New Frontiers of Robo-Advising: Consumption, Saving, Debt Management, and Taxes

Alberto G Rossi
Georgetown University

GEORGETOWN UNIVERSITY

Plan of the Talk

1. Introduction to Robo-advisors
   - What is Robo-advising?
   - Main features of robo-advisors
   - Taxonomy of robo-advisors
2. Roboadvising for
   - Consumption
   - Saving
   - Debt Management and other Households' Decisions
3. Open Questions in Robo-advising

Relevant Material

Robo-advising for Investment Decisions

- "*Robo-advising*," D'Acunto & Rossi
- "*The Promises and Pitfalls of Robo-advising*," D'Acunto, Prabhala & Rossi
- "*Who Benefits from Robo-advising? Evidence from Machine Learning*" Rossi & Utkus
- "*The Needs and Wants in Financial Advice: Human vs Robo-Advising*," Rossi &Utkus
- "*Algorithm Aversion: Theory and Evidence from Robo-advice*," Ramadorai et al.

Robo-advising for Consumption, Saving, Debt and Lending

- "*Robo-Advising for Consumption, Saving, Debt, and Taxes,*" D'Acunto & Rossi
- "*Crowdsourcing Peer Info to Change Spending Behavior*" D'Acunto, Rossi & Weber
- "*Goal Setting and Saving in the FinTech Era*" Gargano & Rossi
- "*How Costly Are Cultural Biases? Evidence from FinTech*" D'Acunto, Ghosh & Rossi
- "Improving Households' Debt Management with Robo-advising" D'Acunto et. al.

What is Robo-advising?

Robo-advising is

1. Generated by a computer algorithm
2. Tailored to clients' characteristics
3. Easy to implement – Automatic execution, Financial education

Unbiased advice delivered electronically is rarely followed (Bhattacharya et al., 2012):

"*You can lead a horse to water, but you can't make it drink!*"

Robo-advising: middle ground btw no-intervention & nudges

Why are Robo-advisors Important?

- Most investors are not financially savvy
- Traditional Financial Advisers could help, but they
  - are expensive
  - generally ineffective (Linnainmaa, Melzer, and Previtero, 2016)
  - they cater mainly to wealthier individuals
- Scope to
  - improve the effectiveness of financial advice
  - increase the number of people who receive advice

Advantages and Disadvantage of Robo-advisors over Traditional Advisors

Advantages. Robo-advisors can

1. offer financial advice for low fees
2. serve individuals with any level of wealth
3. be monitored and improved over time
4. their decisions can be explained to investors and regulators

Disadvantages:

1. many potential clients are algorithmic-averse
2. many algorithms do not work very well

Are All Robo-advisors Created Equal?

We can classify robo-advisors along four dimensions

1. **Personalization of the advice**
   (Target Date Funds as most primitive form of robo-advising)
2. **Involvement of the investor in financial plans and choices**
   (Robo-advisors versus robo-managers)
3. **Investors' discretion to deviate from the automated advice**
   (Libertarianism versus libertarian paternalism)
4. **The presence of any form of human interaction**
   (Pure robo-advisors versus hybrid robo-advisors)

(D'Acunto and Rossi, 2020)

Common Perception of Robo-advising

1. Robo-advising = with automated advice for portfolio allocation

wealthfront

Betterment

FutureAdvisor

Schwab Intelligent Portfolios

Vanguard

SIGFIG

PERSONAL CAPITAL

Balance-Sheet View of Households

BUT individuals decisions are more complex!

The Balance Sheet View of Households

ASSETS

Financial Assets
- Equities
- Bonds
- Funds Retirement..

Human Capital
- Produces income

Durable Assets
- Cars, Housing...
- Produce consumption value

LIABILITIES

Financial Liabilities
- Mortgages
- Credit Card Debt
- Student Loans
- Car Payments...

EQUITY

Balance-Sheet View of Households

Significant advances along several areas.

Examples:

- Robo-advising and the consumption-saving choice
- Robo-advising and borrowing decisions
- Robo-advising and P2P lending investments

Robo-advising and the consumption-saving choice

Difficult to determine the optimal consumption and spending

Even for expert economists!

Solutions implemented. Use big data and robo-advice to:

- Provide understandable rules of thumb (EXAMPLE 1)
- Provide motivation and reinforcement (EXAMPLE 2)

Crowdsourcing Peer Information to Change Spending Behavior

Francesco D'Acunto Boston College
Alberto Rossi Georgetown
Michael Weber Chicago Booth

The STATUS APP

- Income aggregator application (app) called *Status*
- On top of visualizing balance sheet, provides users with:
  - information on spending similar individuals (*peers)*
  - information crowdsourced from representative US data
- Do users react to this information? If yes, how?

The STATUS APP

(INPUTS)

At Signup, users provide Status with:

- Annual Income (can be verified from accounts ex post)
- Age
- Homeownership status
- Location of residence
- Location type—Urban or Rural
- Social Security Number $\rightarrow$ STATUS obtains credit report

Users link their:

- Debit and credit account(s)
- Retirement and investment account(s)

The STATUS APP

(PEER GROUPS)

You

Age
42

Income
$140K

Location
New York, NY

Location Type
Urban

Credit Score
769

Housing Type
Pay Rent

Your Peers 9.9K people

Age Range
40 – 49

Income Range
$100K – $150K

Location
New York, NY

Location Type
All

Credit Score Range
720 – 779

Housing Type
Pay Rent

The STATUS APP

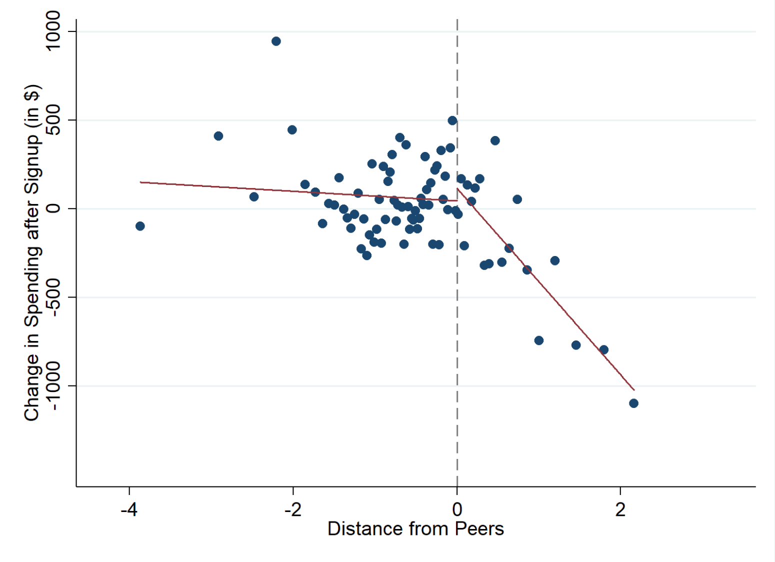
Using the information provided, the STATUS APP:

- Constructs a peer group for each client
- Peers matched on 5 characteristics & w > 5,000 individuals
- STATUS purchases spending data for random US sample
- Compares the client's consumption to that of the peer group
- Information is easy-to-understand and salient

The STATUS APP

(PEER SPENDING)

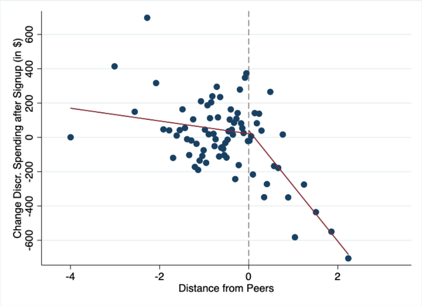
Spending Reaction to Information about Peers

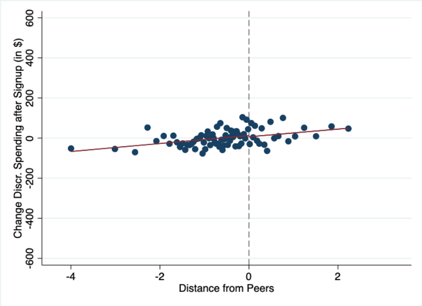


Main Findings

1. Individuals react more when peer group is more informative:
   - peers are more similar
   - peer group has more members
   - peer group is more precise
   - individuals log in more
   - ...
2. Reaction occurs mainly from discretionary spending

Discretionary vs. Non-Discretionary Spending





- Discretionary: outside food & drinks, clothes, entertainment, travels, cash withdrawals
- Non-discretionary: groceries, fees, mortgage payments, tuitions

Conclusions from this Research

- Providing automated advice changes individuals' behavior
- Design matters for individuals' reaction
- Important to think about optimality of the advice provided
- These tools could replace financial planners in the near future

Goal-Setting and Saving in the FinTech Era

Antonio Gargano
University of Houston

Alberto Rossi
Georgetown

Motivation

- Extensive evidence on behavioral biases
  - **Investing**: disposition effect, overconfidence, endowment effect
  - **Saving**: naive diversification, inertia
- Less on how to correct them on a large scale
  - Nudges, reminders, robo-advising
- This paper: FinTech increase saving by helping setting goals

Motivation

- In Economic Theory, goal is a “commitment device”
- Models (Laibson 1997, O’Donoghue and Rabin 1999) predict
  - Present-biased agents would demand commitment devices
  - To facilitate their desired action
- Hard (monetary penalty) v.s. Soft (no penalty). Trade-off
  - Scalability (take-up rate)
  - Effectiveness
- Pre-designed v.s. Self-designed
  - In the typical experimental setting pre-designed
  - Not clear individuals are able to create well-designed goals

This Paper

The effectiveness of soft and self-designed commitment devices in saving decisions

1. **Data** from a FinTech App that allows users to set saving goals

   $\rightarrow$ To quantify the effect

2. **Survey** administered on a random sample of users

   $\rightarrow$ To uncover the economic channel and rule out substitution

Preview of Results

1. Goal-Setting increases savings
   - Effect is causal, diff-in-diff strategy & quasi-natural experiment
   - Effect does not fade away over time (no new toy effect)
   - Not a substitution effect (from accounts outside the App)
   - Strong also for individuals with low propensity to save
     - Low financial literacy, education, income, patience and attention

2. Monitoring Channel rather than goal specificity
   - Consistent with models where agents experience disutility from falling short of their goal, and with goals increasing attention

The App: Gimme5

Developed by Asset Manager AcomeA

Before October 2017: Digital Piggy-Bank

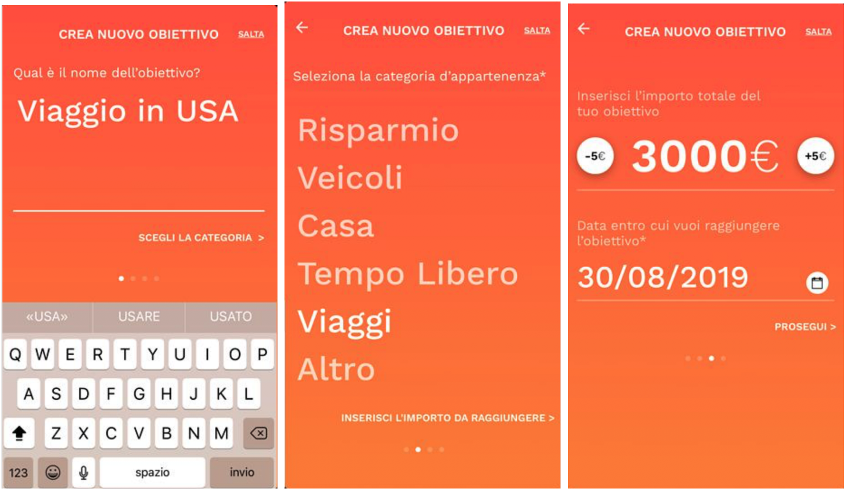
- Investors save small amounts (as small as €5)
- Savings invested in mutual funds
- For each mutual fund chosen, a sub-account is created

After October 2017: Introduced Goal-Setting features

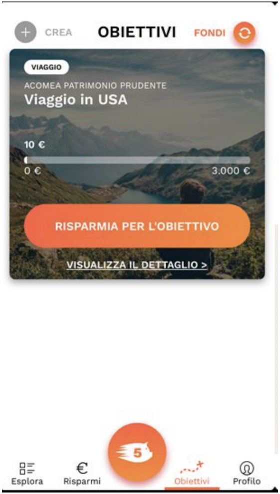
Individuals select:

- Objective/goal, horizon, amount, mutual fund
- Users can still use the App only as Piggy-Bank
- No reminders, automatic saving plans and other nudges

The App: Gimme5



The App: Gimme5



Data

4 Main Sources

- Users
  - 47,643 individuals who created an account since 2014
  - Age, gender, enrollment date, city of residence
- Goal Information
  - Objective/goal, horizon, amount, mutual fund selected
- Deposits and Withdrawals
  - Daily frequency
- Investment Vehicle
  - Name and CUSIP of the mutual fund chosen

Survey

- Third week of March 2021
- Sent by email to random sample of 5,000 users
- 814 responses $\rightarrow$ 16% rate
- Elicit information we cannot observe from data
  1. Saving habits outside the App before and after its adoption
  2. Motivation for using goals & factors influencing achievement
  3. Risk-aversion, impatience, education, income, financial literacy

Summary Statistics

Demographic Characteristics

	N	mean	sd	p1	p25	p50	p75	p99
Male	47,643	0.81	0.39	0.00	1.00	1.00	1.00	1.00
Age	47,216	36.46	11.82	19.00	27.00	35.00	44.00	68.00

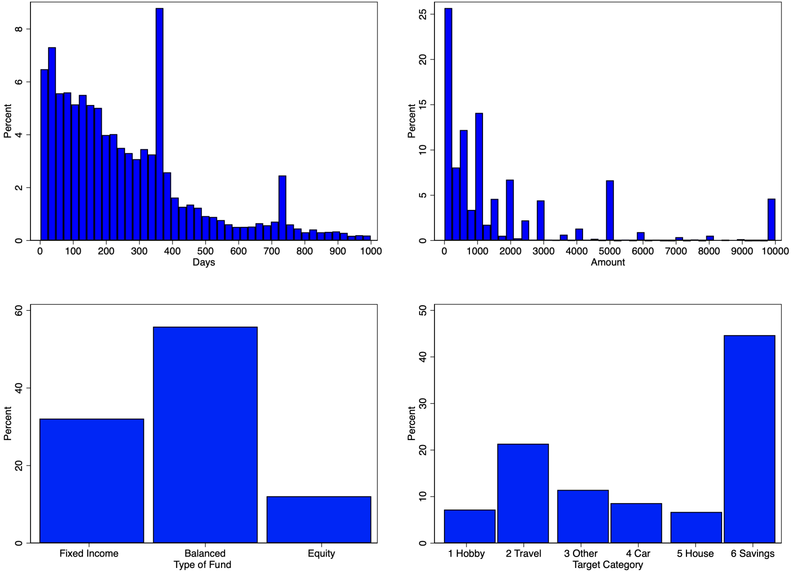
App Usage by Users

	N	mean	sd	p1	p25	p50	p75	p99
Tenure	27,439	11.48	14.02	1.00	1.00	5.33	16.73	59.27
N. Trans./Month	27,439	1.14	0.94	0.08	0.57	1.00	1.41	4.23
Net Deposit/Month	27,439	35.04	96.19	-1.84	0.18	5.01	30.00	463.34

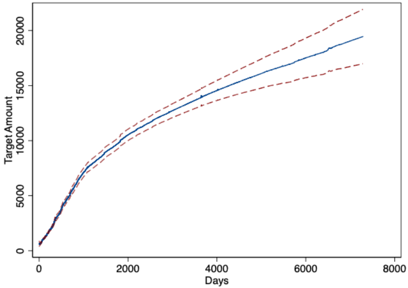
Accounts and Targets

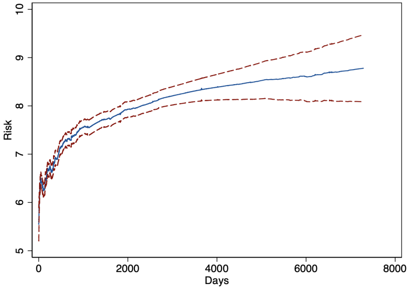
	N	mean	sd	p1	p25	p50	p75	p99
N. of Accounts	47,746	1.11	0.49	1.00	1.00	1.00	1.00	4.00
Target Present	47,746	0.27	0.44	0.00	0.00	0.00	1.00	1.00
N. Targets	17,240	1.43	1.32	1.00	1.00	1.00	1.00	6.00
N. Active Targets	17,240	0.86	0.67	0.00	1.00	1.00	1.00	4.00
N. Closed Targets	17,240	0.29	0.69	0.00	0.00	0.00	0.00	3.00
N. Achieved Targets	17,240	0.28	0.97	0.00	0.00	0.00	0.00	4.00

Goal Characteristics-I



Goal Characteristics-II





Goal-Setting and Saving: Baseline Results

Estimate baseline regression:

$$\textit{M\_Net\_Deposits}_{i,t} = \alpha_i + \alpha_t + \beta \; \textit{Target\_Dummy}_{i,t} + \epsilon_{i,t}$$

where

- $\textit{M\_Net\_Deposits}_{i,t}$: monthly net deposits by user *i*
- $\textit{Target\_ Dummy}_{i,t}$: 1 if *i* has a goal at time *t*
- α_i and α_t: individual and monthly effects
- Standard errors double-clustered at the user and month levels

β: change in monthly savings when users engage in goal-setting

Goal-Setting and Saving: Baseline Results

	Net Deposits	Deposits	Withdrawals
Target Dummy	28.74***	34.56***	5.60***
	(16.37)	(20.24)	(5.67)
User Fixed Effects	✓	✓	✓
Time Fixed Effects	✓	✓	✓
R-Squared	0.34	0.44	0.18
Obs	307,501	307,501	307,501

- Goal-Setting is associated with an increase in saving
- Effect is economically large (€28.74 $\times$ 12=€345 per year)
- Does not control for time-varying individual-specific shocks

Goal-Setting and Saving: User-Account Results

$$M\_Net\_Deposits_{i,j,t} = \alpha_i + \alpha_t + \beta_1\ Target\_Dummy_{i,j,t} + \epsilon_{i,j,t}$$

	Net Deposits	Deposits	Withdrawals
Target Dummy	26.84***	29.40***	1.61
	(18.31)	(19.57)	(1.61)
User Fixed Effects	✓	✓	✓
Time Fixed Effects	✓	✓	✓
User×Time Effects	✗	✗	✗
R-Squared	0.29	0.39	0.16
Obs	347,411	347,411	347,411

- Goal-Setting is associated with an increase in saving
- Effect is economically large (€26.84 × 12=€322 per year)

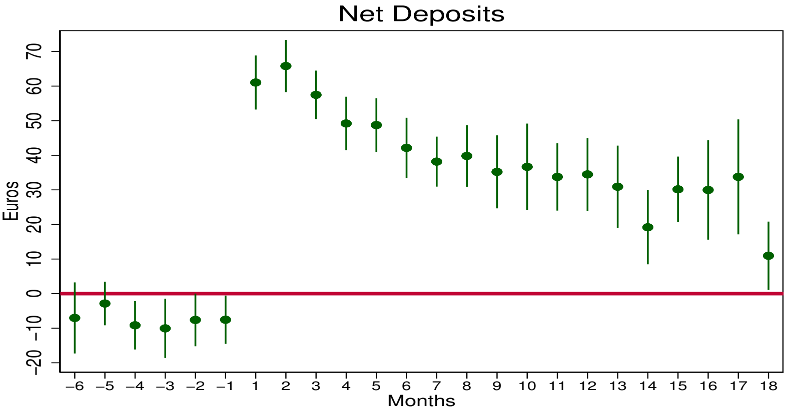
Goal-Setting and Saving: User-Account Results

$$M\_Net\_Deposits_{i,j,t} = \alpha_{i,t} + \beta_1 \; Target\_Dummy_{i,j,t} + \epsilon_{i,j,t}$$

	Net Deposits	Deposits	Withdrawals
Target Dummy	55.16***	56.59***	0.07
	(18.70)	(18.09)	(0.06)
User Fixed Effects	✗	✗	✗
Time Fixed Effects	✗	✗	✗
User×Time Effects	✓	✓	✓
R-Squared	0.56	0.62	0.58
Obs	65,792	65,792	65,792

- Effect is economically large (€55.16 × 12=€662 per year)

Goal-Setting and Saving: Dynamic Specification

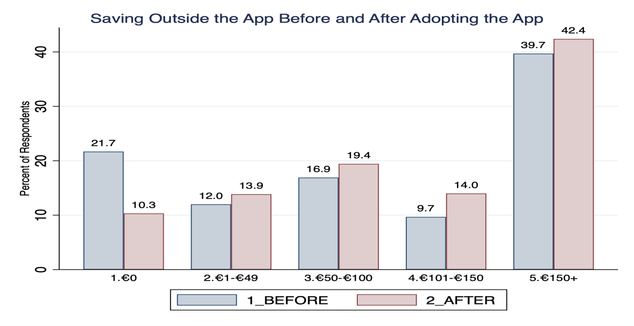


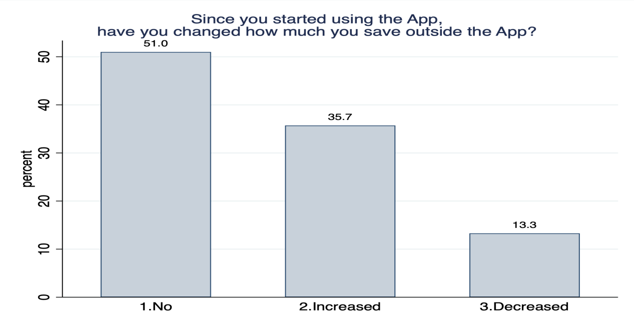
$$M\_Net\_Deposits_{i,j,t} = \alpha_{i,t} + \sum_{s=-6}^{18} \beta_s \; Target\_Dummy_{i,j,s,t} + \epsilon_{i,j,t}.$$

Potential Concerns with the Baseline Results

- Individuals may substitute btw savings in & outside the App
- We do not observe savings in other accounts. In the survey we ask three questions

1. **Since** using Gimme5, how much have you saved on average per month **outside** the App?
2. **Before** using Gimme5, how much have you saved on average per month **outside** the App?
3. **Since** using Gimme5, have you changed how much you saved outside the App?


Saving Outside the App Before and After Adopting the App
Percent of Respondents
0
10
20
30
40
21.7
10.3
12.0
13.9
16.9
19.4
9.7
14.0
39.7
42.4
1.€0
2.€1-€49
3.€50-€100
4.€101-€150
5.€150+
1_BEFORE
2_AFTER


Since you started using the App,
have you changed how much you save outside the App?
percent
0
10
20
30
40
50
51.0
35.7
13.3
1.No
2.Increased
3.Decreased

Goal-Setting and Saving: Identification Strategy

Results so far:

- Do not control for the *endogenous* decision to set goals
- Individual-specific time-varying shocks could be driving
  - the decision to set goals
  - the change in saving we detect

Fortunately, the App developer deployed the App:

- on 122 beta-testers
- 50 days before the official release

→ Implement a diff-in-diff strategy...
...allow to estimate effect of *availability* of goal-setting on saving

Goal-Setting and Saving: Identification Strategy

Specification:

$$M\_Net\_Deposits_{i,t} = \alpha_i + \alpha_t + \beta \; Treated_{i,t} + \epsilon_{i,t},$$

where

- $Treated_{i,t}$ is equal to 1
  - for the 122 beta testers
  - August 2017 (Specification 1)
  - August and September 2017 (Specification 2)

1. Intention-to-treat effect (ITT): β
   - Effect of deploying goal-setting on the population at large
2. Local Average Treatment Effect (LATE): β/fraction of adopters
   - Effect of goal setting for those who actually set goals

Goal-Setting and Saving: Identification Strategy

All Users

	Specification 1	Specification 2
Dummy	20.01***	16.92***
	(6.75)	(4.22)
User FE	✓	✓
Time FE	✓	✓
R^2	0.25	0.25
Obs	68,336	74,232

- Intention-to-treat effect (ITT)
  - €16.92-€20.01 per month, or €203.4-240.12 per year
- Local Average Treatment Effect (LATE)
  - €16.92/0.284=€59.957
- Results hold when we use a matched sample

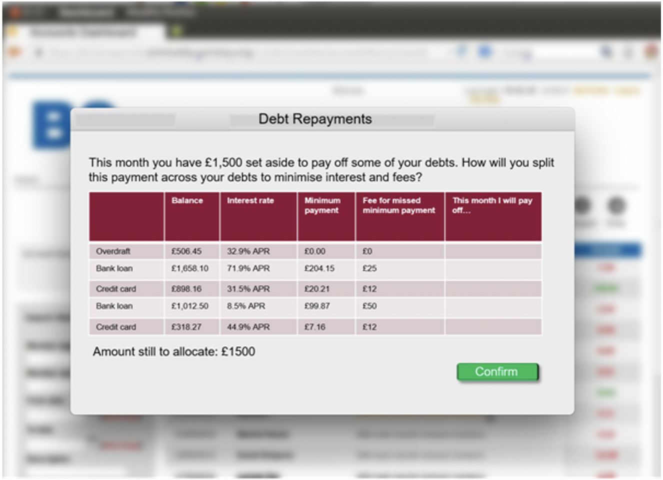
Robo-advising and borrowing decisions

Major problem for a large part of the population:

- Excessive debt
- High interest rates (Credit cards, payday loans)
- Difficult to optimize debt repayment
- Difficult to provide financial literacy effectively

Robo-advisors for managing debt repayment can be a solution (D'Acunto et al., 2020)

Robo-advising and borrowing decisions



Debt Repayments

This month you have £1,500 set aside to pay off some of your debts. How will you split this payment across your debts to minimise interest and fees?

	Balance	Interest rate	Minimum payment	Fee for missed minimum payment	This month I will pay off...
Overdraft	£506.45	32.9% APR	£0.00	£0	
Bank loan	£1,658.10	71.9% APR	£204.15	£25	
Credit card	£898.16	31.5% APR	£20.21	£12	
Bank loan	£1,012.50	8.5% APR	£99.87	£50	
Credit card	£318.27	44.9% APR	£7.16	£12	

Amount still to allocate: £1500

Confirm

(D'Acunto et al., 2020)

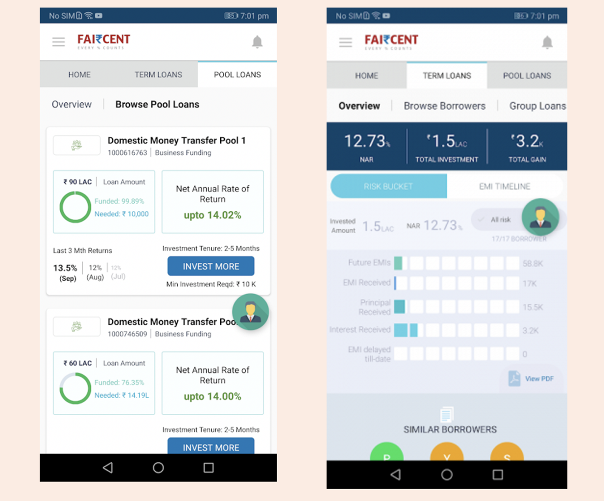
Robo-advising and P2P lending investments

P2P lending could not a viable asset class for small investors

- High default rates
- Difficult for individuals to make diversified investment decisions
- Difficult to monitor the investment decisions

Automated algorithms can help individuals make P2P decisions

Robo-advising and P2P lending investments



(D’Acunto et al, 2020)

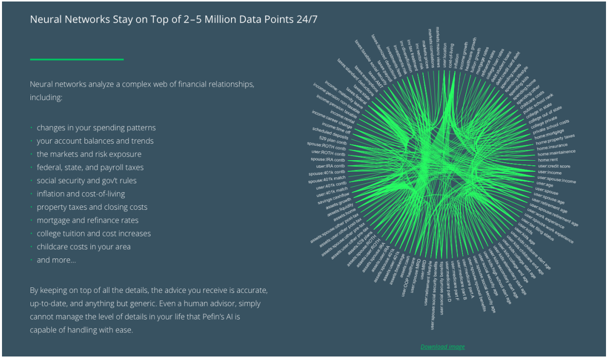
New frontier of robo-advising: the holistic investor view

“*Robo advisers have great potential but the technology is still immature; they’re the rotary phones to today’s iPhone.*" Andrew Lo

New frontier of robo-advising: the holistic investor view

“*Robo advisers have great potential but the technology is still immature; they’re the rotary phones to today’s iPhone.*" Andrew Lo

PEFIN: First AI-based Financial Advisor. Not sure if realistic yet



Open challenges for the future of robo-advising

- How can separate robo-advisors be integrated into a holistic one?
- Algorithmic Aversion: Is Hybrid Robo-Advising a Solution?
- Will Robots Democratize Access to Financial Advice or Exacerbate Inequalities?
- Systemic Implications of Homogenizing Investors Through Robo-Advising