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How Do Investment Ideas Spread through Social Interaction? Evidence from a Ponzi Scheme

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ABSTRACT

A unique data set from a large Ponzi scheme allows me to study word-of-mouth diffusion of investment information. Investors could join the scheme only by invitation from an existing member, which allows me to observe how the idea spreads from one person to the next based on inviter-invitee relationships. I find that the observed social network has a scale-free connectivity structure, which significantly facilitates the diffusion of the investment idea and contributes to the growth and survival of the socially spreading Ponzi scheme. I further find that investors invest more if their inviter has comparatively higher age, education, and income.

SHILLER (2000, 2014) ARGUES THAT INVESTMENT ideas can spread like epidemics among investors, with asset prices influenced by social dynamics. In this paper, I examine whether large-scale social contagion effects among investors exist, and if so, what the information diffusion process looks like.

To do so, I employ a data set in which I directly observe the diffusion of an investment idea from one person to the next. The data set consists of participants of a large investment Ponzi scheme, whereby investors could join only by personal invitation from an existing member, who was referred to as a sponsor. This feature allows me to study the effect of word-of-mouth information at an individual level. Information about the scheme was not publicly available, so

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when a new investor joins, I know that he has learned about the opportunity from the inviter. By observing the inviter-invitee social network, I am able to examine the process through which an investment idea spreads across a population.

The investment scheme, Wincapita, was a Finnish investment operation that was active from 2003 to 2008. Wincapita offered its investors large returns, initially claiming that the profits were generated by sports betting and later by currency trading. In reality, it was a classic Ponzi scheme whereby all incoming cash flows came from new and existing investors, with none of the profits generated by actual trading or investments. The scheme grew very large, ultimately growing to over 10,000 members, approximately 0.2% of the total population of Finland.

The collapse of Wincapita in 2008 led to one of the largest criminal investigations in Finnish history.[1] The data used in this study come from the investigation documents of the Finnish National Bureau of Investigation.[2] The documents allow me to identify over 5,000 Wincapita investors and contain detailed information for over 3,000 investors who were questioned by police. In addition to details about their investments and withdrawals, these data contain information on investors' personal characteristics, such as age, income, location, and education. I combine these data with information on their sponsoring relationships.[3] Because the data were collected from investors in a formal police interview, they do not suffer from many of the typical reporting and selection biases that exist in survey data on social relationships. The interviewing officer's responsibility was to collect facts that could be used as evidence in a court of law.

Several papers provide theoretical models of information diffusion and the structure of information networks among investors.[4] I present empirical evidence on these phenomena. In particular, the data allow me to shed light on the social network structure of information diffusion among investors. Empirical social networks that connect people through different kinds of personal ties exhibit strong structural regularities and differ significantly from random graph networks in which the connections between nodes are evenly distributed

[1] Reported by YLE News on May 5, 2008 ("Wincapitasta tulossa maan laajimpia rikostutkintoja.")

[2] Finnish National Bureau of Investigation, 2010, Esitutkintapöytäkirja 2400/R/61/10.

[3] There was a financial incentive to sponsor others. Sponsors received €200 of (virtual) money for each sponsored investor and 20% of the virtual profits earned by the sponsored investor's investments (I discuss this further in Section I below). A sponsor's sponsor would not receive any portion of these profits, so Wincapita was not a traditional pyramid scheme whereby the profits are determined by the investor's level in the "pyramid."

[4] Stein (2008), Han and Yang (2013), and Andrei and Cujean (2017) model the transmission of information through personal communication between investors. Ozsoylev and Walden (2011) study the asset pricing implications of large information networks. Shiller and Pound (1989), Shiller (2000), and Shive (2010) argue that epidemic models can be used to characterize the diffusion of social interest among investors. For general models of word-of-mouth communication, see Ellison and Fudenberg (1995), Banerjee and Fudenberg (2004), and Cao, Han and Hirshleifer (2011).

(see Jackson and Rogers (2007) for a review). However, because the diffusion of word-of-mouth information is typically unobservable, there is little evidence on whether these structures play a role in the diffusion of information within the networks. In social networks, the distribution of connections per node typically has a heavy right tail, and the average node to node distances are short. I find that both of these characteristics exist in the diffusion process of Wincapita.

In particular, the distribution of the number of connections per node in Wincapita's sponsoring network decays approximately as a power law. The empirical probability of sponsoring k investors is proportional to the power of k, so that $P(k) \sim k^{-\gamma}$ where γ is a constant. The power-law characteristic is visually apparent in a log-log plot, and Kolmogorov-Smirnov test statistics based on a fitted power-law model strongly support the view that the data follow a power law. Networks with this structure are known as scale-free networks, and power-law distributions are very common in empirical social networks (Barabási (2009)). Here, the power law indicates that a small minority of investors are responsible for most of the social effect.

I compare Wincapita's actual sponsoring network to a simulated random network and find that the power-law topology has a dramatic effect on the rate at which information spreads. The random network has the same number of investors, the same percentage of sponsors, and the same average number of sponsored investors per sponsor. The only difference compared to the actual network is that the distribution of the number of sponsored investors follows a Poisson distribution instead of the power law, as in the model of Erdős and Renyi (1959). The results show that an epidemic that spreads through the Wincapita network one step at a time reaches all investors in 15 steps. In comparison, in the simulated network, it takes an average of 161 network steps to reach the same number of investors. When I calibrate a simple Ponzi scheme model to both networks, I find that the actual network can sustain significantly higher payouts relative to investors' investments without collapsing.

The network structure also provides information about the diffusion dynamics of Wincapita. I find that the cumulative number of investors as a function of network distance from the originator of the scheme follows an S-shaped curve. The S-curve implies that information diffusion within social networks progresses in a nonlinear fashion.

I next analyze how social connections within the scheme are related to participants' investment decisions. After controlling for personal characteristics and inviter fixed effects, I find that investors invest statistically significantly more if their inviter has comparatively higher income, age, and education. The marginal effect of the inviter's income is highest when it is just above the invitee's income, suggesting that it may be a reference point in decision making. I also find that sponsors invest more than nonsponsors, which indicates that social behavior and investment behavior are correlated among investors.

This paper contributes to the literature in several ways. First, I show that an investment idea can spread across the population through social interaction, gradually affecting larger and larger groups of people, as predicted by Shiller (2000). The existence of behavior contagion in the capital markets is well documented,[5] but whether word-of-mouth information can lead to large-scale diffusion of behaviors that can be characterized by epidemic models is an open question in the literature. In this paper, I observe an epidemic that is spread solely by word-of-mouth communication.

A major implication of Wincapita's network structure is that an investment idea can spread rapidly and extensively through social interactions even if most people are just passive receivers of information or share the idea with only one or two others. The connectivity structure of scale-free networks is dominated by a few highly connected hubs, and models in network epidemiology show that epidemics arise and spread in scale-free networks at a much faster rate than in random spreading, where each infective individual is equally likely to spread the epidemic (Pastor-Satorras and Vespignani (2001), Barthélemy et al. (2004)). The highly connected hubs facilitate the diffusion of epidemics because, all else being equal, people with many social connections are more likely to be infected early when an epidemic spreads through the network. The models show that an epidemic starting at a random point in any scale-free network will quickly reach a highly connected hub, and in the next stage, the hub will infect a large number of nodes. The model calibration exercise in this paper further shows how this commonly observed social network structure can contribute to the growth and survival of socially spreading Ponzi schemes.

More generally, my findings provide support for the use of a scale-free topology in modeling information networks among investors. Real-world social networks may not be completely pure scale-free networks, but a power-law model clearly characterizes the Wincapita network better than a random graph model. Ozsoylev and Walden (2011) derive asset pricing implications of a scale-free information network between agents and motivate their choice of network topology by the prevalence of scale-free structures in empirical networks.

The observed S-shaped curve in information diffusion is consistent with extant theories on social diffusion among investors. Shiller and Pound (1989), Shiller (2000), and Shive (2010) argue that susceptible-infective-removed type

[5] Shiller and Pound (1989) argue that interpersonal communication significantly affects individual investors' decision. Shiller (2000, 2014) argues that diffusion of investment information across social networks plays a crucial role in the formation of asset pricing bubbles. Empirically, prior evidence indicates that social interaction affects bank run participation (Kelly and Ó Gráda (2000), Iyer and Puri (2012)), professional money managers' portfolios (Hong, Kubik, and Stein (2005), Pool, Stoffman, and Yonker (2015)), retirement plan decisions (Duflo and Saez (2002, 2003)), stock market participation (Hong, Kubik, and Stein (2004), Brown et al. (2008)), trading behavior (Hong, Kubik, and Stein (2005), Ivković and Weisbenner (2007), Hvide and Östberg (2015)), and trust in financial institutions (Gurun, Stoffman, and Yonker (2018)). Personal information networks can also affect investors' trading returns (Ozsoylev et al. (2014)) and they play an important role in illegal insider trading (Ahern (2017)). See Hirshleifer and Teoh (2009) for a general review of behavior contagion in capital markets.

epidemic models commonly used to model the diffusion of diseases can be used to characterize diffusion of interest in individual stocks. Such models imply that the cumulative number of people affected by an epidemic follows an S-shaped logistic curve over time.

The finding that investors invest more relative to their own income if their sponsor has comparatively higher age, income, and education suggests that the source of word-of-mouth information matters, with investors paying more attention to information that comes from a source perceived to be credible. The observation that investors invest more relative to their own income when their sponsor has comparatively higher income is also consistent with "keeping up with the Joneses" behavior.

The results of this paper are also related to the literature on outcome-based learning in investment decisions.[6] The track record of high returns earned by Wincapita members was undoubtedly helpful in recruiting new investors. The relevance of peers' personally generated financial gains, together with the observed S-curve, can explain why social epidemics among investors can take years to develop. Several generations of new investors with personal profits may be required before a socially spreading investment idea reaches a tipping point, infecting a sufficiently large number of investors, that growth is rapid thereafter.

The rest of the paper is organized as follows. Section I provides background on the scheme, describes the data, and summarizes investor characteristics. Section II studies the diffusion of the scheme focusing on network characteristics. Section III examines the role of personal characteristics in the diffusion of investment information. Section IV studies investors' investment decisions. Section V concludes.

I. Background, Data, and Investor Characteristics

This section provides background on Wincapita, describes the data, and summarizes Wincapita investor characteristics. All information in this section (unless otherwise stated) comes from the police investigation documents related to Wincapita.[7]

[6] Shiller (2000) argues that extrapolation from observed high returns can generate naturally occurring Ponzi processes in the market. Kaustia and Knüpfer (2012) show that recent stock returns of peers affect stock market entry decisions. They also argue that extrapolation from others' outcomes can play a part in the success of Ponzi-type securities scams. Han and Hirshleifer (2013) argue that investors are particularly likely to discuss their positive returns with others, which can result in a self-enhancing transmission bias in word-of-mouth communication.

[7] A detailed description of Wincapita's activities is provided in sections 3 to 9 of the police investigation material. Early media reports following the collapse of the scheme contained many inaccuracies related to the details and rules of the scheme, because little information was publicly available. Inaccurate information still exists in many online sources on Wincapita that use these media reports as a reference. The police investigation, which documented details of the scheme, was concluded in 2010.

A. Wincapita as an Investment Scheme

Wincapita[8] was described to its investors as an investment club that could generate significant profits on members' investments. All operations of Wincapita were carried out on the Internet, and investors used the Wincapita website to manage their investment. The website, which could only be accessed with a personal user name and password, provided general information and news about the club and showed investors how their investment performed over time. Money transfers into and out of the club were handled through a British Internet payment service called Moneybookers. Wincapita had an account with Moneybookers and investors could transfer their money using another account with the same service. Most investors set up their own Moneybookers account but they could alternatively transfer their money using a friend's account.

Wincapita's website and account in Moneybookers were the entire scope of the scheme's operations. When investors withdrew money from the scheme, the funds were paid out of the same account used to invest their funds, and no new funds were generated by actual trading or operations at any point. The virtual profits shown on Wincapita's website were totally fictitious and had no link to any real-world investment assets.

The scheme was run solely by one man named Hannu Kailajärvi. He had computer programming experience, but no background in finance. Although some individuals helped with website updates and practical issues at different stages of the club, the police investigation indicates that Kailajärvi was the only person who knew the entire nature of the operation. Kailajärvi's identity was generally known among investors, but he was rarely in direct contact with them and managed the club through the website and e-mail. Investors were led to believe that the club was a much larger international operation. Kailajärvi managed this deception, for example, by using fictitious names in e-mail responses to give the impression that the scheme had a large number of employees. He also set up shell companies abroad, first in Wyoming and later in Panama. In reality, the club did not even have a bookkeeping system or a legal structure. The shell companies provided Wincapita with documentation that could be shown to investors, but they had no actual operations.

B. Timeline of the Events and the End of Wincapita

Wincapita began operating in the fall of 2003 and originally claimed that it was generating profits for investors using a betting system for international horse racing. In early 2005, the club announced that it would shift its focus to currency trading. From that time until the end of the scheme in 2008, the source of income was claimed to be a trading system that could create large

[8] The name of the club changed twice during its existence. Initially, the club was named Giiclub; between 2004 and 2007, it was named Winclub. For clarity, I refer to it as Wincapita throughout the text. Wincapita is also the general name the police investigation documents use when referring to the scheme. In the scheme's internal communications, the name was often spelled with a capital C (WinCapita).

profits by day trading on the EUR/USD exchange rate. Wincapita further stated that it planned to generate additional earnings in the long run by licensing and selling its trading system to international customers. A feature that may have strengthened investors' faith in Wincapita toward the end of its existence was that they could follow trading signals allegedly generated by the club's computer system in real time through a web application. The application showed actual real-time EUR/USD currency data together with different "signal markers," whose functioning was not divulged to investors. Details about the club's operations were often referred to as business secrets, which kept members in the dark about its actual activities. They could follow the profits their investments had earned, but were not informed about the specific transactions or trades that generated them.

Wincapita first came to public attention in September 2007 when an investigative TV-journalist broadcasted a news story about the club and raised doubts about its profit mechanism, speculating that it may function like a Ponzi scheme.[9] Paradoxically, police interview transcripts indicate that the media coverage strengthened many investors' faith in the club. The club continued to operate without any significant reaction from authorities, and a number of investors assumed that the authorities had investigated the club and found its operations to be legitimate.

Wincapita's activities ended in the beginning of March 2008 when Hannu Kailajärvi fled from Finland and shut down the club's website. He evaded the police for nine months and was finally arrested in northern Sweden in December 2008 after an international manhunt. Kailajärvi destroyed the club's records and website while on the run, thus denying investors the ability to withdraw any money from the club. Wincapita's bank account had a balance of €4.8 million at the time of Kailajärvi's disappearance, soon after which the account was frozen by authorities.

Police investigation of Wincapita's bank statements shows that the total amount of funds that investors transferred into Wincapita during its existence exceeded €100 million.[10] The police interview transcripts indicate that the collapse of the club not only led to large financial losses, but also destroyed personal relationships between sponsors and their sponsored investors. The documents contain several mentions of suicides, divorces, and mental health problems following the club's collapse, with the social invitation structure possibly contributing to these consequences. Kailajärvi's disappearance and arrest also sparked conspiracy theories among some Wincapita members, with the interview transcripts indicating that several investors refused to accept that the club had been fraudulent, regardless of the police evidence.

The main reason Wincapita could operate without interference for so long was that it was difficult for the Finnish authorities to obtain information on

[9] The police documents identify this news story, which aired on September 23, as the first public news coverage about the scheme.

[10] This figure comes from police investigation material section 4.4, which provides an analysis of Wincapita's bank statements and investors' aggregate deposits and withdrawals.

its operations. In particular, because of the sponsorship system, there was no publicly available information about the club, and as long as no one suffered any losses, there was no imminent cause for a police investigation. Currency trading is less regulated than most other areas of the financial markets and the Finnish Financial Supervision Authority deemed in the fall of 2007 that, based on available information, Wincapita's operations did not fall under its supervision. Many potential sources of information were located abroad and could not be accessed by the authorities absent clear evidence of a crime: when Wincapita folded, its remaining shell company was in Panama, its bank account was in the United Kingdom, and the website was on a server in Luxembourg.

C. Wincapita's Rules and Investor Incentives

According to police documents, the fictitious returns earned by investors were in the range of several hundred percent over a period of six months (there is some variation depending on the time and source). Kailajärvi destroyed all of Wincapita's records and web content when he fled, so police estimates are based on witness testimonies and copies of material and printouts collected from investors. Records of the virtual funds that investors had in their account were also destroyed.

Wincapita stipulated that when a member made an investment, the invested funds had to stay in the club for a minimum of six months. After that, the funds, including the makeshift profits, could be reinvested or withdrawn (in full or part) from the club upon request. The minimum investment required to join the club increased throughout its existence, to €3,000 by the time the club collapsed. Part of the initial investment was said to cover the fees of the club. Members could gain additional profits by recruiting new investors into the club, but they were not required or expected to do so. Investors received €200 of virtual funds in their Wincapita account for each person they sponsored, as well as 20% of the profits generated by the funds that were invested by their sponsored investors.[11] A sponsor's sponsor would not receive any part of these profits. In addition to 20% of an investor's profits that went to their sponsor, 10% were said to go to the club to cover its costs, so an individual investor would receive a total of 70% of the virtual profits "earned" by their investment.

Wincapita required that sponsors personally know all of the investors who they invite to join the club as the club did not want to attract public attention. A copy of its rules obtained by police shows that Wincapita explicitly forbade members from distributing information about the club through websites, news groups, web forums, mass e-mails, or other forms of public media.

Although public distribution of information about the club was forbidden, active Wincapita investors occasionally organized Wincapita-related meetings

[11] According to police documents, these rules were in place since at least January 1, 2007. There may have been some variation in the figures before that date. The general sponsoring system remained similar over the course of Wincapita's existence. Evidence on Wincapita's rules is recorded in the "Attachments to the Introduction" section of the police investigation material (pages 2294-2339).

that were attended by other club members and friends who were potentially interested in investing in the club. Some of the meetings were purely social events, such as Christmas parties and boat cruises, while others were information sessions about the club and its developments. Wincapita's rules required that the meetings could not be open to the general public and members had to seek permission from the club before they could organize any Wincapita-related event. Police interview records indicate that 11% of the investors questioned had participated in a Wincapita-related meeting.[12]

As Ponzi schemes usually offer significant profits to investors who join early, it is natural to wonder whether certain investors suspected that they were investing in a Ponzi scheme and tried to strategically benefit from it with the intention of reaping the early profits. In the case of Wincapita, it would have been very difficult to carry out such a strategy. Chapter 10 of the Finnish Criminal Code mandates that any financial gain made as a result of criminal activity has to be paid to the state even if the person receiving the gain has not committed a crime and has acted in good faith. After the police investigation began, this law was applied to investors who had made large gains from Wincapita with an amount of their assets equal to their net gain from Wincapita frozen by the authorities.[13] Another factor that would have made such strategic behavior very risky is that investors were required to commit their funds for a period of six months, which is a long time to wait if the scheme might collapse at any moment. Even if some individuals tried to behave strategically despite these considerations, they still would have learned about the scheme from an investor they know personally, and hence the investment decision would have been based on socially transmitted information.

D. Description of Data

The data for this study are hand-collected from the police investigation documents of the main criminal case against Wincapita. The investigation documents have been combined into a single formal document known as a pretrial protocol, under the official document number 2400/R/81/10. The pretrial protocol contains a summary of the police investigation, interview and interrogation transcripts, and copies of relevant evidence, such as bank statements, investigation reports, and e-mails. The document comprises more than 53,000 pages of material, the majority of which is related to individual investors' interviews.

[12] When calculating this percentage, I count as a meeting any event outside a club member's home or workplace that was attended by several club members. Early media reports that followed the collapse of the scheme falsely claimed that most investors had joined Wincapita after attending a club-related meetings or social gatherings. This percentage shows that the majority of investors interviewed never attended any such event.

[13] The final decisions on the loss of assets were made in separate trials for each individual. These separate trials could not begin before a final court decision in the main case against Hannu Kailajärvi. In a similar vein, bankruptcy clawback litigation has also been used to recover false profits from Ponzi scheme investors in many cases in the United States.

The content of the pretrial protocol is public information by court decision, but there are legal restrictions on the collection and use of personal information.[14]

The investor data come from the police interviews of Wincapita members, which were carried out between 2008 and 2010. Details on the data collection and specific definitions of different data items are reported in the Internet Appendix. The interview documents record the full name and social security number or date of birth of all investors interviewed. Data items collected from the investigation material include total invested amount, first invested amount, total withdrawn amount, investor gender, age (at the end of 2007), home coordinates, education level, and a binary variable, indicating whether the person is an entrepreneur. Additionally, I match annual taxable income for 2007 to each investor based on a publicly available income listing that contains earned and capital income for all tax subjects for whom one of the two exceeds €12,000 per year.[15]

I identify sponsorship relationships based on answers to several police interview questions, namely, “Who was your sponsor?,” “Did you sponsor anyone?,” and “Do you know people who were above your sponsor in the Wincapita structure?” These questions were asked in all of the police interviews. Based on the responses to these questions, I am able to identify many investors who were not personally questioned by police, and thus add them to the network.[16]

E. Data Limitations

Because I can only observe people who accepted an offer to join Wincapita, I cannot make causal statements about personal characteristics related to the decision to invest. Moreover, I have to limit investment behavior analyses to explaining the amount invested conditional on joining the scheme. One possible concern that arises is that some sponsors may have tried to target higher income friends because the sponsor benefited from Wincapita profits earned by sponsored investors. The findings in Section III.B suggest that such behavior was either not very common or successful, as most investors’ income is lower than that of their sponsor.

Another limitation is that I have to restrict the sample to investors identified in the police investigation documents. To account for possible selection bias

[14] The Finnish Personal Data Act allows personal data to be collected for scientific research purposes. Registry documentation required by the act has been maintained throughout the data collection. The sensitive nature of the data set limits my ability to match these data with other sources that contain personal information. See Internet Appendix Section III for details. The Internet Appendix is available in the online version of this article on the *Journal of Finance* website.

[15] The listing is “Veropörssi Magazine,” which uses Finnish tax authority data as its source. Published listings of similar scope are not available for other years.

[16] The documents do not provide information on people who were invited to join Wincapita but declined, likely because the police were interested only in actual crime victims. By way of analogy, the data that I have resemble a typical data set on disease contagion in the sense that I can observe the diffusion of an epidemic, but I cannot observe people who were exposed to the epidemic but remained unaffected.

Table I

Statistics on Sample Investors and Data Availability

This table reports summary statistics on sample investors and data availability. Panel A provides statistics on data availability based on the number of observations with nonmissing values for different data items. Place in network refers to investors whose sponsor is known or who have sponsored someone. Location is based on the person's street address. Panel B provides summary statistics on investors' personal characteristics. Detailed variable definitions are provided in Internet Appendix Section II

Panel A: Data Availability (Number of Observations with Each Characteristic)

Place in Network	Year of Joining	Total Invested Amount	First Invested Amount
5,523	3,352	3,323	3,204
Annual Income	Location	Education	All Characteristics
2,806	3,280	2,604	2,128

Panel B: Investor Characteristics

Characteristics As % of Observations				
Female	Entrepreneur	Age < 30	Age > 60	
19.72%	25.91%	9.52%	12.31%	
Age at the End of 2007				
Average	First Quartile	Median	Third Quartile	
46.2	37	46	55	
Education Level				
Basic Education	Upper Secondary Education	Higher Education	Master's Degree	Doctoral Degree
12.83%	49.27%	22.39%	14.98%	0.54%
Annual Income (Thousands of Euros)				
Average	First Quartile	Median	Third Quartile	
47.6	23.9	33.7	48.2	

among the investors who police contacted for an interview, I run robustness checks in which I only include investors who contacted the police by their own initiative. Internet Appendix Section IV provides further discussion on potential data limitations and biases and the approaches that I take to address them. The Internet Appendix also discusses the generalizability of the findings in the light of other Ponzi schemes.

F. Investor Characteristics

Table I reports summary statistics for Wincapita investors. The percentage of investors with higher education (at least a bachelor's degree) is 37.9 and the percentage with higher than mandatory basic education 87.2. Average investor taxable income is €47,650 per year and the median is €33,650. The income distribution has a heavy right tail: the highest 10% earn over €74,400, and three individuals earn more than a million euros per year.[17] Comparisons with

[17] When interpreting the income figures, one should note that the observations do not include people whose income is below €12,000. The professions mentioned in the police documents indicate

Finnish population statistics described in Internet Appendix Section V indicate that both education and taxable income are higher among the Wincapita investor sample than among the general population. A possible explanation is that low-income people did not have any savings to invest in Wincapita.

The taxable income figures may include profits withdrawn from Wincapita during 2007. Investors typically reported their withdrawn funds as capital income, which the tax authority taxed accordingly.[18] Whether Wincapita income should be considered different from other sources of income in this paper's analyses can be debatable. On the one hand, it can raise observed income above its "true" earnings-based level. On the other hand, the withdrawn funds could affect the individuals' behavior similarly as other income sources, especially if investors believed that Wincapita would allow them to sustain a higher income level in the future.[19]

Investor summary statistics also show that males and entrepreneurs, who tend to have high overconfidence based on the previous literature, are well represented in the sample. Males constitute 80% of the investors, and 26% are entrepreneurs. By comparison, the percentage of males among Finnish stock market participants is 58 (Keloharju and Lehtinen (2015)), and according to OECD statistics, 6% of Finnish employed males and 2% of employed females were entrepreneurs in 2008. Males have been linked to overconfident behavior and risk-taking in investment decisions (Barber and Odean (2001), Grinblatt and Keloharju (2009)), and entrepreneurial overconfidence is documented by Cooper, Woo, and Dunkelberg (1988), among others.

Table II, Panel A, reports summary statistics on the invested amounts. The statistics show that the average amount invested in Wincapita is €15,100 with a median of €8,000. These invested amounts represent the total amount of funds an investor transferred into Wincapita during its existence. The invested amounts are economically significant, as the median income of an investor is €34,000 per year and the median investor invested an amount that corresponds to 23% of his annual income gross of taxes. Moreover, Keloharju and Lehtinen (2015) report that the median Finnish stock portfolio in 2015 is worth €4,200, which indicates that the median Wincapita investment is almost twice as large as the combined value of all stock holdings of a typical Finnish stock market participant. The smallest Wincapita investment in the data is €20 and the largest is €1.6 million.

that many individuals who do not have income data are not in working life. People in this category include, for example, students, pensioners, and housewives, as well as individuals who live or work abroad.

[18] The full tax implications of Wincapita income (had it been a real investment scheme) may have been unclear to many investors because of its international nature and opaque business model. Investors who did not report all of their withdrawals as taxable income were not necessarily engaging in deliberate tax evasion.

[19] I cannot observe whether the income figures include income from Wincapita, but in a robustness check, I exclude individuals who made withdrawals when analyzing income differences within the sponsor-sponsored investor pairs. When withdrawers are excluded, the average and median income in the data are €46,200 and €33,300 respectively, with the median still higher than in the general population.

Table II

Statistics on Wincapita Investments and Sponsoring Behavior

This table reports statistics on Wincapita investors' invested and withdrawn amounts, year of joining, and number of sponsored investors. Panel A provides summary statistics on the invested and withdrawn amounts based on the money transferred into and out of Wincapita in euros. Panel B reports the distribution of the sample investors' year of joining. Panel C reports summary statistics on the number of people sponsored by a sponsor (an investor who has invited at least one person into the scheme). Statistics in Panel C also include investors who were not personally questioned by police, but could be identified based on other investors' answers during the police investigation

Panel A: Invested and Withdrawn Amounts (Thousands of Euros)

	Average	Min	p25	p50	p75	Max
Total Invested Amount	15	0.02	4	8	15	1,599
First Invested Amount	6	0.02	3	4	7	126
Amount Withdrawn	37	0.004	2	7	24	1,667
Total Invested Amount Minus Withdrawals	6	−1,527	3	6	13	1,597
Percentage of Investors Who Made Withdrawals				26.5		
Percentage of Investors Who Withdrew at Least €1,000				22.5		
Percentage of Investors Who Withdrew at Least €10,000				10.6		
Percentage of Investors Who Withdrew More Money than They Invested				11.9		

Panel B: Year of Joining

	2003	2004	2005	2006	2007	2008
% of Investors	1.4	7.0	10.1	12.0	43.2	26.3

Panel C: Statistics on the Number of People Sponsored by a Sponsor

	Average	First Quartile	Median	Third Quartile	Max	
Value of the Statistic	3.7	1	2	3	120	
Number of Sponsored People	One	2 to 4	5 to 10	11 to 20	21 to 40	Over 40
Observations	650	498	179	64	26	8

The data further show that the percentage of investors who withdrew money from the scheme is 26.5% with 10.6% withdrawing more than €10,000. Most investors who took money out (56%) withdrew less than they invested. Cases where an investor claims to have exited the scheme before its collapse are rare, accounting for 1.2% of the observations.

Panel B of Table II reports the distribution of investors' year of joining. Most investors joined during the last years of the scheme, with 43% joining in 2007 and 26% joining in 2008 before the demise of the club. Based on the annual values, the growth of Wincapita can be described as exponential: an exponential curve ($y_t = ae^{bt}$) fitted to annual observations of the number of new investors has an R^2 of 90.1%, whereas a linear model has an R^2 of 61.5%.[20] The data also

[20] When fitting the curve, I multiply the number of investors who joined in 2003 by 3 and the number of investors who joined in 2008 by 6 to account for the fact that the first investors joined in September 2003 and the scheme ended at the beginning of March 2008.

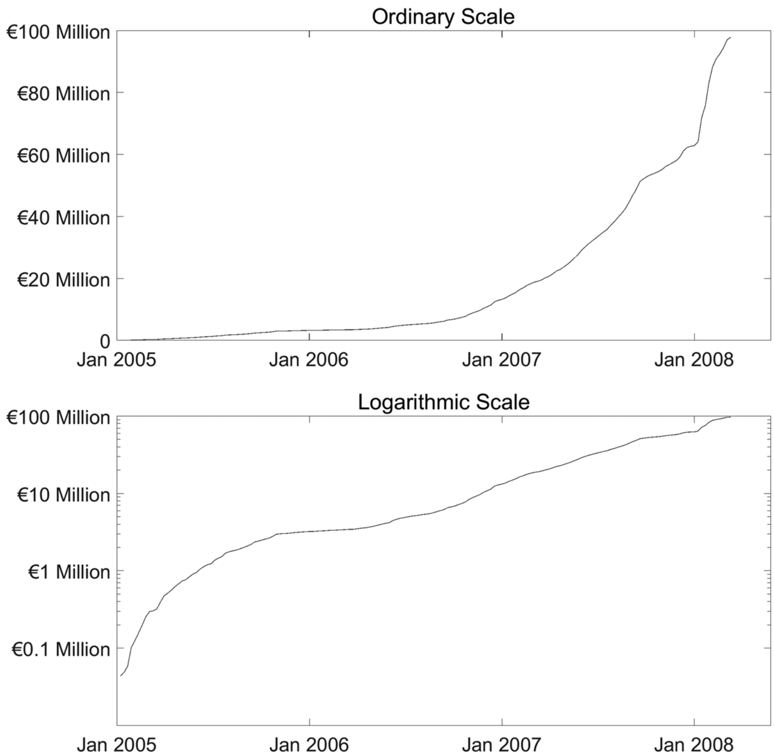

Figure 1. The cumulative amount of funds invested in Wincapita since January 1, 2005. This figure shows the cumulative amount of funds invested in Wincapita between the beginning of 2005 and the collapse of the club in 2008. The figure is based on weekly observations of the amount of new funds transferred into Wincapita's account. The amounts invested before 2005 are not available with weekly accuracy in the police documents and therefore are not included in the figure. The y-axis has ordinary scale in the upper graph and logarithmic scale in the lower graph.

show that it takes a relatively long time for the scheme to be transmitted from one person to the next: for the 1,248 sponsor-sponsored investor pairs for which I can identify the month of joining for both investors, the average difference in their time of joining is 10.7 months and the median is 7 months.

As an alternative way to measure the growth of the scheme, in Figure 1, I plot the cumulative amount of new funds invested in the scheme between January 2005 and March 2008 based on the weekly amount of funds transferred into Wincapita's Moneybookers account. As can be seen, the cumulative invested amount shown grows almost linearly in logarithmic scale after the first few months, which also supports the view that the growth of the scheme was exponential. Compared to a sample of 376 Ponzi schemes prosecuted by the SEC (Deason, Rajgopal, and Waymire (2015)), Wincapita is considerably larger than the median scheme based on both invested funds (median $14.7 million) and the number of investors (median 150).

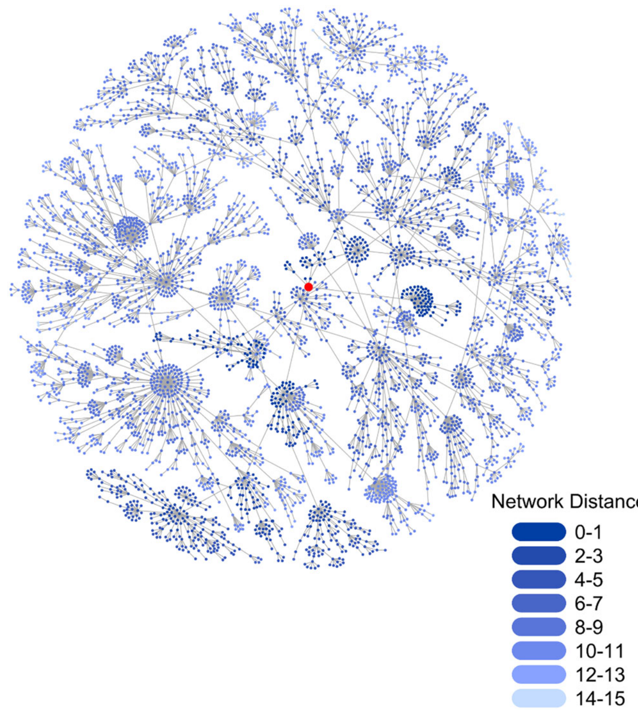

Figure 2. Wincapita's sponsoring relationships as a social network. This graph illustrates Wincapita as a social network. The dots are individual investors and the lines connecting them represent the sponsoring relationships. The larger dot in the middle is the originator of the scheme, Hannu Kailajärvi. The graph includes all investors who can be linked to Hannu Kailajärvi through a chain of sponsors. It is drawn using the Fruchterman-Reingold (1991) algorithm. The distances between points are determined by the algorithm and have no economic interpretation as such. Investors with different network distances are denoted with different color shades. Here, network distance measures the number of sponsors between an investor and Hannu Kailajärvi. Kailajärvi is directly connected to seven investors in the graph. (Color figure can be viewed at wileyonlinelibrary.com)

II. Wincapita as a Social Network

In this section, I study Wincapita's sponsoring relationships as a social network. Specifically, I analyze the connectivity structure of the sponsoring network, the geographic diffusion of the scheme, and the cumulative number of affected investors as a function of network distance.

A. The Structure of the Sponsoring Network and Geographic Diffusion of the Scheme

Figure 2 provides a network graph of the sponsoring relationships based on all investors who can be connected to Hannu Kailajärvi through the chain of sponsors. The large dot in the middle represents Hannu Kailajärvi. The figure can be interpreted as a tree diagram showing how the investment scheme spread from one person to the next. In the popular press, Ponzi schemes are often depicted as pyramids, where each old investor appoints a fixed number of new members. This characterization does not fit the network structure observed in Figure 2, which shows large clusters of investors connected to certain sponsors and most investors not sponsoring another investor.

The network structure also shows that an investor's social influence often extends beyond the people to whom he is directly connected. For instance, if an investor in Figure 2 sponsors another investor, in 39% of cases, at least one of the sponsored investors is also a sponsor who spreads the idea further. The household finance literature has little to say on how widely peer effects spread beyond the first step in social networks.

Figure 3 provides two maps that depict the geographic coverage of Wincapita. The first map illustrates the geographic network of sponsoring relationships based on the home locations of sponsors and their sponsored investors. The areas that have a large number of connections correspond roughly to the largest cities in Finland, and most geographic hubs are also connected to one another. The map indicates that investment ideas travel with people, and even distant cities can have a large number of connections between them. This implies that the routes that are typically traveled by people may be a better predictor of the geographic diffusion of word-of-mouth information than the distance between areas.

The second map summarizes the geographic coverage of the scheme based on the number of sample investors as a percentage of the population in Finnish municipalities. Most municipalities have investors, and 18 out of the 19 Finnish administrative regions (maakunta) are covered. The only exception is the Swedish-speaking autonomous region of the Åland islands.

B. Connectivity Structure of the Sponsoring Network

I next analyze the distribution of the number of sponsored investors among sponsors (investors who invited others into Wincapita). The degree distribution, which captures the distribution of the number of connections per node, is of significant interest in network analysis because it determines the connectivity structure of a network and hence affects the flow of information in social networks (Barabási (2002)).

A common observation in empirical studies on communication within social groups is that the large majority of individuals in a group obtain most of their socially transmitted information from a very small subset of people.[21] Many empirical social networks also have a scale-free connectivity structure whereby

[21] Lazarsfeld, Berelson, and Gaudet (1948) and Katz and Lazarsfeld (1955) provide seminal results on this phenomenon. The fact that a few socially powerful individuals, "market mavens," are important for the diffusion of word-of-mouth information on consumer products is widely recognized in marketing (see, e.g., Feick and Price (1987)). In the field of financial economics, Benartzi and Thaler (2007) provide anecdotal evidence, suggesting that powerful social influencers have a strong impact on retirement plan decisions within a supermarket chain. Banerjee et al.

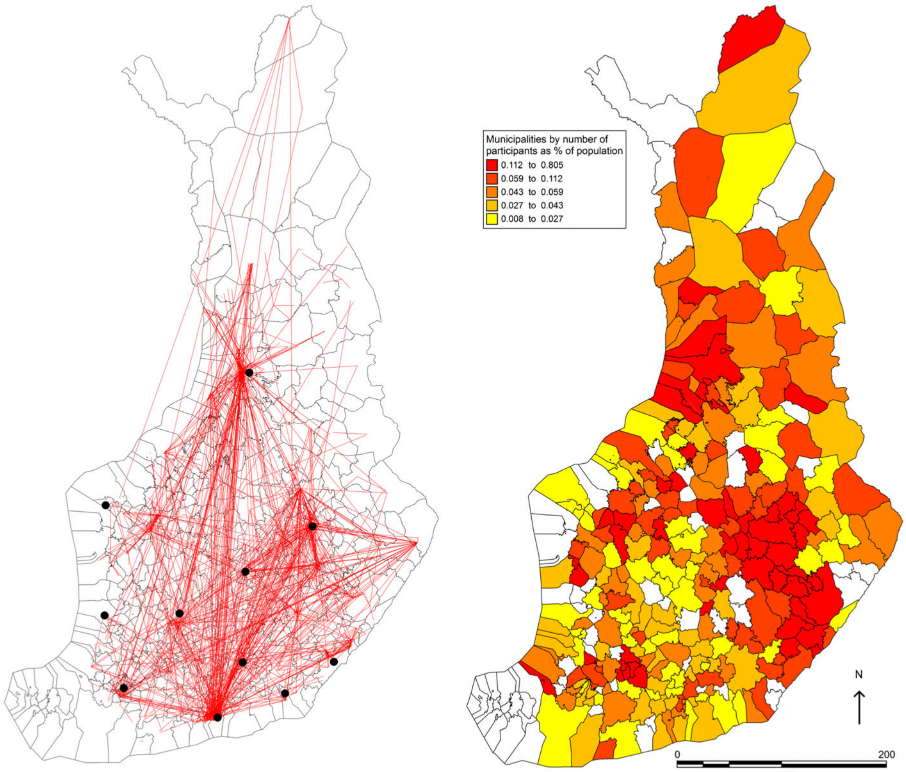

Figure 3. The geographic coverage of Wincapita. This figure provides two maps illustrating the geographic coverage of Wincapita. Both maps are based on the investors who were questioned by police. The map on the left shows Wincapita's sponsoring relationships on a map of Finland. The red lines represent the sponsoring relationships and each line connects an investor and a sponsor. Investors' locations are based on the home addresses reported in the police interview documents. The lines are drawn based on all observations for which both the investor's location and the sponsor's location are known. Investors whose location is outside Finland are excluded. The map also shows the borders of Finnish municipalities in the background. The black circles show the locations of the largest cities in Finland. The locations indicated by the circles include the Helsinki metropolitan area and the 10 next largest cities. The map on the right shows statistics on the number of Wincapita investors as a percentage of the population in different municipalities. The percentages are calculated as the number of investors questioned divided by the total population of the municipality. Different percentage range categories are denoted with different colors and the range corresponding to each color is reported in the figure. The municipalities with white background color do not have any investors in the sample. The true Wincapita investor densities are higher than those shown in the map because the reported percentages are based only on the investors who were questioned by police. (Color figure can be viewed at wileyonlinelibrary.com)

(2014) show that individuals can identify the influencers in their community even if they are not aware of its social network structure. Galeotti and Goyal (2010) provide an economic model that explains the existence of a few powerful influencers through the costs of acquiring personal information.

the heavy right tail of the degree distribution approximately follows a power-law distribution (Barabási 2002, 2009).[22] If the connections between network nodes are instead formed randomly, so that all node pairs have an equal probability of being connected, the connectivity follows a Poisson distribution (Erdős and Rényi (1959)).

I find that Wincapita's degree distribution is highly skewed. Table II, Panel C, shows that 25% of the scheme's investors are sponsors. The average number of sponsored investors across sponsors is 3.72 and the median is 2.0. The largest number of sponsored investors in the data is 120, with 2% of sponsors sponsoring more than 20 investors. To provide evidence on whether the degree distribution exhibits power-law characteristics, I employ two samples. The main sample is based on all sponsoring relationships in the data. The second sample is based on those investors who contacted the police on their own initiative. I refer to the second sample as the restricted sample. (Internet Appendix Section I provides information on why certain people may have been contacted by the police). The restricted sample serves as a robustness check for both possible missing sponsor-investor relationships and possible selection bias among those investors who were approached by the police. In the restricted sample, the number of investors sponsored by sponsor i is given as the number of investors who approached the police themselves and identified sponsor i as their sponsor.

The power-law relationship $P(k) \sim k^{-\gamma}$ implies that logarithms of k and logarithms of the corresponding empirical frequencies are linearly related. Figure 4 provides histograms of the number of sponsored investors for both samples and also log-log graphs of empirical frequencies and the cumulative probability distribution $P(k)$. The log-log plots for both samples approximately follow a straight line after the first observations, indicating that there is negative linear dependency between the two log-variables. The linear shapes in the graphs are consistent with a power-law distribution and the slope is somewhat steeper in the restricted sample.

If the connections between nodes in a network are formed randomly as in the Erdős-Rényi (1959) model, the connectivity always follows a Poisson distribution with a peak at some $P(k)$ and a variance of k equal to the mean k. The histograms in Figure 4 do not indicate such a pattern. In the main sample, the mean is 3.72 and the variance is 46.7, and in the second (restricted) sample, the mean is 1.94 and the variance is 3.96. Based on these figures, the distributions are too overdispersed to fit a Poisson model, and the structure of the network is clearly different from a uniformly random model.

As a more formal test, I fit a power-law model to the data using maximum likelihood optimization. I follow the standard procedure for power-law

[22] The most commonly offered explanation for the power-law distributions observed in empirical social networks is preferential attachment, whereby people with many social connections are more likely to generate new connections in the future. This snowball effect in connectivity over time can result in a power-law distribution in the number of connections per node (Barabási and Albert (1999)). A large number of other empirical regularities in economics and finance also have a power-law form (Gabaix (2009)).

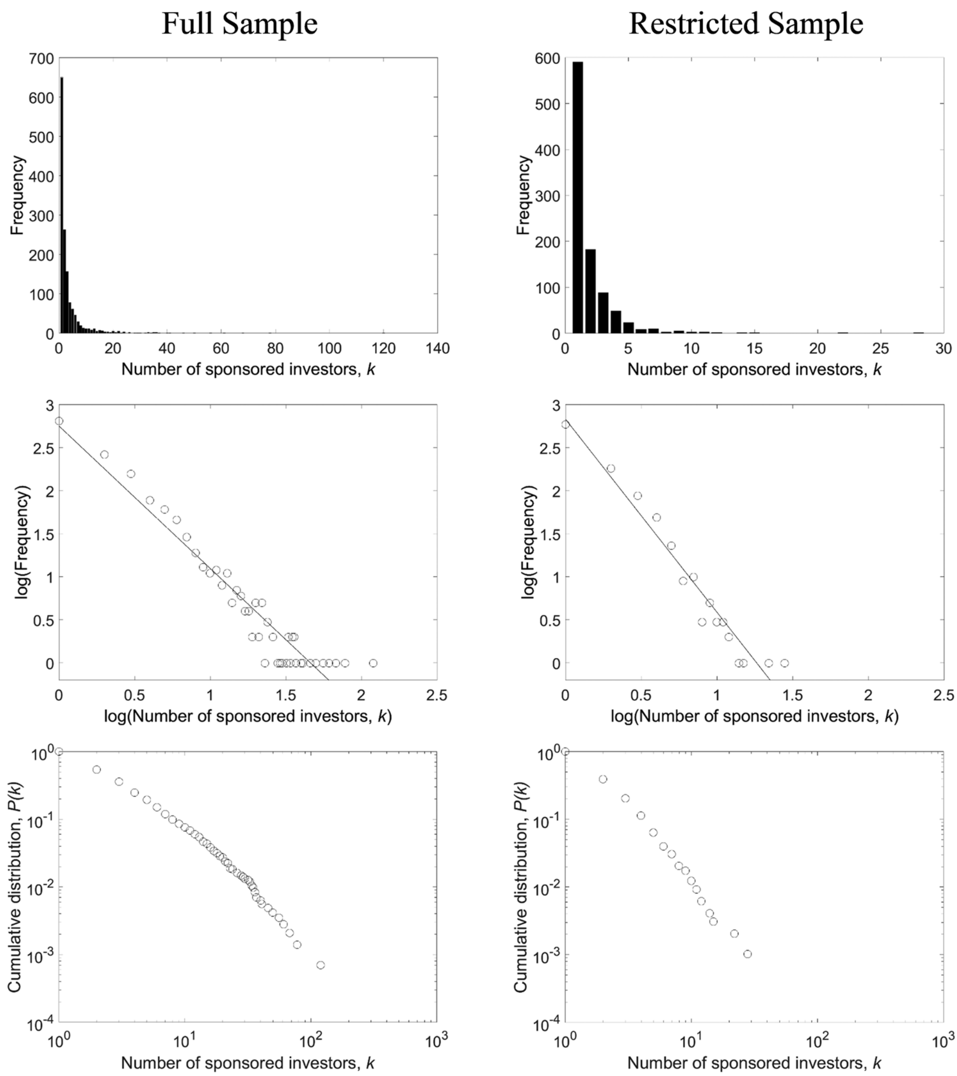

Figure 4. Histograms and log-log plots based on the number of sponsored investors. These histograms and log-log plots show the distribution of the number of investors sponsored by a sponsor in the Wincapita sample. The graphs on the left are based on all observations in the sample and the graphs on the right are based on the restricted sample (investors who contacted police by their own initiative). The histograms plot the frequency of observations on the y-axis and the number of sponsored investors on the x-axis. The log-log graphs in the middle plot log(frequency) based on the number of observations on the y-axis and log(number of sponsored investors) on the x-axis. They also include a fitted linear regression line based on the individual plots. The log-log graphs in the bottom of the figure plot the cumulative probability $P(k)$ on the y-axis and the number of sponsored investors on the x-axis.

tail analysis and fit a power-law distribution where $P(X = k) = k^{-\gamma}$ for distribution values exceeding some threshold value $k_{\min}$.[23] The fitted parameters are $\gamma = 2.38$ and $k_{\min} = 5$ in the main sample and $\gamma = 3.34$ and $k_{\min} = 4$ in the restricted sample. The corresponding Kolmogorov-Smirnov p-values are 0.7139 and 0.9999. These results strongly support the hypothesis that the data have a power-law tail.[24]

To test whether the observed skewness in the degree distribution can be explained by differences in investors' time of joining, I also fit similar power-law models to subsamples consisting of investors who joined during the same year. The number of people sponsored by sponsor i in year t is given as the number of investors who joined Wincapita in year t and identified sponsor i as their sponsor. The power-law relationship exists also in these subsamples from the six years between 2003 and 2008. The lowest p-value is 0.45 in 2004, and the average is 0.86. The average γ from the models is 2.59.

The findings indicate that a power-law model clearly provides a better characterization of the sponsoring network compared to a random graph model, and the diffusion pattern is consistent with an underlying scale-free social network among investors.

C. The Actual Wincapita Network Compared to a Simulated Network

How different would the diffusion process look if the sponsoring distribution followed a Poisson model instead of the power law? I compare the actual Wincapita network shown in Figure 2 to a simulated random network with a Poisson distribution for the number of sponsored investors. I form the simulated network so that the first sponsor is the originator of the scheme and each newly sponsored investor is a sponsor himself with probability p. The number of new investors sponsored by each sponsor is drawn from a Poisson distribution with mean λ. The probability p is equal to the percentage of sponsors in the actual Wincapita network and λ is the average number of sponsored investors among sponsors. I continue adding nodes until the simulated network has the same number of nodes as the actual network.[25] The only difference between the actual and the simulated networks is the distribution of the number of sponsored investors. Both networks have the same probability of being a sponsor (p) and the same average number of investors sponsored by a sponsor (λ).

[23] More specifically, I use the power.law.fit function of package igraph in R programming language. The function is run with the default plfit implementation, which finds the optimal values for $k_{\min}$ and γ using the method of Clauset, Shalizi, and Newman (2009). The reason the parameter $k_{\min}$ is used in empirical power-law distribution fitting is that most observed real-world power-law distributions follow the power law closely only after some threshold level (Newman (2005)).

[24] Note that small p-values (e.g., less than 0.05) indicate that the test rejects the hypothesis that the original data could have been drawn from the fitted power-law distribution.

[25] If the simulation ends up in a stage where the network ceases to grow, because the most recently joined investors have not sponsored anyone, I draw another realization of Bernoulli trials with probability p for the investors who joined in the latest period (i.e., the investors who have the longest network distance to the originator).

Table III

The Actual Wincapita Network Compared to a Simulated Random Network

This table compares the actual Wincapita network to a simulated random network that has the same number of nodes. In the simulated network, the distribution of the number of sponsored people among sponsors follows a Poisson distribution. The mean of the Poisson distribution is equal to the corresponding mean in the actual Wincapita network. The simulated network is formed so that the first sponsor is the originator of the scheme and each newly sponsored investor is a sponsor himself with probability *p,* which is equal to the percentage of sponsors in the actual network. The number of new investors sponsored by each sponsor is drawn from the Poisson distribution. New nodes are added until the simulated network has the same number of nodes as the actual network. The only difference between the actual and the simulated networks is the shape of the distribution of the number of sponsored people. The reported statistics include the maximum network distance required to reach the originator of the scheme, the number of investors within different network distance intervals relative to the originator of the scheme, and the average network distance to the originator of the scheme among all investors. Statistics for the simulated network are based on 10,000 simulation rounds, and mean values, percentiles, and standard deviations are reported for each statistic

	Actual Network	Simulated Network (Statistics Based on 10,000 Simulation Rounds)				
		Mean	*SD*	p25	p50	p75
Network Distance Required to Reach All Investors	15	161	75	102	154	213
Number of Investors with a Network Distance 0 to 5 to the Originator	764	58	38	32	46	71
Number of Investors with a Network Distance 0 to 10 to the Originator	4,177	136	99	72	105	163
Number of Investors with a Network Distance 0 to 15 to the Originator	4,774	235	186	121	173	180
Average Network Distance to the Originator	8.0	97.4	39.4	66.0	93.8	125.4

The shift from a power-law distribution to a Poisson distribution has a dramatic effect on how the number of investors grows as a function of network distance to the originator of the scheme. Table III provides summary statistics comparing the actual network to the simulated random network based on 10,000 simulation rounds. In the actual Wincapita network, all investors are within 15 steps of the originator of the scheme, whereas in the simulated network, it takes an average of 161 steps to reach the same number of investors. Similarly, in the Wincapita network, 4,177 investors have a network distance of 10 steps or fewer to Hannu Kailajärvi, whereas in the simulated network, an average of only 136 investors are within the same distance. Internet Appendix Figure IA.1 provides a network graph based on the simulated network and the contrast to the actual network is clearly visible.

I also analyze how the observed network structure can contribute to the survival of Ponzi schemes. Ponzi schemes need a constant flow of money from new investors to finance payouts to existing investors. Because investors can be reached through fewer social steps in a scale-free network, the network topology can allow socially diffusing Ponzi schemes to maintain a higher payout ratio without running out of money. I calibrate a simple Ponzi scheme model to the actual Wincapita network and the simulated random networks to analyze this phenomenon. In the model, the Ponzi scheme grows step by step through the network, starting from the originator of the scheme. At $t_{1,}$ the people who are directly connected to the originator join the scheme, and at t_2, the people who are connected to them join, and so on until all of the investors in the network have joined. All investors remain in the scheme once they have joined, and thus there are no exits in the model.

I assume that each investor pays the same invested amount I at the time of joining and makes no further investments. Each period, the scheme pays the same fixed payment P calculated as a percentage of I to those investors who were members of the scheme at the end of the previous period. I calculate the highest value P the scheme can pay investors so that the scheme does not have a negative cash balance once it has covered the whole network. In other words, I calculate the highest payout the scheme can afford while remaining operational. Investors who joined in the last period will receive one payment of P.

I find that the actual network can sustain a payout ratio that is more than five times as high as the highest possible payout ratio in the average simulated network. The highest possible P for the actual Wincapita network is 0.125, while the average value for the simulated networks is 0.024. Taken together, the simulation results demonstrate that the observed network topology can contribute to the growth and survival of Ponzi schemes.

D. Implications of the Scale-Free Connectivity Structure

The scale-free network literature offers a formal explanation for why information spreads significantly faster in networks that have a power-law degree distribution. Because of the power law, the structure of all scale-free networks is dominated by a few highly connected hubs, and by construction, scale-free networks have very short average node-to-node distances (Cohen and Havlin (2003)). Furthermore, models in network epidemiology show that epidemics spread through scale-free networks at a much faster rate than in random spreading models where each infective individual is equally likely to spread the epidemic (Pastor-Satorras and Vespignani (2001), Barthélemy et al. (2004)). An epidemic starting at a random point in any scale-free network will quickly reach a highly connected hub, and in the next stage, the hub will infect a large number of nodes. In other words, investors with many social connections facilitate the diffusion of an epidemic because their large number of social connections means that they are more likely to be infected early, and once they are infected,

Table IV

The Relationship between Network Distance and the Number of Sponsored Investors

This table reports how the number of sponsored investors varies as a function of network distance. Network distance is calculated as the number sponsors between investor i and the originator of the scheme (Hannu Kailajärvi) in the sponsoring network. Panel A reports statistics based on fixed network distance intervals of four units and Panel B reports statistics based on network distance quartiles. The quartiles are formed by sorting all investors into groups based on their network distance. Reported statistics for each interval include the number of observations, the percentage of sponsors among the investors, the average number of sponsored people per investor, and the average number of sponsored people per sponsor

Panel A: Network Distance and the Number of Sponsored Investors Based on Fixed Network Distance Intervals

Network Distance Range	0 to 3	4 to 7	8 to 11	12 to 15
Observations	396	1,137	3,036	204
% of Sponsors	25.0	28.7	23.7	12.3
Average Number of Sponsored People per Investor	1.576	1.425	0.809	0.319
Average Number of Sponsored People per Sponsor	6.303	4.969	3.417	2.600

Panel B: Network Distance and the Number of Sponsored Investors Based on Network Distance Quartiles

	Quartile 1	Quartile 2	Quartile 3	Quartile 4
Network Distance Range	0 to 6	7 to 8	9	10 to 15
Observations	1,001	1,250	1,132	1,390
% of Sponsors	28.3	31.0	23.1	17.1
Average Number of Sponsored People per Investor	1.524	1.480	0.701	0.429
Average Number of Sponsored People per Sponsor	5.392	4.780	3.027	2.519

they will spread the epidemic to a large number of people who are within one social step in the network.

In line with this idea, while most investors in the Wincapita network are directly connected only to their sponsor, they are typically only a short network distance away from a highly connected network hub, which connects them to a much larger number of people. The average investor in the sponsoring network of Figure 2 is connected to only two other investors, but the number of people within two steps is 20.5 and the number of people within three steps is 76.5. These values are much higher than, for example, in a network where every person has connections to exactly two other investors in addition to their sponsor.

Consistent with the idea that people with many preexisting social connections heard about Wincapita earlier than others, I also find that highly connected nodes are reached in the early stages of the Wincapita epidemic.[26] Table IV divides investors into groups based on fixed network distance intervals and network distance quartiles using the number of sponsors between the investor and the originator of the scheme as network distance. The average number of people sponsored by an investor in a group decreases monotonically with network distance.

Another implication of the scale-free network structure is that even weakly contagious word-of-mouth epidemics can spread widely in the population. Traditional susceptible-infective-removed type epidemic models, such as those referred to in Shiller's (2000) famous book, *Irrational Exuberance*, predict a critical threshold for the propagation of an epidemic throughout a population. If a disease is less infectious than that epidemic threshold, the epidemic will die out, whereas epidemics with a spreading rate above the threshold will multiply exponentially and penetrate the entire system. Pastor-Satorras and Vespignani (2001) show that in scale-free networks, the epidemic threshold always converges to zero. In other words, even weakly contagious epidemics will spread widely and persist in scale-free networks. This well-known property has been used to explain the rapid diffusion and persistence of sexually transmitted diseases and computer viruses (Barabási (2009)).[27]

In the financial economics context, the scale-free epidemic model explains how socially transmitted investment ideas can spread rapidly even if the average investor discusses them with only a few other people. It also implies that the social epidemics characterized by Shiller (2000) do not necessarily require a high transmission rate to spread extensively, and can arise even if most investors do not distribute information further. Thus, any policy campaign aimed at starting or stopping an epidemic of this kind should focus on identifying the highly connected hubs that play a vital role in the network's connectivity—a scale-free communication network is resilient to random removal of nodes, but collapses quickly if the hubs are removed (Albert, Jeong, and Barabási (2000)).

One may ask to what extent the network topology findings of this paper generalize to other settings. While Wincapita participants may differ from typical retail investors in many respects, a growing body of literature shows that social networks are structurally similar across many different cultural and sociodemographic groups around the world. At least on this basis, there is no obvious reason to believe that the social connections of Wincapita participants are fundamentally different from the connections among other people.

[26] A counterfactual scenario could be, for example, that the power law exists in the data for a reason that is completely unrelated to underlying social connections. Under such a scenario, the number of connections can be independent of network distance.

[27] This follows from the empirical observation that human sexual contacts and computer networks also have a scale-free network structure (Barabási (2009)).

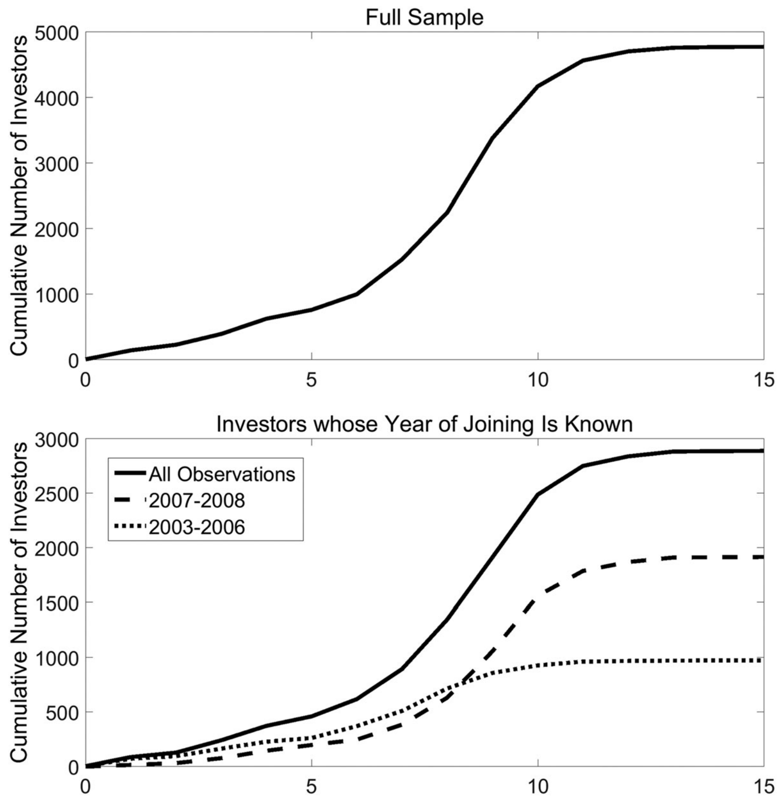

Figure 5. Network distance and the cumulative number of investors. This figure provides graphs depicting the cumulative number of investors at different network distances. Network distance captures the number of sponsors between an investor and the originator of the Wincapita scheme (Hannu Kailajärvi) in the sponsoring network. The structure of the network is shown in Figure 2. The graphs are based on investors for whom the chain of sponsors can be traced continuously to the originator of the scheme. The upper graph is based on all sample investors and the lower graph is based on investors whose year of joining is known. The lower graph includes separate curves based on subsamples of investors who joined Wincapita during 2003 to 2006 and 2007 to 2008.

E. Network Distance and the Diffusion Dynamics of Wincapita

I next use the Wincapita network to characterize how the aggregate number of investors affected by an investment idea grows as a function of social distance from the originator of the idea. This analysis provides insights into the diffusion dynamics of word-of-mouth information within social networks.

Figure 5 provides a graph depicting the cumulative number of investors in Wincapita as a function of network distance. The curve shows how the size of the scheme grows if it starts at Hannu Kailajärvi and spreads across the network depicted in Figure 2 one step at a time. The curve is S-shaped, indicating that the diffusion of information progresses in a nonlinear fashion. The median distance to Kailajärvi is eight steps, with the growth rate slowing down after nine steps. Other graphs in Figure 2 indicate that the S-curve also exists in subsamples consisting of investors who joined during different time periods. Internet Appendix Figure IA.2 shows that a similar pattern does not exist in the simulated random network described in Section II.C.

The S-shaped curve is interesting, as it is in line with the predictions of epidemic models of investor behavior proposed by Shiller and Pound (1989), Shiller (2000), and Shive (2010). In these models, the number of people affected by an idea or behavior grows approximately exponentially in the early stages of the social epidemic. The growth rate then slows down over time because there are fewer people left who are willing to adopt the idea but have not already done so. These models therefore imply an S-shaped pattern in information diffusion.

There are at least two potential explanations for why the growth rate of Wincapita slows down after a relatively low number of social steps. One possibility is that investors who are late joiners find it more difficult to recruit new investors because the subset of their friends who would be potentially interested in the scheme have already joined. The scale-free epidemic literature offers a second, complementary network theory-based explanation. If social networks are scale-free, late joiners are more likely to have few social connections and fewer potential friends to invite.

III. Investor Characteristics and the Diffusion of Wincapita

In this section, I study the role of personal characteristics in the spreading of Wincapita. I analyze how sponsors differ from other investors and I also study differences and similarities in personal characteristics within the sponsor-sponsored investor pairs.

A. Who Are the Sponsors?

Table V provides statistics on the personal characteristics of sponsors compared to nonsponsors. Sponsors have on average higher taxable income than nonsponsors, and they are more likely to be male. The difference in average annual income is €7,400 and the percentage of females is nine percentage points lower than among nonsponsors. For legal reasons, I cannot provide detailed personal information about the most active sponsors, but the statistics show that they are also typically male on a high income. Based on the police interviews, most of them have an occupation or position that puts them in contact with a large number of people on a daily basis. Examples include business-to-business sales representatives, corporate managers, and people who are active within religious communities. This is consistent with the idea that people with a large preexisting social network were the most powerful spreaders of Wincapita.

B. How Do the Investors Differ from Their Sponsors?

Table VI reports statistics on relative differences in personal characteristics

Table V

Personal Characteristics of Sponsors Compared to Nonsponsors

This table compares Wincapita sponsors to nonsponsors based on personal characteristics. The table also reports statistics for subsamples of sponsors who sponsored at least 10, 20, or 30 people. The reported statistics are average and median age (calculated at the end of 2007), average and median taxable income (thousands of euros), the percentage of females, the percentage of people with higher than mandatory basic education, and the percentage of people with higher education (bachelor's degree or higher). The income statistics are based on taxable income in 2017. Statistics are based on investors who were personally interviewed by police. The table also reports simulation-based p-values for the difference between sponsors and nonsponsors. The two-sided p-value is based on a simulation where the same number of sponsors is selected randomly among all sample investors. It measures the probability that the difference between randomly assigned sponsors and nonsponsors is at least as large as the empirically observed difference based on 1,000 simulation rounds

Panel A: Nonsponsors Compared to Sponsors

	Nonsponsors	Sponsors	Simulation-Based p-Value for the Difference
Observations	2,530	858	
Median Age	47	45	0.076
Average Age	46.4	45.0	0.005
Median Income (Thousands of Euros)	32.8	35.2	0.015
Average Income (Thousands of Euros)	45.7	53.1	0.017
% of Females	21.3	12.4	0.000
% with Higher than Mandatory Education	86.6	88.8	0.118
% with Higher Education	38.1	37.2	0.649

Panel B: Statistics for the Most Active Sponsors

	Sponsors Who Sponsored at Least 10 People	Sponsors Who Sponsored at Least 20 People	Sponsors Who Sponsored at Least 30 People
Observations	92	33	13
Median Age	48	48	56
Average Age	47.8	49.3	53.9
Median Income (Thousands of Euros)	52.0	116.5	127.4
Average Income (Thousands of Euros)	113.1	194.0	259.7
% of Females	12.0	9.1	0.0
% with Higher than Mandatory Education	81.3	74.1	75.0
% with Higher Education	33.3	25.9	33.3

between sponsors and their sponsored investors. The sponsor has comparatively higher income in 64% of sponsor-sponsored investor pairs, is older in 51% of the pairs, and is of same gender in 81% of the pairs. The sponsor's education level is comparatively higher in 21% of investor pairs and lower in 26%

Table VI
Sponsors Compared to Their Sponsored Investors

This table compares sponsors to their sponsored investors based on personal characteristics and geographic location. The reported statistics are based on all sponsor-sponsored investor pairs where the measured statistic is available for both investors. Panel A reports statistics based on age, income, and geographic distance. Age is measured at the end of 2007 and income is the person's taxable income in 2007. Relative age differences are based on the year of birth. Geographic distance is calculated based on the street addresses reported in the police interview. Panel B reports the percentage of observations in which the sponsor is relatively older or younger, has the same gender, has higher taxable income, and has a relatively lower or higher education level

Panel A: Statistics Comparing Investors to Their Sponsors Based on Age, Income, and Location

	p25	p50	p75	Average	Std. Dev.	*N*
Sponsor's Age Minus Investor's Age	−6	1	9	1.4	13.8	2,013
Sponsor's Income Minus Investor's Income	−10	9.5	73.1	65	187.8	1,682
Geographic Distance (Kilometers)	4.4	16.1	80.5	76.4	130.4	2,057

Panel B: Statistics on Sponsoring Relationships

Sponsor Is Older	51.20%
Sponsor Is Born in the Same Year	5.40%
Sponsor Is Younger	43.40%
Sponsor Is of Same Gender	80.70%
Sponsor Has Relatively Higher Income	64.00%
Sponsor Has Relatively Higher Education Level	21.40%
Sponsor Has the Same Education Level	52.70%
Sponsor Has Relatively Lower Education Level	25.90%

of investor pairs. Average geographic distance between an investor and their sponsor is 76 km, with a median distance of 16 km. Internet Appendix Section VI provides further analysis of these differences and, using a simulation that accounts for the network topology, shows that the differences in income and age are statistically significant.

On average, most investors resemble their sponsor in terms of personal characteristics. Table VII reports pairwise Pearson correlations in personal characteristics between an investor and a person who is connected to him through the sponsorship chain and n steps closer to the originator of the scheme. The correlation coefficients show that the similarity extends to people who are within two steps in the social network. While this finding is not very surprising, the homophily in social interactions is nevertheless relevant for explaining differences in investment behavior across social and demographic groups. Word-of-mouth communication that takes place mainly within homogeneous social groups, rather than across them, can strengthen homogeneity in economic behavior within the groups (Granovetter (2005)) and preclude or slow down the convergence of behaviors in the population (Golub and Jackson (2012)). It can also facilitate the diffusion of new ideas within social groups in which members share characteristics that make a particular idea more attractive to them (Jackson (2014)).

Table VII

Correlation in Personal Characteristics as a Function of Network Distance

This table shows how correlation in personal characteristics within the Wincapita network varies as a function of social network distance. The correlation coefficients are calculated based on investor pairs where each investor i is linked to another investor j who joined the scheme before i and is part of the chain of sponsors that connects i to the originator of the scheme. Network distance is the number of sponsors between i and j in the network. For example, an investor who has network distance zero to investor i is his sponsor, and investor who has network distance one to investor i is his sponsor's sponsor. The table reports pairwise Pearson correlation coefficients, which are calculated based on all investor pairs with nonmissing values for the data item. With continuous variables (age and income), I exclude the highest and lowest 1% of values in the sample to limit the effect of outliers. The variables measuring personal characteristics include age (at the end of 2007), education (a binary variable that takes the value 1 if the individual has higher than secondary education), gender (a binary variable that takes the value 1 if the individual is female), and income, which measures taxable income for year 2007. p-Values for each coefficient are reported below the coefficient value.

Network Distance	0	1	2	3	4
Age					
Coefficient	0.3287***	0.1580***	−0.0147	−0.0897***	−0.0472*
p-Value	0.0000	0.0000	0.5495	0.0002	0.0677
Education					
Coefficient	0.2510***	0.1251***	−0.0167	−0.0207	−0.0049
p-Value	0.0000	0.0001	0.5746	0.4904	0.8860
Gender					
Coefficient	0.1898***	0.0519***	0.0158	0.0244	−0.0142
p-Value	0.0000	0.0037	0.4055	0.2111	0.4894
Income					
Coefficient	0.0600**	0.0307	−0.0453	0.0526*	−0.0742**
p-Value	0.0269	0.3380	0.1666	0.0981	0.0418

**, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

IV. Sponsoring Relationships and Invested Amounts

Next, I study how social connections within the scheme are related to the investment behavior of individual investors. I capture investors' willingness to invest in Wincapita as the total amount of money they invested in the scheme over its existence divided by their annual income. In all of the analyses, I exclude the highest and lowest 5% of these scaled invested amounts to ensure that the findings are not driven by extreme tails of the distribution.[28]

[28] As before, annual income is based on year 2007. The exclusion of the 5% tails sets the range of the scaled invested amounts between 0.03 and 1.35. For comparison, the lowest value in the data is 0.005 and the highest value is 18.19.

A. Do Sponsors Invest More than Nonsponsors?

I start by comparing sponsors' invested amounts to nonsponsors' invested amounts. This comparison reveals whether investors who invited others put their own money where their mouth is. Based on the invested amount as a percentage of annual income, the median sponsor invests over 50% more compared to the median nonsponsor. The median value among nonsponsors is 0.20 and the average is 0.35, while among sponsors, the median is 0.31 and the average is 0.48 (t-value for the difference is 7.79).[29]

Why do investors who sponsor others invest more? The simplest explanation is that investors who are most enthusiastic about Wincapita both invest more and are more likely to tell others about the scheme. Another explanation may be related to social utility (Hong, Kubik, and Stein (2004), Bursztyn et al. (2014)): the sponsors successfully convinced others to join and investors may derive utility from investing in the same asset as their peers due to, for example, the possibility of discussing the investment with their friends or relative wealth concerns.

Ponzi schemes require a steady flow of funds from new or existing investors to stay alive, and investors who both invite others and personally invest more can potentially contribute to the scheme's survival, particularly in the early stages. Using the model described in Section II.C, Internet Appendix Section VII examines how the higher net investments of sponsors can contribute to the sustainable payout ratio of the Ponzi scheme. A calibration exercise suggests that the highest possible payout ratio of the Wincapita network increases over five times as much as the highest possible payout ratio of the simulated random network when compared to a situation in which sponsors and nonsponsors make the same investment.[30] The scale-free network topology amplifies this effect, as there are fewer payment periods after the initial investment.

B. Sponsors' Personal Characteristics and Investment Decisions

Next, I study how Wincapita members' investment decisions are related to the personal characteristics of their sponsors. Here, I focus primarily on the effect of relative differences in personal characteristics because social interactions typically occur among people who are similar (McPherson, Smith-Lovin, and Cook (2001)). Characteristics that are statistically related to invested

[29] The difference between sponsors and nonsponsors exists even if the investors who withdrew money from Wincapita are excluded. In this case, the median is 0.21 for nonsponsors and 0.32 for sponsors, with the t-value for the difference in means equal to 6.08. Internet Appendix Section VII shows that the difference between sponsors and nonsponsors is also statistically significant in regressions that control for personal characteristics and in regressions that explain invested amounts net of withdrawals instead of total invested amounts.

[30] In the actual Wincapita network, the ratio increases by 0.0083 from 0.1253 to 0.1336. In the simulated random network, it increases on average by 0.0016 from 0.0241 to 0.0257. These findings indicate a 7% increase relative to the situation in which sponsors and nonsponsors make the same investment.

amounts can provide insights into the economic motivations for following peers' advice in investment decisions.

The existence of peer effects in investment decisions is well documented (Hong, Kubik, and Stein (2004), Brown et al. (2008), Kaustia and Knüpfer (2012)), but little is known about the personal characteristics of influencers. A field experiment by Bursztyn et al. (2014) shows that investors are particularly likely to imitate a financially sophisticated peer. Although most studies find that investors have a tendency to imitate peers, Beshears et al. (2015) find that upward social comparisons can discourage people from investing based on peers' information.

I run regressions in which the dependent variable is the invested amount divided by annual income. I measure the effect of the sponsor's personal characteristics using dummy variables for investors whose sponsor has relatively higher income, whose sponsor is older, whose sponsor is of the same gender, whose sponsor has comparatively higher education, and whose sponsor has comparatively lower education. The education level is based on the three categories defined earlier. I also run specifications that include log(distance to sponsor in kilometers) as an additional variable. All of the regressions include taxable income, taxable income squared, age, age squared, a dummy for females, a dummy for entrepreneurs, dummies for the two highest education-level categories, dummies for the investor's year of joining, and a dummy for sponsors as control variables. The squared values for age and income control for possible nonlinear effects.

I run these regressions with and without sponsor fixed effects. Investors are not matched randomly with their sponsors, and thus, it is possible that the personal characteristics of the sponsor are correlated with those of the people he sponsors. Sponsor fixed effects effectively control for peer group fixed effects as well as for any joint unobservable characteristics shared by different investors with the same sponsor. Some sponsors may also be better at selling the investment idea than others. I cluster standard errors by year the investor joins the scheme.

The results are reported in Table VIII. As can be seen, investors invest more if their sponsor has comparatively higher taxable income and age, and the sponsor's relative education level also affects invested amounts. In almost all cases, the coefficients are economically and statistically more significant when sponsor fixed effects are included. The dummy for investors with a higher income sponsor is positive and statistically significant at the 5% level in each specification with coefficients ranging between 0.03 and 0.04 without sponsor fixed effects and between 0.09 and 0.12 when they are included. The coefficients with sponsor fixed effects imply an increase of 26% to 52% relative to the median invested amount. All coefficients on the older sponsor dummy are statistically significant and positive, and all coefficients on the lower education sponsor dummy are statistically significant and negative. The coefficient on investors whose sponsor has comparatively higher education is statistically significant only when sponsor fixed effects are included. The same-gender dummy and

Table VIII

Sponsor's Personal Characteristics and the Total Amount of Funds Invested in Wincapita

This table reports results from cross-sectional OLS regressions in which the dependent variable is the total amount of funds an investor invested in Wincapita divided by his annual income. The main independent variables measure the investor's difference relative to his sponsor in terms of personal characteristics and geographic location. They include separate dummies for investors whose sponsor has higher taxable income (based on taxable income from 2007), investors whose sponsor is older, investors whose sponsor has a comparatively higher education level, investors whose sponsor has a comparatively lower education level, and log(distance to sponsor) measured in kilometers. The measured education level is based on three categories: investors who have only mandatory basic education, investors whose highest degree is from an upper secondary school, and investors who have a higher education degree. The regressions also include a dummy variable for investors who are sponsors. All regressions include the following unreported control variables: annual income, annual income squared, a dummy variable for females, age, age squared, a dummy variable for entrepreneurs, and dummies for the two highest education-level categories defined earlier. Annual income is the person's taxable income in 2007 and age is measured at the end of 2007. All regressions include dummies for the investor's year of joining. Regressions in columns (4) to (6) include sponsor fixed effects. t-Statistics are reported in brackets below the coefficients. Standard errors are clustered by the year of joining

	(1)	(2)	(3)	(4)	(5)	(6)
Sponsor Has Higher Income	0.032	0.040	0.039	0.098	0.121	0.108
	[3.52]	[4.23]	[4.21]	[5.46]	[6.16]	[4.28]
Sponsor Is Older	0.032	0.032	0.028	0.049	0.069	0.075
	[2.81]	[2.69]	[2.67]	[2.23]	[3.80]	[4.05]
Sponsor Is of Same Gender	−0.033	−0.043	−0.048	−0.047	−0.052	−0.078
	[−0.51]	[−0.77]	[−0.77]	[−1.10]	[−1.13]	[−1.65]
Sponsor Has Higher Education		0.008	0.008		0.063	0.055
		[0.43]	[0.34]		[3.25]	[2.47]
Sponsor Has Lower Education		−0.036	−0.041		−0.132	−0.130
		[−4.49]	[−6.08]		[−5.01]	[−5.05]
Log(Distance to Sponsor)			−0.001			0.004
			[−0.61]			[0.80]
Sponsor Dummy	0.124	0.126	0.131	0.153	0.153	0.163
	[9.96]	[6.20]	[5.64]	[3.38]	[3.48]	[3.21]
Personal Controls	Yes	Yes	Yes	Yes	Yes	Yes
Sponsor Fixed Effects	No	No	No	Yes	Yes	Yes
N	1,024	854	821	768	645	613
R^2	0.129	0.131	0.135	0.392	0.413	0.416

the coefficient on log(geographic distance to sponsor in kilometers) are not statistically significant.

Internet Appendix Section VIII reports results from additional robustness checks. The results show that the findings above cannot be explained by observations in which the sponsor and the investor invested the same default amount or by selection bias among investors who were contacted by the police. The higher income sponsor dummy is statistically significant even if sponsors who withdrew funds are excluded. The Internet Appendix also shows that sponsors' absolute (as opposed to relative) personal characteristics are not statistically significantly related to the invested amounts.

Age, education, and income are potential sources of personal status and credibility, and the results so far are consistent with the idea that investors invest more based on the information that comes from a credible and trustworthy source. A heuristic known as a question substitution may contribute to the social diffusion of investment mistakes in Wincapita. When faced with a difficult question, people often answer an easier one instead (Kahneman (2011)). Some investors may have exchanged the more complex question "Do I trust this investment scheme?" to the simpler question "Do I trust the person who is telling me about this investment scheme?"

C. Relative Income Differences and Invested Amounts

Next, I study the relationship between income differences and invested amounts in more detail to better understand whether the sponsor's income level is a reference point that influences decision making. I also analyze the effect of income differences at the neighborhood level.

There are at least two explanations for why investors would pay attention to the income difference relative to their sponsor when deciding how much to invest in Wincapita. First, if higher income sponsors are considered more credible and trustworthy, investors may make judgments about these characteristics relative to their own income level, rather than on an absolute basis. Second, it is possible that the sponsor's income level matters because of relative wealth concerns or "keeping up with the Joneses" behavior. Wincapita was a get-rich-quick scheme and investors may have been worried about losing compared to their peers if they did not invest similarly, which could have induced lower income investors to invest more. The finding that investors invest more relative to their own income when their sponsor has comparatively higher income is consistent with "keeping up with the Joneses."

Previous studies show that relative wealth concerns can influence the investment decisions of retail investors. In a field experiment by Bursztyn et al. (2014), most participants who invest in the same asset as their peers mention relative return or consumption concerns as a motivating factor for their decision. Hong et al. (2014) find that local status concerns affect individual investors' trading and risk-taking. Prior evidence further shows that relative income differences affect behavior at the neighborhood level. For instance, Luttmer (2005) finds that neighbors' relatively higher earnings are associated with lower levels of self-reported happiness and Kumar (2009) finds that investors who earn less than their neighbors invest more in lottery-type stocks.

If peers' wealth or income is a reference point in decision making, the marginal effect of the income difference should be strongest when the sponsor's income is close to the investor's own income. Figure 6 illustrates three hypothetical scenarios on the relationship between income differences and invested amounts. In these graphs, the sponsor's annual income minus the investor's own income is plotted on the horizontal axis and the investor's invested

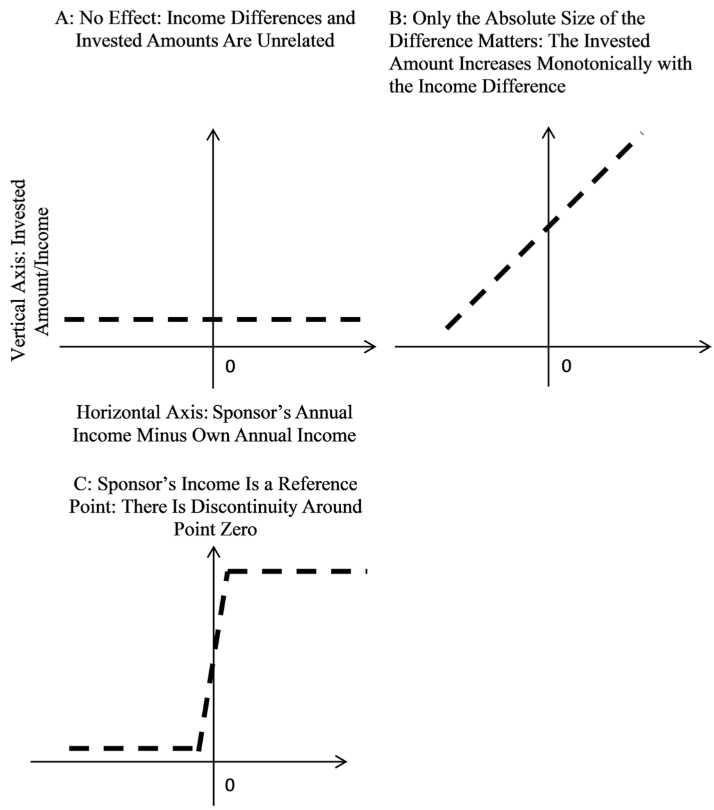

Figure 6. Hypothetical scenarios on the relationship between invested amounts and relative income differences. This figure depicts three hypothetical scenarios on the relationship between investors' invested amounts and the income difference relative to the sponsor. Each graph plots the sponsor's income minus the investor's own income on the horizontal axis and the investor's invested amount divided by his annual income on the vertical axis. The dashed line depicts the relationship between the two variables. The two axes meet at the origin, where the investor's income is equal to the sponsor's income. In Panel A, the invested amounts and the income differences are unrelated. In Panel B, the invested amounts increase monotonically with the income difference, but there is no discontinuity around point zero. In Panel C, the sponsor's income is a reference point that affects decision making. The invested amounts increase with the income difference, but there is a strong discontinuity around the point where the sponsor's income is equal to the investor's own income.

amount divided by annual income is plotted on the vertical axis. If there is no correlation between the two variables, the graph is flat. If the invested amount increases with the sponsor's relative income, the graph is monotonically increasing. Moreover, if the sponsor's income is a reference point, there should be discontinuity around the point where the investor's income is equal to the sponsor's income.

To examine this relationship empirically, I first sort investors into deciles based on the sponsor's annual income minus the investor's own annual income.

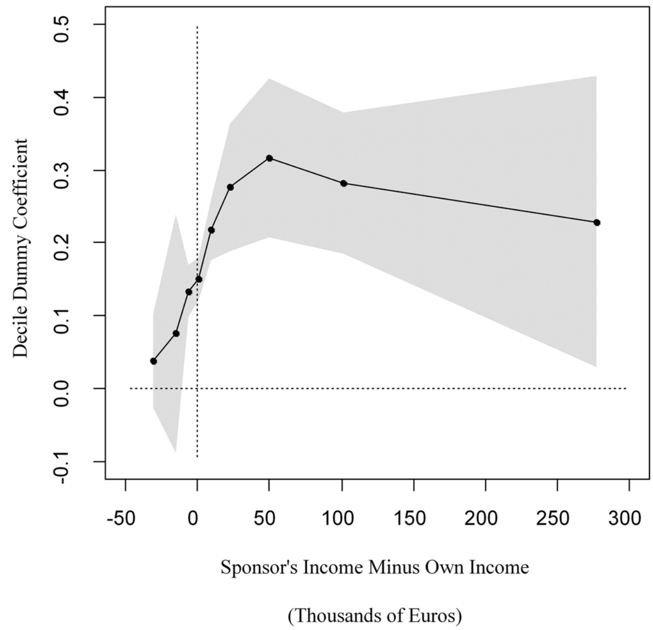

Figure 7. The relationship between income difference relative to the sponsor and Wincapita investments. This figure shows how individual investors' invested amounts in Wincapita as a percentage of annual income vary with the relative difference in taxable income between an investor and his sponsor. The figure is based on a regression in which the dependent variable is the total amount of funds an investor transferred into Wincapita divided by his annual taxable income. The explanatory variables are dummies for the top nine deciles of the sponsor's taxable income minus the investor's own taxable income. The omitted category is the first decile where the sponsor's income minus own income has the lowest values. The regression includes dummies for investors' year of joining and sponsor fixed effects. The observations consist of all investors in Wincapita for whom the data are available. In the figure, each dot combines a coefficient value (measured on the vertical axis) with the corresponding decile value (measured on the horizontal axis) and the individual dots are connected with a line. The gray area shows the 95% confidence interval for the coefficients based on standard errors clustered by the year of joining. All taxable income values are based on taxable income in 2007.

I then run a regression explaining total invested amount divided by annual income with dummies for the top nine deciles. The regression includes year of joining dummies and sponsor fixed effects. Figure 7 shows how the decile dummy coefficients vary and includes confidence intervals. The horizontal axis plots the sponsor's income minus own income and the vertical axis measures the coefficient value. All coefficients show the difference relative to the first decile, which is the omitted category.

The shape of the curve is consistent with the hypothesis that the sponsor's income is a reference point. The marginal effect of the income difference is higher around the point where the sponsor's income is equal to the investor's own income. The marginal increase is highest just above zero in the area between the fifth decile (€900) and the sixth decile (€9,450). The coefficients do

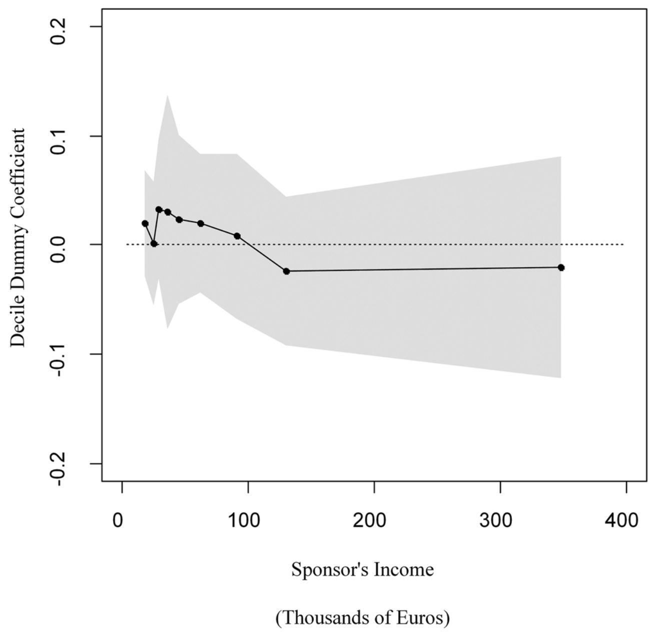

Figure 8. The relationship between sponsor's income and Wincapita investments. This figure shows how individual investors' invested amounts in Wincapita as a percentage of annual income vary with their sponsor's annual income. The figure is based on a regression in which the dependent variable is the total amount of funds an investor transferred into Wincapita divided by his annual taxable income. The main explanatory variables are dummies for the top nine deciles of the sponsor's income. The omitted category is the first decile where the sponsor's income has the lowest values. The regression includes dummies for investors' year of joining. The observations consist of all investors in Wincapita for whom the data are available. Each dot combines a coefficient value (shown on the vertical axis) with the corresponding decile value (show on the horizontal axis) and the individual dots are connected with a line. The gray area shows the 95% confidence interval for the coefficients based on standard errors clustered by the year of joining. All taxable income values are based on taxable income in 2007.

not increase monotonically with the income difference, and deciles 9 and 10 are below the peak. The coefficients for deciles 4 to 9 are statistically significant at the 1% level and the coefficient for decile 10 is significant at the 10% level.

I also test whether the absolute income of the sponsor is related to invested amounts. To do so, I sort investors into deciles based on their sponsor's taxable income and run a similar regression as above. The only difference is that I cannot include sponsor fixed effects because they would overlap with the sponsor's income. Figure 8 shows that none of the decile dummies is statistically significant, and there is no trend in the coefficients. The contrast between the two figures suggests that the sponsor's relative, rather than absolute, income affects investment decisions.

I next analyze whether relative income differences also matter at the neighborhood level, as shown by Kumar (2009). I run regressions explaining total invested amount divided by annual income using a dummy variable for investors whose income is below the median income in their postal code area.[31] The regressions include sponsor fixed effects and the same investor-level control variables used in Table VIII. Some specifications additionally include the median income of the postal code area to control for the possibility that it is related to the invested amount.

Table IX reports the results. The dummy for investors whose income is below the median income in the postal code area is statistically significant and positive with coefficient values ranging between 0.07 and 0.10. These findings suggest that, all else being equal, investors who earn less than their neighbors invest more in Wincapita. The median income level of the postal code area is not statistically significant in any specification.

Taken together, the above results indicate that Wincapita participants' investment decisions are influenced by relative income differences. This finding can be explained by social learning whereby peers' credibility is assessed relative to the investor's own income level, or by relative wealth concerns. If "keeping up with the Joneses" behavior plays an important role here, the investment decisions of the Ponzi scheme participants may not be driven solely by expectations of unusually high returns, but also by the fear of losing relative to peers.

V. Conclusion

The Wincapita investigation documents provide information about the process through which investment ideas spread from one person to the next. The analyses of this paper show that this process cannot be characterized by models of information diffusion whereby investment ideas are transmitted evenly from one investor to a fixed number of peers. Instead, a small fraction of investors is responsible for most of the observed social effect, while most investors are passive information receivers who adopt the idea but do not spread it further. These findings suggest that social network structures play an important role in the diffusion of investment ideas with a few powerful individuals that have many social connections significantly facilitating the diffusion process.

The observations of this paper also contribute to the discussion on the benefits and harms of peer effects in financial decision making. Although investors' social learning can produce welfare-improving outcomes in many situations, for example, through higher stock market participation and better portfolio diversification, the evidence of this paper indicates that it can also spread and exacerbate investment mistakes.

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[31] Postal code income data are from the same year as investors' income data. Based on 2014 statistics of Statistics Finland, the median Finnish postal code area has a population of 474, with an average of 1,781.

Table IX

Income Difference Relative to the Postal Code Median and the Total Amount of Funds Invested in Wincapita

This table reports results from cross-sectional OLS regressions in which the dependent variable is the total amount of funds an investor has invested in Wincapita divided by his annual income. The main independent variable is a dummy that takes the value 1 if the investor's taxable income is below the median taxable income in the postal code area of his home. Other reported independent variables are the median income in the postal code area in thousands of euros and dummies for investors whose sponsor has higher taxable income (based on taxable income from 2007), investors whose sponsor is older, investors whose sponsor has a comparatively higher education level, investors whose sponsor has a comparatively lower education level, and a dummy for investors who are sponsors. The measured education level is based on three categories: investors who have only mandatory basic education, investors whose highest degree is from an upper secondary school, and investors who have a higher education degree. All regressions also include the following unreported control variables: annual income, annual income squared, a dummy variable for females, age, age squared, a dummy variable for entrepreneurs, and dummies for the two highest education-level categories defined earlier. Annual income is the person's taxable income in 2007 and age is measured at the end of 2007. All regressions include dummies for the investor's year of joining, and sponsor fixed effects. *t*-Statistics are reported in brackets below the coefficients. Standard errors are clustered by year of joining

	(1)	(2)	(3)	(4)
Investor's Income Is Below the Postal	0.089	0.096	0.070	0.072
Code Area Median Income	[3.07]	[2.95]	[2.46]	[2.54]
Median Income in the Postal Code Area		−0.003		−0.001
(Thousands of Euros)		[−1.25]		[−0.38]
Sponsor Has Higher Income			0.115	0.114
			[5.82]	[5.79]
Sponsor Is Older			0.070	0.070
			[4.46]	[4.46]
Sponsor Is of Same Gender			−0.065	−0.064
			[−1.36]	[−1.33]
Sponsor Has Higher Education			0.067	0.067
			[3.70]	[3.68]
Sponsor Has Lower Education			−0.126	−0.126
			[−4.78]	[−4.68]
Sponsor Dummy	0.140	0.140	0.155	0.155
	[6.62]	[6.64]	[3.80]	[3.82]
Personal Controls	Yes	Yes	Yes	Yes
Sponsor Fixed Effects	Yes	Yes	Yes	Yes
N	1,407	1,407	645	645
R^2	0.424	0.425	0.418	0.418

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix S1: Internet Appendix.
Replication Code.