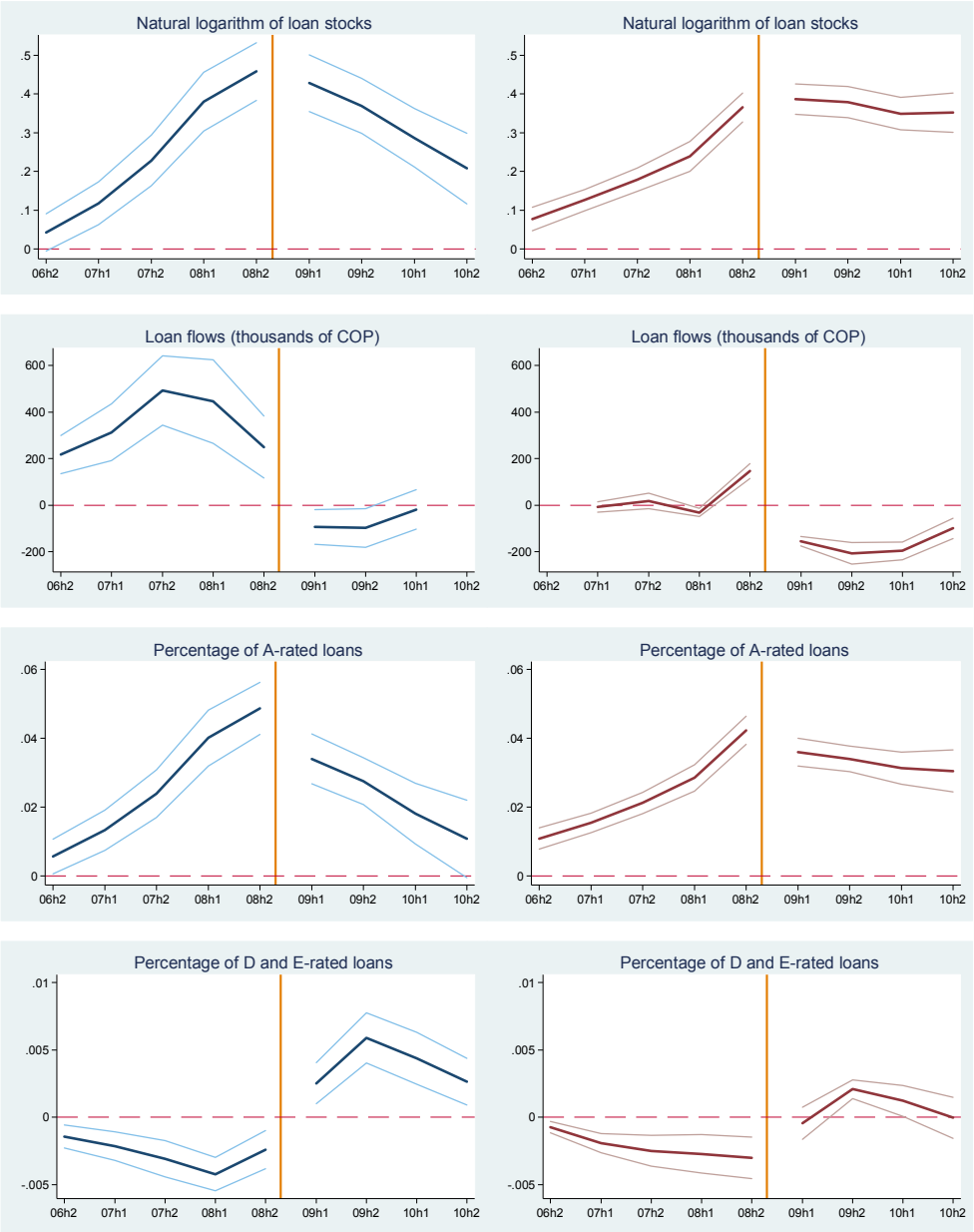
Figure 2: β_t for consumer loans. Left hand plots: highest quintile of investments; right hand plots: lowest quintile of investments. Fixed-effects panel data regression results with 90% confidence bands and clustered standard errors (municipalities). The vertical line indicates when the pyramids were shut down.

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.

We also study whether there are differences in financial behavior after the pyramids were shut down, comparing investors who lost money and those who actually made a profit. Our prior hypothesis is that, once the pyramids were gone, winners would use the proceeds of their investments to reduce the extra debt they had acquired investing in them. We thus expect their loan stocks to have fallen at a faster rate. We also expect that the winners would have better ex-post credit ratings 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 pyramids were illegal or that they would collapse at that time. 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 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 than the losers' stock of loans, as we anticipated. We also find that the ex-post loan ratings deteriorated more for the winners, a result that is at odds with our prior assumptions: we 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 of them, fewer than a quarter actually had loan ratings in the dataset.

Figure 3: β_t for consumer loans - winners and losers. Fixed-effects panel data regression results with 90% confidence bands and clustered standard errors (municipalities). The regression is estimated for individuals who could be correlated with the SISBEN data. The vertical line indicates the time when the pyramids were shut down. Plots on the left are for winners, those on the right, for losers.



5. Impact on deposits

One popular story told by the founder of DMG around the time the government took control and shut the firm down was that he was being pursued by a bank-conspiracy. His rationale was that the higher yields offered by his business

reduced the deposits that banks were able to attract from the public. Consistent with this claim, Carvajal et al. (2009) mention that there is anecdotal evidence that some of the schemes they analyzed diverted deposits from the financial sector. We estimate—again as far as we are able to tell, for the first time in the literature—whether and by how much the pyramids impacted deposits. We find that the pyramids had significant effects on deposits.

As mentioned, the Superfinanciera does not record data on deposits at the individual level. To study the pyramids' impact on deposits, we exploit the municipal variability in deposits (which the Superfinanciera does report) and the intensity of the pyramids' presence in respective municipalities (we build municipal variables that work as proxies of the relative importance of the pyramids.)

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, again using the location of individuals, we first sum the total amount invested by individuals matched to each municipality, and then calculate the ratio of this statistic 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. The summary statistics of the intensity of pyramids in municipalities. Investors per capita, 14+: I_{pc}. Total municipal investments/municipal expenditures: *K/E*.

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

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

$$y_{ijt} = \beta_{jo} + \beta_{j1}T + \sum_{t=1}^{T} \lambda_t + \sum_{t=1}^{T} \beta_{2jt} X_i \lambda_t + \varphi_i + \varepsilon_{ijt} \,, \qquad (2)$$

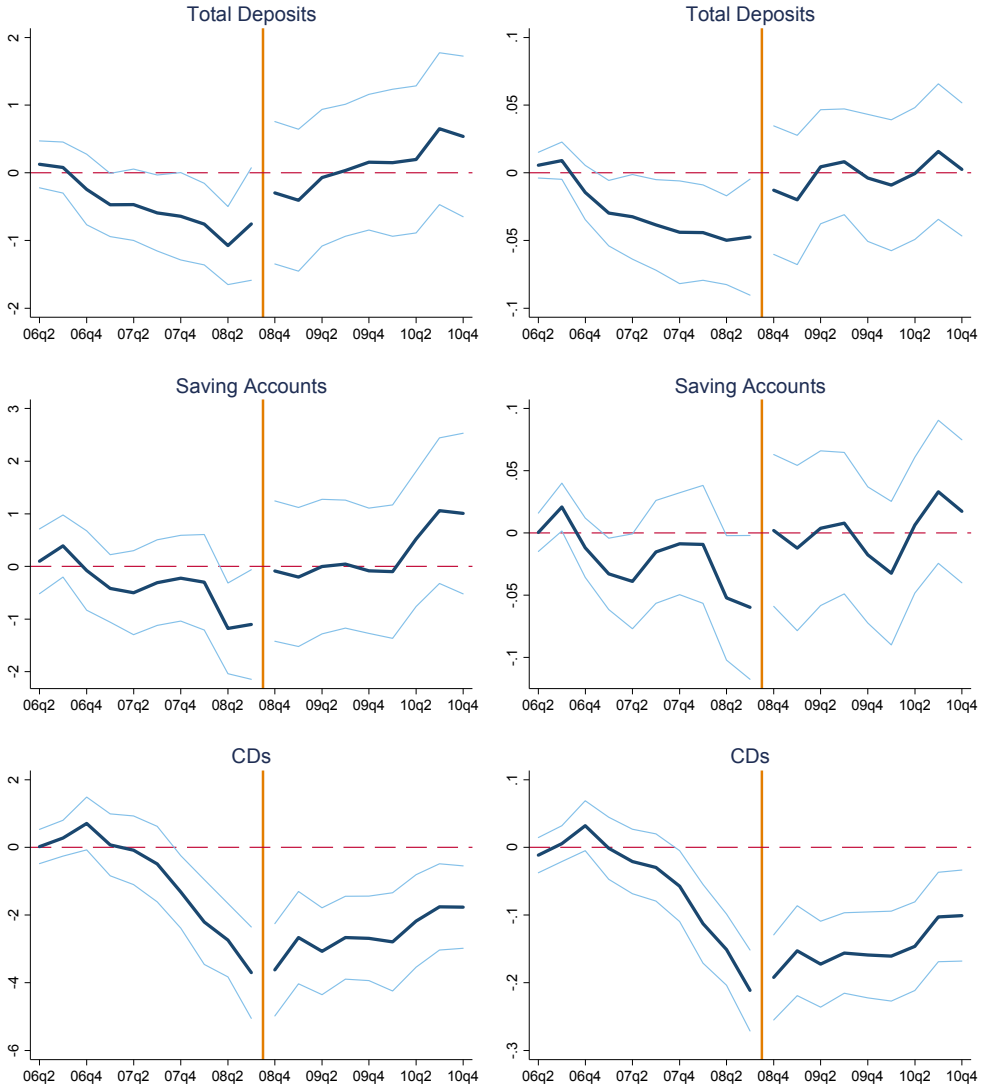
where y_{ijt} refers to the deposits of type j at time t in municipality i in constant pesos and expressed in logs. We estimate this for three types of deposits: total deposits, deposits in savings accounts, and certificate deposits (CDs), which the Superfinanciera records at a quarterly frequency by municipality.[14] β_{j0} is a constant, T is a time trend, and λ_t are quarterly time effects. X_i is either I_{pc} or K/E in municipality i. φ_i is a municipal fixed effect and ε_{ijt} is the error term.[15] We report the results with errors clustered at the municipal level. The results without clusters and with clusters at the state (*departamento*) level yield similar conclusions.[16]

The parameter of interest, β_{2jt}, represents 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_{2jt} should be negative. To summarize our findings, we plot β_{2jt} with 90% confidence bands in Figure 4 for three types of deposits (j) and two proxies of the intensity of Ponzi schemes in the municipalities (X). The left columns use I_{pc}, the right ones, K/E to identify the effects.

The two top plots—that is, those that look at the pyramids' 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 below 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 the pyramids ended, the coefficients again become insignificant.

[14] 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.
[15] We drop the interaction of 2006-I to avoid multicollinearity.
[16] Available from the authors upon request.

Figure 4: $\boldsymbol{\beta_{2jt}}$ **and 90% confidence bands.** The left hand panels are estimated with $j = I_{pc}$; the right hand panels are estimated with $j = K/E$; confidence bands use errors clustered at the municipality level.



What does the size of the coefficients tell us? At the trough for 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 fall if I_{pc} or K/E change by one standard deviation; on the other hand, the table reports the predicted effect on deposit j 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 4—that is, for either the second or third quarters of 2008, the quarters immediately prior to the pyramids being shut down.

As reported in Table 4, a one standard deviation increase in I_{pc} reduces total deposits in a municipality by 2.7%. In the top five municipalities for 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: one standard deviation increase in *K/E* reduces total deposits in the municipalities 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 4, 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* decreased the 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.

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

Total Deposits			
$\beta_{2,\ 08q2}$*SD	-2,7%	$\beta_{2,\ 08q2}$*SD	-2,4%
$\beta_{2,\ 08q2}$*Mean Top 5	-20,4%	$\beta_{2,\ 08q2}$*Mean Top 5	-22,3%
Saving accounts			
$\beta_{2,\ 08q2}$*SD	-2,9%	$\beta_{2,\ 08q3}$*SD	-2,9%
$\beta_{2,\ 08q2}$*Mean Top 5	-22,3%	$\beta_{2,\ 08q3}$*Mean Top 5	-26,8%
CDs			
$\beta_{2,\ 08q3}$*SD	-9,2%	$\beta_{2,\ 08q3}$*SD	-10,2%
$\beta_{2,\ 08q3}$*Mean Top 5	-70,1%	$\beta_{2,\ 08q3}$*Mean Top 5	-94,6%

The bottom panels in both Figure 4 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 investment in pyramids. That is indeed what the results suggest. Both the size and the persistence of the effects are great. 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%; the same statistic, using *K/E* to identify the effect, suggests a reduction of 10.2% in CDs. For the top five municipalities vis-à-vis the presence of pyramids, 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 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, an amount corresponding to 22% of the total deposits of the country's largest bank.

While Ponzi schemes are more common that thought even in developed countries, our understanding of their consequences is mostly anecdotal. Using a unique dataset—merging the universe of investors in the pyramids with their loan records in the formal financial sector—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. A one standard deviation increase in the municipal presence of the pyramids decreased deposits in saving accounts by 2.9% and CDs by more than 9%. *After* the firms were shut down, the ex-post loan ratings of investors deteriorated: nonperforming loans increased by 35% 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.

Beyond being able to pinpoint the effects of Ponzi schemes on the financial behavior of households—as far as we can tell, for the first time in the literature—we believe the lessons learned here extend beyond them. Indeed, some of the effects we were 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 Kindelberger, in his comprehensive history of financial crises (Kindelberger and 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." That 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 related to the studying of the loans, loan ratings and deposits in the financial sector of individuals who invested in assets, and whose behavior we later associate with bubble-like patterns.

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Appendix

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. Table 5 summarizes the results of this analysis, which allow us to conclude that, effectively, no significant differences in observable characteristics exist between the treatment and control groups.

Table 5. Treatment and control groups, descriptive statistics.

Invested in DRFE					
Variables	Mean Control	Mean Treatment	Mean Difference	Imbens Statistic	Significance Imbens
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	3,072	3,101	-0,029	-0,018	

Household head's earnings	$ 160.703	$ 172.144	-$ 11.441	-0,036	
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	3,522	3,882	-0,360	-0,204	
Household head's earnings	$ 275.459	$ 352.992	-$ 77.533	-0,179	
Household's per capita income	$ 124.556	$ 166.102	-$ 41.546	-0,047	
SISBEN score	18,348	21,212	-2,864	-0,240	
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	0,072	0,053	0,019	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	3,156	3,144	0,012	0,007	
Household head's earnings	$ 189.895	$ 202.264	-$ 12.369	-0,038	
Household's per capita income	$ 76.675	$ 80.887	-$ 4.212	-0,029	
SISBEN score	14,676	14,453	0,223	0,023	

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 earnings of the head of the household, the proportion of kids in a household, household size, the household head's years of education, the household head's mean earnings, and the household's per capita income. All these variables were measured during the second wave of SISBEN, conducted between 2003 and 2007, and which collected information on 32.5 million individuals nationwide. (The total population in 2008 was 44.5 million.) This allows us to obtain investors' socioeconomic characteristics prior to the end of the pyramids. Estimates of the probit model are given in Table 6.

Table 6. Probit estimates

Variable	Coefficient	SE
Age	-0.003***	0.000
Income	0.000***	0.000
Sisben score	0.004***	0.000
Years of education	0.029***	0.001
Married	-0.012***	0.002
Widowed	0.055***	0.002
Single/Divorced	0.038***	0.005
Male	-0.011***	0.001
Household head's years of education	0.011***	0.001
Proportion of kids	-0.018***	0.002
Household size	-0.005***	0.001
Household head's earnings	0.000***	0.000
Household's per capita income	-0.000	0.000
State dummy 1	0.251***	0.045
State dummy 2	0.278***	0.044
State dummy 3	0.322***	0.044
State dummy 4	0.305***	0.042
State dummy 5	0.328***	0.041
State dummy 6	0.185***	0.048
State dummy 7	0.283***	0.043
State dummy 8	0.344***	0.041
State dummy 9	0.246***	0.046
State dummy 10	0.376***	0.036
State dummy 11	0.378***	0.040
State dummy 12	0.285***	0.044
State dummy 13	0.350***	0.040
State dummy 14	0.254***	0.047
State dummy 15	0.350***	0.039

State dummy 16	0.358***	0.038
State dummy 17	0.362***	0.043
State dummy 18	0.201***	0.047
State dummy 19	0.215***	0.047
State dummy 20	0.260***	0.045
State dummy 21	0.187***	0.048
State dummy 22	0.279***	0.045
State dummy 23	0.172***	0.048
State dummy 24	0.090*	0.049
State dummy 25	0.204***	0.050
State dummy 26	0.290***	0.043
State dummy 27	0.478***	0.030
State dummy 29	0.088	0.060
State dummy 30	0.106	0.068
State dummy 31	0.127**	0.053
State dummy 32	0.196**	0.100
State dummy 33	0.211***	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 Andres) is dropped to avoid collinearity. Likewise, the comparison category for marital status is *Cohabitation*. *** p<0.01, ** p<0.05, * p<0.1.

The estimation results in Table 6 indicate that, according to our model, the probability of investing in Ponzi schemes negatively correlates with age, being married, being male, household size, and larger proportions of kids. Larger households with larger proportions of kids and lower per capita incomes probably cannot spare any money to invest in Ponzi schemes, and thus definitely act against the probability of investing. On the other hand, the probability of investing positively correlates with being widowed, single or divorced. Likewise, it seems to relate positively to a household head's earnings, and with being located in the states of Putumayo (State dummy 27), Cundinamarca (State dummy 11) and Nariño (State dummy 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 6 depicts the kernel densities of the propensity scores for both investors (treat) 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 & Rodriguez-Oreggia, 2009). This leaves us with 269,855 investors and the same number of controls.

Figure 6. Kernel densities of propensity scores for investors and non-investors in the SISBEN survey.