Household Responses to Phantom Riches

CEPR European Conference on Household Finance, Turin 2023

Samuli Knüpfer[*], Ville Rantala[†], Erkki Vihriälä[*], Petra Vokata[‡]

[*]Aalto University, [†]University of Miami, [‡]Ohio State University

Motivation

Phantom Riches

= illusion of attaining substantial wealth through investments

- E.g. bubbles or **scams**
- Direct effect: redistribution of wealth
- Indirect effect: suboptimal decisions due to distorted beliefs

This paper: **First microanalysis of household responses to investment fraud**

- Economically important, \$20 billion a year (U.S. prosecuted)
- Existence of fraud may reduce trust in legitimate investments too

Motivation

Phantom Riches

= illusion of attaining substantial wealth through investments

- E.g. bubbles or **scams**
- Direct effect: redistribution of wealth
- Indirect effect: suboptimal decisions due to distorted beliefs

This paper: **First microanalysis of household responses to investment fraud**

- Economically important, $20 billion a year (U.S. prosecuted)
- Existence of fraud may reduce trust in legitimate investments too

Motivation

Phantom Riches

= illusion of attaining substantial wealth through investments

- E.g. bubbles or **scams**
- Direct effect: redistribution of wealth
- Indirect effect: suboptimal decisions due to distorted beliefs

This paper: **First microanalysis of household responses to investment fraud**

- Economically important, $20 billion a year (U.S. prosecuted)
- Existence of fraud may reduce trust in legitimate investments too

Motivation

Phantom Riches

= illusion of attaining substantial wealth through investments

- E.g. bubbles or **scams**
- Direct effect: redistribution of wealth
- Indirect effect: suboptimal decisions due to distorted beliefs

This paper: **First microanalysis of household responses to investment fraud**

- Economically important, \$20 billion a year (U.S. prosecuted)
- Existence of fraud may reduce trust in legitimate investments too

Motivation

Phantom Riches

= illusion of attaining substantial wealth through investments

- E.g. bubbles or **scams**
- Direct effect: redistribution of wealth
- Indirect effect: suboptimal decisions due to distorted beliefs

This paper: **First microanalysis of household responses to investment fraud**

- Economically important, \$20 billion a year (U.S. prosecuted)
- Existence of fraud may reduce trust in legitimate investments too

Motivation

Phantom Riches

= illusion of attaining substantial wealth through investments

- E.g. bubbles or **scams**
- Direct effect: redistribution of wealth
- Indirect effect: suboptimal decisions due to distorted beliefs

This paper: **First microanalysis of household responses to investment fraud**

- Economically important, \$20 billion a year (U.S. prosecuted)
- Existence of fraud may reduce trust in legitimate investments too

Motivation

Phantom Riches

= illusion of attaining substantial wealth through investments

- E.g. bubbles or **scams**
- Direct effect: redistribution of wealth
- Indirect effect: suboptimal decisions due to distorted beliefs

This paper: **First microanalysis of household responses to investment fraud**

- Economically important, $20 billion a year (U.S. prosecuted)
- Existence of fraud may reduce trust in legitimate investments too

Setting: "Wincapita" ponzi scheme

- Largest investment scam and police investigation in Finnish history (€100 million damages)

- 3,000 identities of victims from police interviews

- Merge with register-based data

Identification advantages to uncover causal effects:

- People could join only after invitation by a member of network $\rightarrow$ only few could join

- Diffusion of scheme creates heterogeneity in treatment intensity $\rightarrow$ instrument for entry year with network distance to origin

Setting: "Wincapita" ponzi scheme

- Largest investment scam and police investigation in Finnish history (€100 million damages)

- 3,000 identities of victims from police interviews

- Merge with register-based data

Identification advantages to uncover causal effects:

- People could join only after invitation by a member of network $\rightarrow$ only few could join

- Diffusion of scheme creates heterogeneity in treatment intensity $\rightarrow$ instrument for entry year with network distance to origin

Setting: "Wincapita" ponzi scheme

- Largest investment scam and police investigation in Finnish history (€100 million damages)

- 3,000 identities of victims from police interviews

- Merge with register-based data

Identification advantages to uncover causal effects:

- People could join only after invitation by a member of network → only few could join

- Diffusion of scheme creates heterogeneity in treatment intensity → instrument for entry year with network distance to origin

Setting: "Wincapita" ponzi scheme

- Largest investment scam and police investigation in Finnish history (€100 million damages)
- 3,000 identities of victims from police interviews
- Merge with register-based data

Identification advantages to uncover causal effects:

- People could join only after invitation by a member of network → only few could join
- Diffusion of scheme creates heterogeneity in treatment intensity → instrument for entry year with network distance to origin

Setting: "Wincapita" ponzi scheme

- Largest investment scam and police investigation in Finnish history (€100 million damages)
- 3,000 identities of victims from police interviews
- Merge with register-based data

Identification advantages to uncover causal effects:

- People could join only after invitation by a member of network $\rightarrow$ only few could join
- Diffusion of scheme creates heterogeneity in treatment intensity $\rightarrow$ instrument for entry year with network distance to origin

Setting: "Wincapita" ponzi scheme

- Largest investment scam and police investigation in Finnish history (€100 million damages)

- 3,000 identities of victims from police interviews

- Merge with register-based data

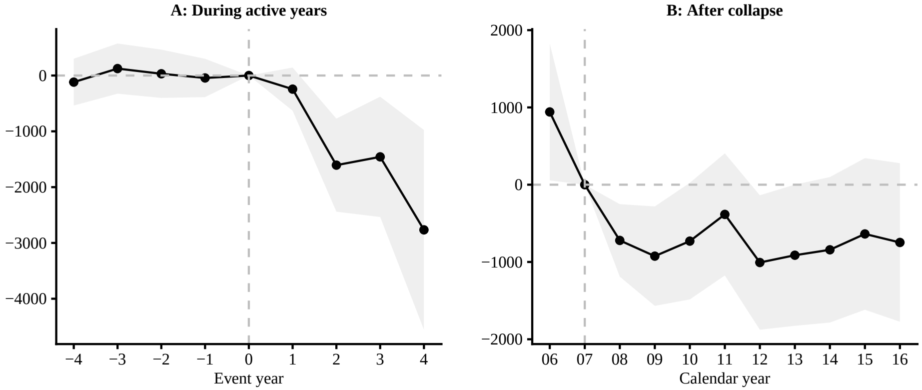
Identification advantages to uncover causal effects:

- People could join only after invitation by a member of network $\rightarrow$ only few could join

- Diffusion of scheme creates heterogeneity in treatment intensity $\rightarrow$ instrument for entry year with network distance to origin

Main findings

Income (1) declines after joining the scheme (labor supply) and (2) after the scheme collapse (financial distress)

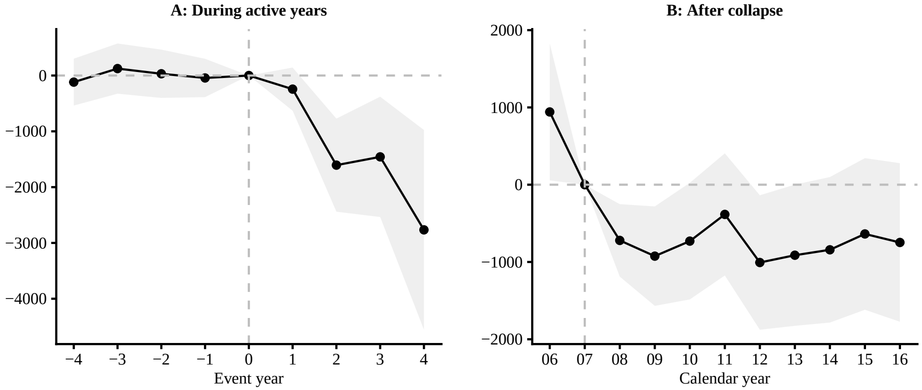


Economic magnitude: 6 % of labor income, cumulatively > invested amount

Other outcomes: Unemployment and sickness benefits ↑, Loans ↑, Divorces ↑, Delegated vs. direct investments ↓

Main findings

Income (1) declines after joining the scheme (labor supply) and (2) after the scheme collapse (financial distress)

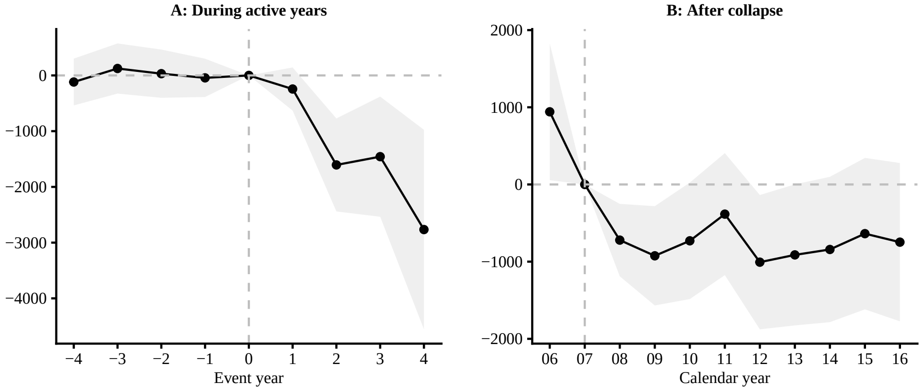


Economic magnitude: 6 % of labor income, cumulatively > invested amount

Other outcomes: Unemployment and sickness benefits ↑, Loans ↑, Divorces ↑, Delegated vs. direct investments ↓

Main findings

Income (1) declines after joining the scheme (labor supply) and (2) after the scheme collapse (financial distress)



Economic magnitude: 6 % of labor income, cumulatively $>$ invested amount

Other outcomes: Unemployment and sickness benefits $\uparrow$, Loans $\uparrow$, Divorces $\uparrow$, Delegated vs. direct investments $\downarrow$

Data and Background

Register data

- Statistics Finland
  - Demographics, labor and family variables, loans
  - Panel of Finnish population over nearly two decades
- Finnish Tax Administration
  - Direct equity and mutual fund holdings
- Finnish Defense Forces
  - IQ scores

Summary statistics

- Scheme active 2003–2008 (6 entry-year cohorts)
- Average (median) investment: €15,400 (€8,000)
- Median wealth loss at collapse **€6,100 (2008 entrants) – €106.700 (2003 entrants)**
  - Scheme promised annual returns of several hundred percent
- Victim characteristics relative to population
  - More males
  - Higher income and financial wealth
  - Average IQ
  - More entrepreneurs

Empirical Design

Event-study difference-in-differences with tightly matched control group

1. Match (CEM) each Ponzi scheme investor to control individuals on
   - Earned income, capital income, income trend
   - Birth year, gender
   - Labor market status, stock market participation

2. Event-study D-i-D design

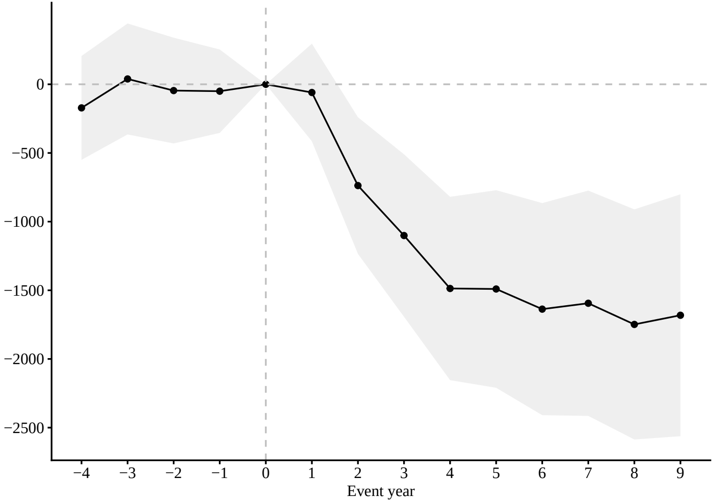
$$y_{i,c,t} = \alpha_{i,c} + \lambda_{c,t} + \sum_{\substack{n=-q \\ n \neq 0}}^{n=m} \delta_n \mathbf{1}_{i=\text{investor}} \mathbf{1}_{j=n} + \epsilon_{i,c,t},$$

$y_{i,c,t}$ is calendar year t labor income, $\alpha_{i,c}$ are individual-cohort fixed effects, $\lambda_{c,t}$ are cohort-year fixed effects, $\mathbf{1}_{i=\text{investor}}$ is an indicator variable equal to 1 for the scheme investors, and $\mathbf{1}_{j=n}$ is an indicator variable equal to 1 for event-year j.

Results

Pooled event-year design around entry for all cohorts

Combining effects during active years and after collapse



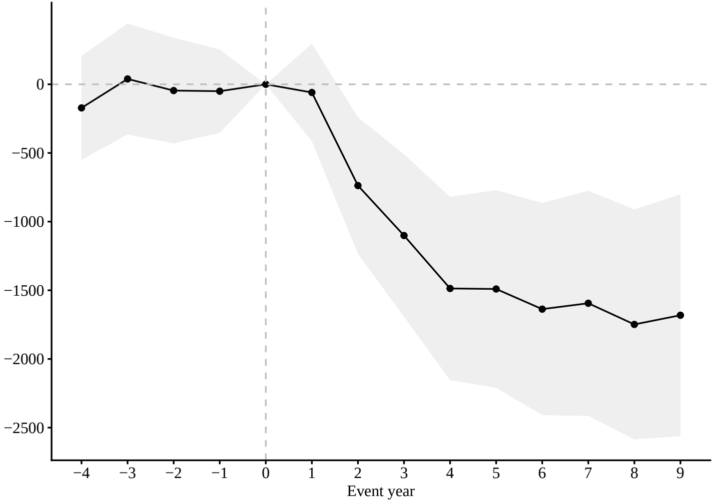
Labor income loss:
€1,300 (6 %) annually

Lifetime loss: €24,080

> avg. invested amount

Pooled event-year design around entry for all cohorts

Combining effects during active years and after collapse



Labor income loss: €1,300 (6 %) annually

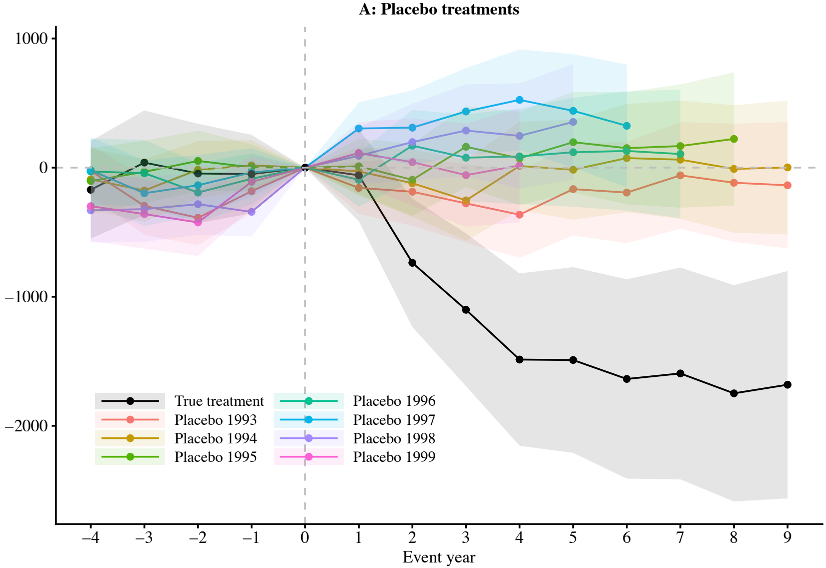
Lifetime loss: €24,080

> avg. invested amount

Threats to identification

1. Matching: do victims have lower average earnings potential than controls? $\rightarrow$ would predict victims underperform controls in also other time periods

1. Matching algorithm does not find income declines in placebo studies



Threats to identification

1. Matching: do victims have lower average earnings potential than controls? $\rightarrow$ but do not find victims underperform controls in other time periods
2. What if victims select entry year based on expectations of (low) future income? $\rightarrow$ use exogenous variation in treatment intensity

Threats to identification

1. Matching: do victims have lower average earnings potential than controls? $\rightarrow$ but do not find victims underperform controls in other time periods
2. What if victims select entry year based on expectations of (low) future income? $\rightarrow$ use exogenous variation in treatment intensity

2. More exposed victims decrease income more during active years

Instrumenting year of entry

All entry-year cohorts experience labor-income loss relative to controls (match in 2002)
Here we study heterogeneity of income loss during active years by exposure intensity

IV = Network distance to founder

	Δ Income$_{02-07}$	
	OLS	IV
Entry year	**835.5*** **	**1370.5** **
	(3.15)	(2.36)
Observations	1,829	1,829
$Adj.R^2$	0.005	0.003
F-test		448.3

Threats to identification

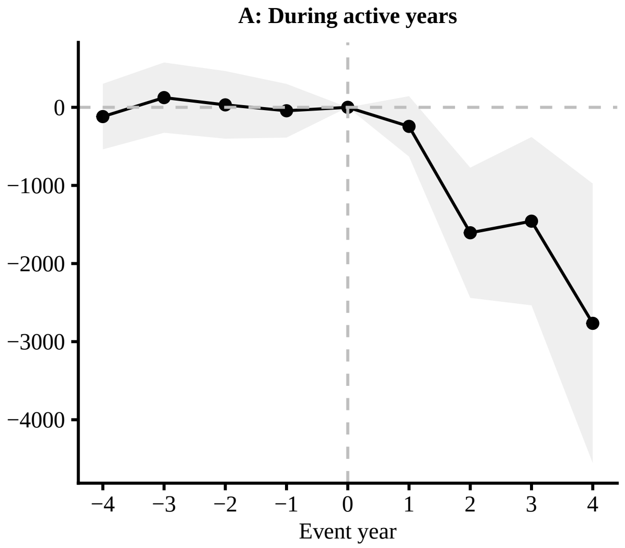
1. Matching: do victims have lower average earnings potential than controls? $\rightarrow$ but do not find victims underperform controls in other time periods
2. What if victims select entry year based on expectations of (low) future income? $\rightarrow$ but larger effects for more exposed victims
3. Other robustness
   - Alternative matching specs yield similar results Link
   - Effects over 2003–08 $\rightarrow$ not due to financial crisis that arrived to Finland in 2009

Threats to identification

1. Matching: do victims have lower average earnings potential than controls? $\rightarrow$ but do not find victims underperform controls in other time periods
2. What if victims select entry year based on expectations of (low) future income? $\rightarrow$ but larger effects for more exposed victims
3. Other robustness
   - Alternative matching specs yield similar results Link
   - Effects over 2003–08 $\rightarrow$ not due to financial crisis that arrived to Finland in 2009

Interpretation

1. Response to entry: labor supply response to wealth shock

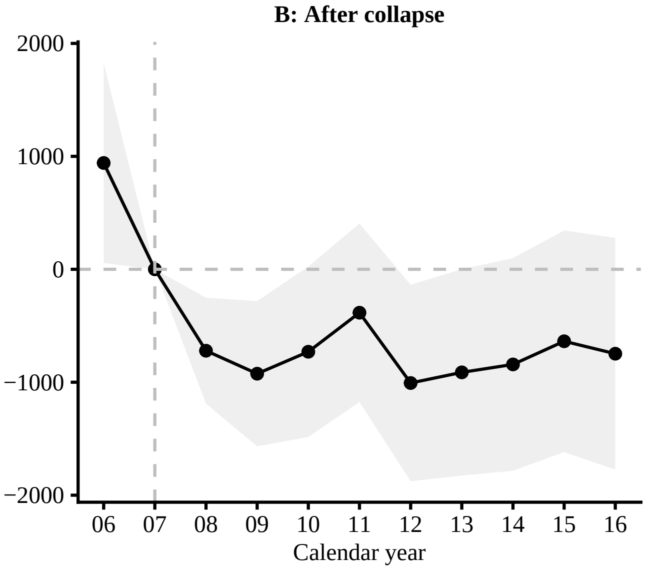


Consistent with standard lifecycle models (Heckman 1974)

Economic magnitude similar to responses to lotteries (Cesarini et al 2017, Golosov et al 2023)

Anecdotal evidence in police interviews

2. Response to collapse: financial stress at collapse



Inconsistent with standard lifecycle models

Consistent with models of financial stress (Sergeyev et al 2022)

Consistent with survey evidence of fraud victims and supported by anecdotes in police interviews

Income drop larger if enter earlier and if withdraw funds Link

2. Response to collapse: financial stress at collapse

Income loss at collapse as function of wealth loss

Proxy for financial stress: wealth loss at collapse
IV = year of entry (gains in the scheme increase with active time)

	Δ Income$_{07-08}$	
	OLS	IV
Wealth loss	**-0.007*** **	**-0.012** **
	(-2.17)	(-2.69)
Observations	2,567	2,567
$Adj.R^2$	0.0015	0.0002
F-test		2,226.4

€25,000 wealth loss or an additional year of participation $\rightarrow$ €275 income loss

Other outcomes consistent with negative effects of fraud

Table: Effect of fraud victimization on other long-term outcomes

	Estimate	t-stat	N	Adj. R^2	Pre-mean
Unemp. and sickness benefits	0.020	(3.05)	899,457	0.27	0.17
Divorced	0.012	(2.39)	899,457	0.79	0.12
Has mortgage	0.019	(2.23)	884,356	0.63	0.44
Has consumer loan	0.038	(4.42)	884,356	0.47	0.35
Has directly held stocks	0.010	(1.59)	844,314	0.81	0.32
Has equity mutual funds	-0.012	(-1.52)	844,314	0.66	0.31

Note: Difference in average outcome in nine years after scheme collapse relative to three years before entry

Conclusion

First microanalysis of household responses to investment fraud

- 6 % labor income loss
  - Income declines after joining the scheme (labor supply)
  - . . . and in the year of collapse (financial stress)

- Unemployment, indebtedness, divorces $\uparrow$, delegated vs. direct investments $\downarrow$

- Lifetime income loss exceeds loss of invested capital $\rightarrow$ indirect costs contribute substantially to social costs of fraud

Appendix

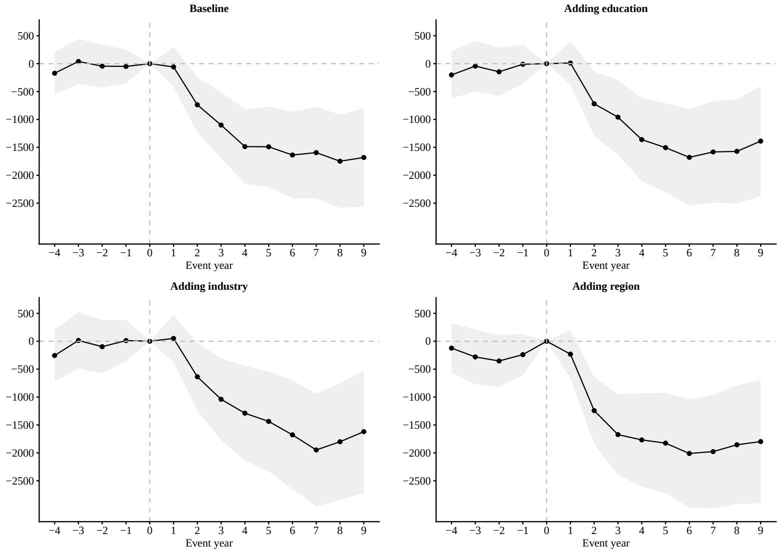


Figure: Labor income by matching scheme

Back

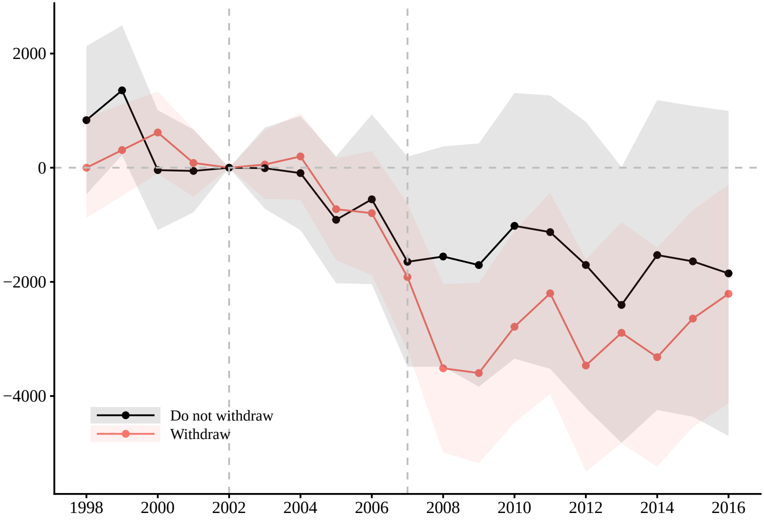


Figure: Effect of fraud on labor income by withdrawals

Back