#### Personal Recommendations and Portfolio Quality CEPR European Conference on Household Finance 2023

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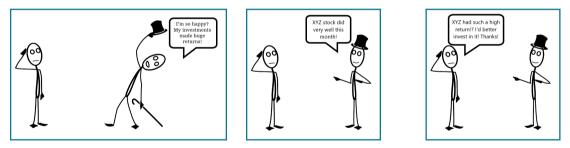
#### Personal finance is a hit on TikTok

The Economist, 2022



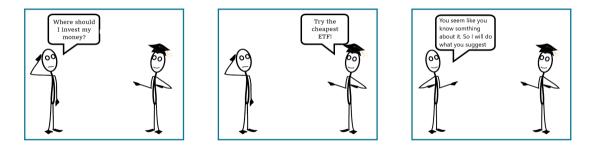
#### Introduction

How social interaction about finances can work (theory (Han *et al.*, 2022) and empirical (Heimer & Simon, 2015; Escobar Pradilla & Pedraza, 2019; Lim *et al.*, 2020; Huang *et al.*, 2021)):



#### **Return-biased transmission**

#### An alternative view on social interaction in finance



#### **Expertise-based transmission**

This paper

#### We test predictions on

	Expertise-based	<b>Return-biased</b>
What determines social interactions?	Recommender's experience and portfolio quality	Recommender's portfolio <mark>returns</mark>
What assets are passed on?	Lower volatility and fees, higher expected returns Active or passive funds	Assets with higher and ex- treme returns Lottery stocks

Investigates what drives the social interaction about finance among personally connected individuals:

• Expertise vs Returns

And what are the consequences of social interaction for Followers' portfolios?

Using referral campaign from an online bank + Detailed portfolio information

#### Findings

Strong overlap between Recommenders and Followers' portfolios:

–  $\approx 17\%$  vs  $\approx 0\%$  (placebo matched peers);

Decisions to recommend and follow (positive overlap) are

- NOT related to Recommenders' portfolio returns;
- (+) associated with Recommender's age, income and AUM;
- (+) correlated with Recommender's portfolio quality (RL & RSRL);
- More likely if Recommender invests in ETFs ( $\approx 20\%$ ).

Followers are:

- 49% more likely to invest in funds if the Recommender invests in funds;
- twice less likely to copy lottery and attention stocks than funds from the Recommender;
- better diversified with portfolio quality highly correlated with Recommenders' portfolios

# Data and methodology

## Data from a large German online bank 2003 - 2017 Data

258,000 randomly selected clients with a detailed transaction (including securities accounts) and sociodemographic (age, gender, income) data

- Detailed data on portfolio composition
- Investors have access to 900,000 assets

#### Referral campaign active from 2012 - 2017

- Bank customers can recommend a person via their online bank by sending a Facebook message or a link via email
- 20 Euro or non-cash (mixers, suitcases, headphones or coffee machines)
- 515 Recommender Follower pairs
- On average  $\approx$  1 successful referral per Recommender



# **Portfolio Overlap**

## Overlap analysis helps separate true peer effects Methodology

Most factors that could explain peer effects operate at the level of the portfolio

- Correlated risk aversion, background risk, or local bias
- → The overlap (share of common securities in Follower portfolio) in individual assets is our evidence for peer effects

$$Overlap_i^F = \frac{\sum_{k=1}^K V_k \mathbb{1}_{k=m}}{\sum_{k=1}^K V_k}$$

We fix the Recommender's portfolio one month prior to the Follower joining the bank to establish the direction of causality and construct placebo pairs to examine how rare overlap is

## Overlap is significantly higher for Followers Overlap



Placebos: Matched Followers & Matched Recommenders.

Overlap distribution Overlap with all investors

# **Social Interaction**

#### Testing predictions on social interactions

	Expertise-based	Return-biased
What determines social interac- tions?	Recommender's experience and portfolio quality	Recommender's portfolio returns
What assets are passed on?	Lower volatility and fees, higher expected returns Active or passive funds	Assets with higher and ex- treme returns Lottery stocks

Sending function - Recommender's decision to talk about the investment

$$s(R,Q) = \beta R + \gamma Q + \delta$$

where R - return on Recommender's investment and  $\beta$  is sensitivity to the return;

- $-\delta$  is the rate of *conversability* of the investment propensity to provide financial advice;
- Q Recommender's portfolio quality and  $\gamma$  propensity for investors of different quality to give financial advice (addition to Han *et al.* (2022))
  - measured by Log Return Loss and Log Relative Sharpe Ratio Loss Details

#### Sending advice is not related to returns among Recommenders

 $Recommendation_{i,t} = \alpha + \frac{\beta_1}{R_{i,t}^R} + \frac{\gamma_1}{Q_i^R} + \mathbf{X}'_{\mathbf{i}} \mu_1 + \delta_{k,t} + \epsilon_{i,t}$ 

All Recommenders				Success	ful recomm	endation
Portfolio returns		-0.0000**	-0.0000*	0.0052	0.0116	0.0117
		(0.0000)	(0.0000)	(0.0136)	(0.0117)	(0.0118)
Passive returns	0.0130			0.0039		
	(0.0107)			(0.0140)		
Active returns	0.0017			0.0173		
	(0.0027)			(0.0159)		
R: Log Return loss	-0.0004		-0.0004	-0.0005		-0.0004
	(0.0004)		(0.0004)	(0.0010)		(0.0010)
R: RSRL	0.0000		-0.0000	0.0000		-0.0000
	(0.0007)		(0.0007)	(0.0015)		(0.0015)
Demographics	Yes	Yes	Yes	Yes	Yes	Yes
Region#Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	111,643	111,643	111,643	23,809	23,809	23,809

#### Recommenders have higher portfolio quality relative to other investors

	All	Recommend	ers	Successful recommendation		
	(1)	(2)	(3)	(4)	(5)	(6)
Portfolio returns × 100	0.0003 (0.0007)	0.0003 (0.0007)	0.0003 (0.0007)	-0.0001** (0.0000)	-0.0000 (0.0000)	-0.0001** (0.0000)
Log return loss		-0.0002*** (0.0000)	¢.		-0.0004** <sup>,</sup> (0.0000)	*
Log Relative Sharpe ratio loss			-0.0017*** (0.0001)			-0.0009*** (0.0000)
Demographics	Yes	Yes	Yes	Yes	Yes	Yes
Region#Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,996,207	4,996,205	4,996,207	4,911,863	4,911,861	4,911,863

Recommenders also have higher income, almost 3 times larger AUM, and 2 times as large portfolios.

**Receiving Function** - the probability the investor adopts Recommender's investment strategy

$$r(R) = aR + bR^2 + cQ + d,$$

where *a* - persuasiveness of higher Recommender's return;

- **b** more/less attentio to extreme returns;
- d fixed propensity to follow advice;
- c the importance of Recommender's portfolio quality (innovation to Han et al. (2022))

What drives the decision to follow the recommendation (positive overlap)?

#### **Receiving Function**

 $PosOverlap_{f,t+x} = \alpha + \frac{\beta_1}{R_{f,t}^R} + \frac{\mu_1}{Q_{f,t}^R} + \mathbf{X'_i}\mu_1 + \delta_{k,t} + \epsilon_{i,t}$ 

		Returns		Portfolio	quality	Comb	oined
R: Portfolio return	0.565					0.655	0.608
	(0.614)					(0.597)	(0.607)
R: Active return		-0.115					
		(0.232)					
R: Passive return			1.898**				
			(0.830)				
R: Log Return loss				-0.061**		-0.062**	
				(0.026)		(0.027)	
R: RSRL					-0.092**		-0.093***
					(0.036)		(0.036)
Demographics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region#Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	374	374	374	374	374	374	374

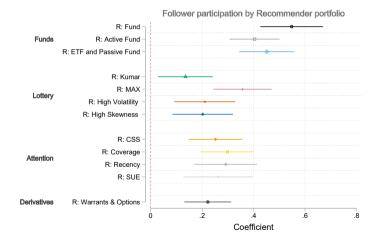
## **Asset Class Participation and Portfolio Quality**

## Testing predictions on portfolio composition

	Expertise-based	<b>Return-biased</b>
What determines social interactions?	Recommender's experience and portfolio quality	Recommender's portfolio <mark>returns</mark>
What assets are passed on?	Lower volatility and fees, higher expected returns Active or passive funds	Assets with higher and ex- treme returns Lottery stocks

#### Participation in different asset classes

#### $Participation_{i,k,t}^{j} = \alpha + \gamma Recommender Participation_{i,k,t}^{j} + \mathbf{X}'_{\mathbf{i},\mathbf{k},\mathbf{t}}\beta + \delta_{i,k} + \epsilon_{i,k,t}$



#### Peer effects in portfolio quality

$$y_{i,k} = \alpha + \gamma Follower_{i,k} + \mathbf{X}'_{\mathbf{i},\mathbf{k}}\beta + \delta_{i,k} + \epsilon_{i,k}$$

	Log	Return Ic	SS	Log Rela	Log Relative Sharpe ratio loss			
	(1)	(2)	(3)	(4)	(5)	(6)		
Follower	-0.27***	-0.11**	-0.05	-0.28***	-0.10***	-0.08**		
	(0.05)	(0.05)	(0.05)	(0.03)	(0.03)	(0.03)		
Follower Controls	No	No	Yes	No	No	Yes		
Region FE	No	Yes	Yes	No	Yes	Yes		
Year FE	No	Yes	Yes	No	Yes	Yes		
Region#Year FE	No	Yes	Yes	No	Yes	Yes		
Observations	25605	25605	25605	25605	25605	25605		
Adjusted $R^2$	0.001	0.055	0.086	0.002	0.212	0.222		

Controls: gender, age, age sq, income proxy, academic title, main bank dummy, joint account dummy, robo-advice user.

# Conclusions

#### Conclusion I

Peer effects lead to overlap in portfolio composition and similarities in portfolio quality

ightarrow Scope for both good and bad advice about individual assets to spread through social networks

Understanding the social-advice mechanism in personal interaction is paramount for understanding whether peer effects propagate good or bad investment behavior

- Decision to recommend is NOT correlated to returns;
- Decision to follow is NOT correlated to returns and (+) related to Recommednder's portfolio quality and participation in ETFs;

#### Expertise-based transmission mechanism is supported.

#### Conclusion II - we observe a different type of social links

Recommenders-Follower pairs are characterized by a personal relationship that likely precedes the observed financial advice

→ Recommenders may be incentivized by reputational costs, social utility (Bursztyn *et al.*, 2014), or 'warm glow' to recommend sound financial advice

Resulting Followers' portfolios are on average *better diversified* and Followers are more likely to invest in *ETFs*.

# Appendix

#### References I

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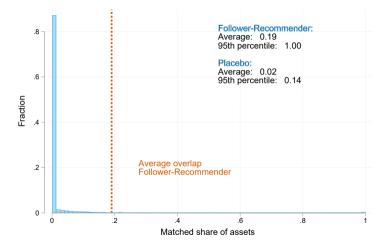
# Sample selection and methodology

Sample selection:

- We select customers with active trading accounts and with non-zero AUM
- Select individuals who joined the bank after 2012
- We select the first twelve months of trading to avoid learning and luck influencing portfolio choice

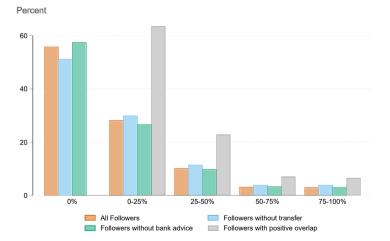


#### Overlap between each Follower with ALL investors





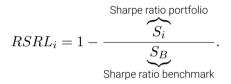
#### **Overlap Distribution**



Back

#### Portfolio quality based on a CAPM-model Calvet et al. (2007)

Relative Sharpe Ratio loss – Measure of diversification loss



Return Loss – Lost return due to choosing portfolio instead of benchmark and cash





#### Participation across asset classes

	(1)	(2)	(3)
	Fund	Lottery	Attention
Recommender: Funds	0.526***	-0.207***	-0.203***
	(0.062)	(0.064)	(0.064)
Recommender: Lottery	-0.255***	0.326***	0.349***
	(0.046)	(0.060)	(0.058)
Recommender: Attention	-0.264***	0.325***	0.322***
	(0.046)	(0.060)	(0.059)



#### Participation: Followers vs General Sample

		Funds		Lottery			Attention				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Fund	Active	Passive	Kumar	MAX	Volatility	Skewness	CSS	CVRG	Recency	SUE
Follower	0.045**	0.054**	0.054**	-0.006	-0.008	-0.001	-0.011	-0.011	0.003	0.004	0.004
	(0.018)	(0.021)	(0.021)	(0.013)	(0.018)	(0.014)	(0.017)	(0.016)	(0.016)	(0.018)	(0.013)
Region#Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dep. var. mean	0.687	0.346	0.440	0.150	0.371	0.152	0.249	0.227	0.212	0.340	0.133
Dep. var. std dev	(0.464)	(0.476)	(0.496)	(0.358)	(0.483)	(0.359)	(0.433)	(0.419)	(0.409)		(0.339)
Observations	25605	25605	25605	25605	25605	25605	25605	25605	25605	25605	25605
Adjusted $R^2$	0.072	0.047	0.155	0.089	0.244	0.080	0.138	0.132	0.118	0.226	0.120



#### Return Loss components

$$\ln RL_i = \ln(Er_m^e) + \ln w_i + \ln \beta_i + \ln \left(\frac{RSRL_i}{1 - RSRL_i}\right).$$

	Return loss $\ln(RL_i)$	Risky share $\ln w_i$	Risky portfolio beta $\ln eta_i$	Diversification loss $\ln\left(\frac{RSRL_i}{1-RSRL_i}\right)$
Follower	-0.05	0.16***	0.08***	-0.14***
	(0.05)	(0.04)	(0.03)	(0.05)
Follower Controls	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Region#Year FE	Yes	Yes	Yes	Yes
Observations	25605	25587	25605	25605
Adjusted $R^2$	0.086	0.046	0.131	0.241