Horn, Matthias; Schneider, Julian; Oehler, Andreas

Do transactions on social trading platforms predict the stock market behavior of the aggregate private sector?

Date of secondary publication: 23.07.2024

Version of Record (Published Version), Article

Persistent identifier: urn:nbn:de:bvb:473-irb-966633

Primary publication

Horn, Matthias; Schneider, Julian; Oehler, Andreas (2024): „Do transactions on social trading platforms predict the stock market behavior of the aggregate private sector?“. In: Finance research letters, Vol. 66, Nr. 105668, pp. 1-13, New York: Elsevier Science, doi: 10.1016/j.frl.2024.105668.

Finance Research Letters 66 (2024) 105668

Contents lists available at ScienceDirect

Finance Research Letters

journal homepage: www.elsevier.com/locate/frl

Do transactions on social trading platforms predict the stock market behavior of the aggregate private sector?

Matthias Horn[a,*], Julian Schneider[b], Andreas Oehler[c]

[a] *Postdoc, Department of Finance, Bamberg University, Bamberg, Germany*
[b] *Department of Finance, Bamberg University, Bamberg, Germany*
[c] *Full Professor and Chair of Finance, Bamberg University, Bamberg, Germany*

A R T I C L E I N F O

JEL Classification:
G11
G14
G23
G40
G41
G50

KeyWords:
Social trading
Herding
Fintech
Attention-induced trading
Retail Investor Behavior

A B S T R A C T

We analyze the relation between virtual stock holding changes on a social trading platform and stock holding changes of all private investors in a national economy. Our data sources are the social trading platform *wikifolio*.com and the *Securities Holdings Statistics-Base plus* (*SHS-base*) of the German central bank. We find that the transactions of signal providers on *wikifolio.com* are a good proxy for aggregate transactions of private investors – mirrored by the *SHS-base* – during the same month, and a good predictor for the aggregate transactions of the private investors in the following month.

1. Introduction

In social trading, individual investors, so-called signal providers, make their investment decisions available on a trading platform to other investors, so-called followers, who automatically copy these decisions in real time (Döring et al., 2015; Oehler et al., 2016; Horn et al., 2020). The behavior of followers, signal providers, as well as determinants of the decision who to follow on social trading platforms are extensively researched.[1] However, it is unclear whether the transactions of signal providers are related to transactions of investors outside of social trading networks.

Although herding within social trading networks is well documented (Gemayel and Preda, 2018b; Tang et al., 2017), it seems far-fetched that the herding behavior spills over to investors outside the social trading network: Social trading is a tiny fraction of the

We would like to thank Samuel Vigne (the editor), Igor Loncarski and Matej Marinč (the guest editors), an anonymous referee, Matthias Pelster and participants of the 2nd Conference on INternational Finance; Sustainable and Climate Finance and Growth in Ljubljana for helpful comments and suggestions. All remaining errors are our own.

* Corresponding author at: Chair of Finance, Bamberg University, Kaerntenstrasse 7, 96045 Bamberg, Germany.
E-mail address: matthias.horn@uni-bamberg.de (M. Horn).

[1] See, e.g., Deng et al., 2023; Erdős et al., 2022; Gemayel and Preda, 2018a; Glaser and Risius, 2018; Kromidha and Li, 2019; Lee and Ma, 2018; Liêu and Pelster, 2020; Oehler and Schneider, 2023; Pelster, 2017; Pelster and Breitmayer, 2019; Pelster and Hofmann, 2018; Röder and Walter, 2019; Schneider and Oehler, 2021; Wohlgemuth et al., 2016.

https://doi.org/10.1016/j.frl.2024.105668
Received 21 July 2023; Received in revised form 26 March 2024; Accepted 30 May 2024
Available online 3 June 2024

Table 1
Descriptive statistics.

	Mean	Std. Dev.	Min	25 perc	Median	75 perc	Max
$Ret_{i,t\;1}$	1.54	12.47	91.06	3.51	.87	5.93	428.57
$MaxRet_{i,t\;1}$	1.56	.66	2.72	1.15	1.52	1.92	7.50
$Price_{i,t\;1}$	2.60	1.47	4.61	1.64	2.77	3.64	6.83
$MCap_{i,t\;1}$	19.86	2.31	11.61	18.17	19.64	21.49	25.49
$IVol^{t\;1}_{i,\;t\;6}$	2.49	10.62	.00	1.35	1.81	2.50	605.24
$ISkew^{t\;1}_{i,t\;6}$	.38	1.23	10.60	0.09	.30	.74	11.29
$Trans_{i,t}$	3.33	1.70	.00	2.08	3.50	4.65	7.80
$Acc_{i,t}$	2.69	1.44	.00	1.61	2.83	3.83	6.27

aggregate stock portfolio of the private sector[2] and members of social trading networks trade frequently (Döring et al., 2015) while most private investors show inertia (Bonaparte and Cooper, 2009; Brunnermeier and Nagel, 2008). However, recent findings show that many retail investors open accounts at FinTechs that offer commission free trading and that facilitate active trading by gamification and simplicity (Welch, 2022; Barber et al., 2022). Furthermore, all private investors – no matter whether they participate in stock markets via social trading platforms, online brokers, or their local bank – face the same search problem: Which are the stocks to invest in?

This search problem leads retail investors to buy attention-grabbing stocks, i.e., stocks that are frequently discussed in social networks, stocks with lottery-like features, and high news coverage (Bali et al., 2011, 2021; Barber and Odean, 2008; Barber et al., 2022; Han et al., 2022; Kumar, 2009). Hence, stocks that are frequently traded and discussed on social trading platforms should also attract the attention of investors that are not on the platform and vice versa. Therefore, we hypothesize that the transactions on a social trading platform proxy the aggregate behavior of private investors.

Observing the stock market behavior of a representative sample of private investors is difficult. Data of online retail brokers is restricted to those who are willing to use the internet and likely underrepresent older investors. Data from household/consumer surveys are not frequent enough and do not include stock-level information. We are aware of only one dataset that captures stock holdings of all private investors within a corresponding country/national economy: The *Securities Holdings Statistics-Base plus* (henceforth *SHS-base*) of the German central bank.[3] Moreover, since 2012, a social trading platform that is predominantly used by German individual investors has been operating: *wikifolio.com* (henceforth *wikifolio*). An important feature of *wikifolio* is that signal providers' portfolios are virtual, i.e., signal providers do not directly execute real money transactions on common stock exchanges. Instead, *wikifolio* acts like a market maker for the signal providers (comparable to CFD brokers) – who sometimes even trade with virtual money. Therefore, we refer to the transactions of signal providers as virtual transactions or virtual stock holding changes. Furthermore, these virtual stock holdings (changes) are not captured by the *SHS-base* and do not mechanically change holdings in the *SHS-base*.[4]

We find that the transactions of signal providers on *wikifolio* are a good proxy for aggregate transactions of private investors – mirrored by the *SHS-base* – during the same month, particularly for stocks with high market capitalization. Furthermore, transactions on *wikifolio* are a good predictor for the aggregate purchase transactions of the private investors in the following month and even related to sell transactions of stocks with small market capitalization, although with smaller effect size and explanatory power. Our findings have important implications for regulators, investors, and researchers.

2. Data and methodology

2.1. Aggregate private sector holdings data and dependent variable

Our analysis covers the period from January 2013 to June 2017, i.e., our results are not impacted by the cryptocurrency-hypes or the COVID pandemic. As there is no reporting limit, *SHS-base* data include a wide selection of assets which are only held by few investors. Due to German investors' significant home bias (Oehler et al., 2017) as well as the small bid-ask spreads and popularity of

[2] At the end of the observation period, assets under management by *wikifolio* were about 225 million euros (see https://www.welt.de/print/die_welt/finanzen/article163727970/Wikifolio-Papiere-reduzieren-das-Ausfallrisiko.html) while German private households held individual stocks (excluding stock mutual funds etc.) worth more than 300 billion euros (see https://www.bundesbank.de/dynamic/action/de/statistiken/zeitreihen-datenbanken/zeitreihen-datenbank/723452/723452?tsId=BBK01.CEFI0J&listId=www_v1f_14gv511&dateSelect=2022).

[3] See Bade et al., 2017; Blaschke et al., 2022 for a data report.

[4] Please note that wikifolio offers exchange traded certificates that investors can buy to replicate the performance of the underlying wikifolio. If a retail investor buys such a certificate, the certificate holding of the investor is listed in the SHS-base (comparable to holding a mutual fund) – not the stock holdings of the underlying wikifolio. We do not include the certificate holdings in our analysis. Wikifolio certificates are issued by Lang & Schwarz. For hedging purposes, Lang & Schwarz will buy and sell some stocks traded by signal providers on wikifolio. This will have an influence on the institutional holdings of a stock. However, we assume that the changes induced by the hedges of Lang & Schwarz are negligible in size compared to the holdings of all households since even the total assets under management of wikifolio are only a tiny fraction of the aggregate stock portfolio of the private sector.

Table 2
Pearson correlations.

	$D\Delta SHS^h_{i,t}$	$D\Delta Trans^{Buy}_{i,t}$	$D\Delta Trans^{Sell}_{i,t}$	$D\Delta Acc^{Buy}_{i,t}$	$D\Delta Acc^{Sell}_{i,t}$	$Ret_{i,t\ \ 1}$	$MaxRet_{i,t\ \ 1}$	$MCap_{i,t\ \ 1}$	$IVol^{t\ 1}_{i,\ t\ 6}$	$ISkew^{t\ 1}_{i,t\ 6}$	$Trans_t$
$D\Delta Trans^{Buy}_{i,t}$	.05***										
$D\Delta Trans^{Sell}_{i,t}$	0.04**										
$D\Delta Acc^{Buy}_{i,t}$	.06***										
$D\Delta Acc^{Sell}_{i,t}$	.01										
$Ret_{i,t\ \ 1}$	0.06***	0.06***	.05***	0.05***	.05***						
$MaxRet_{i,t\ \ 1}$	.05***	.10***	0.10***	.06***	0.08***	.07***					
$MCap_{i,t\ \ 1}$	0.02**	0.43***	.49***	0.29***	.38***	.04***	0.46***				
$IVol^{t\ 1}_{i,\ t\ 6}$	.01	.06***	0.04**	.01	0.04**	.01	.15***	0.12***			
$ISkew^{t\ 1}_{i,t\ 6}$	0.03***	.11***	0.13***	.06***	0.11***	.19***	.12***	0.19***	.22***		
$Trans_{i,t}$	.03***	0.53***	.61***	0.43***	.57***	.07***	0.11***	.63***	0.06***	0.17***	
$Acc_{i,t}$	.03***	0.53***	.63***	0.41***	.55***	.08***	0.15***	.68***	0.07***	0.18***	.98***

Notes: We provide Pearson correlation coefficients. The symbols ***, **, and * denote significance at the 1 %, 5 %, and 10 % level, respectively.

Table 3

Panel regressions with $D\Delta SHS^h_{i,t}$ as dependent variable and *wikifolio* transaction/account buy pressure indicators of the same month as independent variable.

	Net buy transactions on *wikifolio*; $\Delta Trans_{i,t} > 0$ (models (1) and (2)) and $\Delta Acc_{i,t} > 0$ (models (3) and (4))				Net sell transactions on *wikifolio*; $\Delta Trans_{i,t} < 0$ (models (5) and (6)) and $\Delta Acc_{i,t} < 0$ (models (7) and (8))			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$D\Delta Trans^{Buy}_{i,t}$	.120***	.231***						
	(0.021)	(0.026)						
$D\Delta Trans^{Sell}_{i,t}$					0.063	.054		
					(0.041)	(0.044)		
$D\Delta Acc^{Buy}_{i,t}$			.116***	.262***				
			(0.022)	(0.034)				
$D\Delta Acc^{Sell}_{i,t}$							0.004	.129***
							(0.037)	(0.045)
$Ret_{i,t-1}$		0.046***		0.043***		0.001		0.015
		(0.008)		(0.006)		(0.006)		(0.010)
$MaxRet_{i,t-1}$		.374***		.475***		.463***		.253
		(0.097)		(0.087)		(0.158)		(0.148)
$MCap_{i,t-1}$		0.107		0.109**		0.132*		0.109
		(0.065)		(0.058)		(0.077)		(0.066)
$IVol^{t-1}_{i,t-6}$		.009**		.006***		.004		0.008***
		(0.003)		(0.002)		(0.007)		(0.003)
$ISkew^{t-1}_{i,t-6}$		0.133**		0.152***		0.126		0.041
		(0.065)		(0.050)		(0.084)		(0.079)
$Trans_{i,t}$		.545***				0.170		
		(0.090)				(0.101)		
$Acc_{i,t}$				.721***				0.382***
				(0.114)				(0.088)
α	0.420**	1.30	0.373	1.71*	1.35***	1.66	1.26***	2.42
	(0.209)	(1.20)	(0.233)	(1.01)	(0.307)	(1.67)	(0.296)	(1.53)
R^2	.003	.03	.003	.03	.001	.009	.000	.012
N	11,388	11,388	11,388	11,388	4,350	4,350	4,350	4,350
#stocks	440	440	440	440	428	428	428	428

Notes: We provide coefficients of pooled OLS regressions with Driscoll-Kraay standard errors (in parentheses) and the respective R^2 for the regression model of *Equ. 1* with the aggregate private transaction indicator $D\Delta SHS^h_{i,t}$ as dependent variable. The symbols ***, **, and * respectively denote statistical significance at the one, five, and ten percent level. Example: Regressing $D\Delta SHS^h_{i,t}$ on the social trading transaction buy pressure indicator $D\Delta Trans^{Buy}_{i,t}$ without controls yields a coefficient of 0.120 with statistical significance at the one percent level (corresponding to a Driscoll-Kraay standard error for the coefficient estimate of 0.021).

stocks in the German DAX index family (Herberger et al., 2020), we focus on the about 400 stocks that have at least once been listed in the CDAX[5] during our observation period. We focus on monthly changes in aggregate household holdings in the *SHS-base*, which are defined as the market value of stock *i* held by the private sector ($HCap_{i,t}$) divided by the stock's market capitalization ($MCap_{i,t}$). The corresponding measure is constructed as follows (Fecht et al., 2018):

$$H^h_{i,t} = \frac{HCap_{i,t}}{MCap_{i,t}}.$$

Monthly changes in holdings, $\Delta SHS^h_{i,t}$, are then defined as:

$$\Delta SHS^h_{i,t} = H^h_{i,t} - H^h_{i,t-1}.$$

$\Delta SHS^h_{i,t}$ is not impacted by price movements of stock *i*. Thus, we are left with changes driven by private sector transactions. Due to households' inertia, we expect a cluster of stocks with small magnitudes of $\Delta SHS^h_{i,t}$. Within this cluster, few small transactions triggered by noise can have a relatively large influence. To mitigate this effect and to obtain a variable reasonably suited for a regression analysis, we use deciles as threshold values for all net sales as well as for all net purchases per month. Subsequently, the variable $\Delta SHS^h_{i,t}$ is transformed into a discrete numerical variable ranging from negative ten (highest level of net sales) to positive ten (highest level of net buys). The resulting variable, $D\Delta SHS^h_{i,t}$, is referred to as aggregate private transaction indicator.

[5] The CDAX is a broad German stock index comprising all prime and general standard equities; thus, the CDAX presents a reasonable proxy for the German stock market (Oehler and Schneider, 2022).

Table 4

Panel regressions with $D\Delta SHS^{h}_{i,t}$ as dependent variable and *wikifolio* transaction/account buy pressure indicators of the previous month as independent variable.

	Net buy transactions on *wikifolio*; $\Delta Trans_{i,t\ \ 1} > 0$ (models (1) and (2)) and $\Delta Acc_{i,t\ \ 1} > 0$ (models (3) and (4))				Net sell transactions on *wikifolio*; $\Delta Trans_{i,t\ \ 1} < 0$ (models (5) and (6)) and $\Delta Acc_{i,t\ \ 1} < 0$ (models (7) and (8))			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$D\Delta Trans^{Buy}_{i,t\ \ 1}$	.127***	.213***						
	(0.020)	(0.025)						
$D\Delta Trans^{Sell}_{i,t\ \ 1}$					.008	.102**		
					(0.048)	(0.046)		
$D\Delta Acc^{Buy}_{i,t\ \ 1}$			.120***	.217***				
			(0.021)	(0.020)				
$D\Delta Acc^{Sell}_{i,t\ \ 1}$							.036	.116**
							(0.044)	(0.045)
$Ret_{i,t\ \ 1}$		0.032***		0.031***		0.018*		0.043***
		(0.007)		(0.008)		(0.010)		(0.013)
$MaxRet_{i,t\ \ 1}$		.559***		.663***		.464***		.169
		(0.155)		(0.165)		(0.149)		(0.207)
$MCap_{i,t\ \ 1}$		.066		.064		0.145**		0.075
		(0.062)		(0.069)		(0.064)		(0.059)
$IVol^{t\ \ 1}_{i,\ t\ \ 6}$		.002		.001		0.002		.059
		(0.007)		(0.004)		(0.003)		(0.099)
$ISkew^{t\ \ 1}_{i,t\ \ 6}$		0.143**		0.141**		0.051		0.116
		(0.059)		(0.065)		(0.089)		(0.084)
$Trans_{i,t}$		.243***				0.059		
		(0.089)				(0.098)		
$Acc_{i,t}$				.317***				0.109
				(0.100)				(0.105)
α	0.579**	4.03***	0.528**	4.19***	0.700*	2.14	0.626**	1.21
	(0.231)	(1.18)	(0.220)	(1.00)	(0.352)	(1.47)	(0.292)	(1.43)
Adj. R^2	.003	.016	.003	.016	.000	.008	.000	.011
N	11,234	11,234	11,234	11,234	4,273	4,273	4,273	4,273
#stocks	435	435	435	435	425	425	425	425

Notes: We provide coefficients of pooled OLS regressions with Driscoll-Kraay standard errors (in parentheses) and the respective R^2 for the regression model of *Equ. 1* with the aggregate private transaction indicator $D\Delta SHS^{h}_{i,t}$ as dependent variable. The symbols ***, **, and * respectively denote statistical significance at the one, five, and ten percent level. Example: Regressing $D\Delta SHS^{h}_{i,t}$ on our *wikifolio* transaction buy pressure indicator $D\Delta Trans^{Buy}_{i,t\ \ 1}$ without controls yields a coefficient of 0.127 with statistical significance at the one percent level (corresponding to a Driscoll-Kraay standard error for the coefficient estimate of 0.020).

2.2. Virtual transaction data and independent variables

We apply aggregate monthly signal provider transaction data from the *wikifolio* social trading platform[6] to obtain the number of monthly net buy / sell transactions with regard to individual assets:

$$\Delta Trans_{i,t} = \frac{TransBuy_{i,t}\quad TransSell_{i,t}}{Trans_{i,t}},$$

where $TransBuy_{i,t}$ is the number of buy transactions, $TransSell_{i,t}$ is the number of sell transactions, and $Trans_{i,t}$ is the total number of purchase and sell transactions with regard to stock *i* in month *t* on the *wikifolio* platform. In addition, we construct a variable based on the number of signal provider accounts trading stock *i* in month *t*:

$$\Delta Acc_{i,t} = \frac{AccBuy_{i,t}\quad AccSell_{i,t}}{Acc_{i,t}},$$

where $AccBuy_{i,t}$ is the number of accounts which conduct at least one buy transaction and $AccSell_{i,t}$ is the number of accounts which conduct at least one sell transaction regarding stock *i* in month *t*, and $Acc_{i,t}$ depicts the total number of accounts trading stock *i* in month *t*.

[6] See Oehler et al. (2016); Oehler and Schneider (2023) for comprehensive descriptions of the wikifolio platform.

Table 5

Quantile regressions with $D\Delta SHS^h_{i,t}$ as dependent variable and *wikifolio* transaction buy pressure indicators of the same month as independent variable.

	Net buy transactions on *wikifolio*; $\Delta Trans_{i,t} > 0$			Net sell transactions on *wikifolio*; $\Delta Trans_{i,t} < 0$		
	25th-percentile	50th-percentile	75th-percentile	25th-percentile	50th-percentile	75th-percentile
$D\Delta Trans^{Buy}_{i,t}$	.208***	.466***	.216***			
	(0.028)	(0.048)	(0.019)			
$D\Delta Trans^{Sell}_{i,t}$				0.054	.056	.153***
				(0.053)	(0.070)	(0.047)
$Ret_{i,t-1}$	0.048***	0.099***	0.024***	0.013	0.040	0.001
	(0.006)	(0.011)	(0.004)	(0.008)	(0.025)	(0.007)
$MaxRet_{i,t-1}$	.107	.173	311**	.204	.852***	.315*
	(0.118)	(0.200)	(0.153)	(0.206)	(0.313)	(0.190)
$MCap_{i,t-1}$	1.02***	0.400***	1.11***	.916***	.362***	1.16***
	(0.034)	(0.080)	(0.033)	(0.053)	(0.100)	(0.052)
$IVol^{t-1}_{i,t-6}$	.017	.007	0.000	.000	.019	.005
	(0.025)	(0.063)	(0.078)	(0.043)	(0.074)	(0.045)
$ISkew^{t-1}_{i,t-6}$	0.025	0.096	0.205***	0.038	0.055	0.113
	(0.048)	(0.091)	(0.051)	(0.085)	(0.141)	(0.088)
$Trans_{i,t}$	0.445***	1.24***	1.30***	0.685***	0.673***	.389***
	(0.061)	(0.112)	(0.043)	(0.065)	(0.133)	(0.092)
α	26.07***	2.52	23.29***	22.77***	8.32***	26.45***
	(0.740)	(1.80)	(0.875)	(1.36)	(2.48)	(1.14)
Pseudo R^2	.067	.050	.105	.045	.008	.075
N	11,388	11,388	11,388	4,350	4,350	4,350
#stocks	440	440	440	428	428	428

Notes: We provide coefficients of quantile regressions with time-fixed effects, their standard errors (in parentheses) and the respective R^2 for the regression model of *Equ. 1* with the aggregate private transaction indicator $D\Delta SHS^h_{i,t}$ as dependent variable. The variance–covariance matrix of the estimators is obtained via 50 bootstrap replications. The symbols ***, **, and * respectively denote statistical significance at the one, five, and ten percent level. Example: Regressing $D\Delta SHS^h_{i,t}$ on the social trading transaction buy pressure indicator $D\Delta Trans^{Buy}_{i,t}$ with 25th-percentile regressions yields a coefficient of 0.208 with statistical significance at the one percent level (corresponding to a bootstrapped standard error for the coefficient estimate of 0.028).

Barber and Odean (2008) show that attention is particularly relevant for buy decisions.[7] Hence, we differentiate between stocks that are net purchases ($\Delta Trans^{Buy}_{i,t}$ for $\Delta Trans_{i,t} > 0$ and $\Delta Acc^{Buy}_{i,t}$ for $\Delta Acc_{i,t} > 0$) and stocks that are net sales ($\Delta Trans^{Sell}_{i,t}$ for $\Delta Trans_{i,t} < 0$ and $\Delta Acc^{Sell}_{i,t}$ for $\Delta Acc_{i,t} < 0$) in month *t* on the social trading platfrom. We apply deciles as threshold values, and transform $\Delta Trans^{Buy}_{i,t}$ and $\Delta Acc^{Buy}_{i,t}$ into discrete numerical variables with values from one to ten ($D\Delta Trans^{Buy}_{i,t}$ and $D\Delta Acc^{Buy}_{i,t}$) as well as $\Delta Trans^{Sell}_{i,t}$ and $\Delta Acc^{Sell}_{i,t}$ ($D\Delta Trans^{Sell}_{i,t}$ and $D\Delta Acc^{Sell}_{i,t}$) into discrete numerical variables with values from negative ten to negative one to make these variables comparable to our dependent variable $D\Delta SHS^h_{i,t}$. That is, regarding stocks for which in month *t* the number of buy transactions (buying accounts) most substantially exceeds the number of sell transactions (selling accounts) the variable $D\Delta Trans^{Buy}_{i,t}$ ($D\Delta Acc^{Buy}_{i,t}$) takes the value ten. Likewise, the variable $D\Delta Trans^{Sell}_{i,t}$ ($D\Delta Acc^{Sell}_{i,t}$) takes the value negative ten for stocks for which the number of sell transactions (selling accounts) most substantially exceeds the number of buy transactions (buying accounts). We refer to $\Delta Trans_{i,t}$, $D\Delta Trans^{Buy}_{i,t}$, and $D\Delta Trans^{Sell}_{i,t}$ as *wikifolio* transaction buy pressure indicators and to $\Delta Acc_{i,t}$, $D\Delta Acc^{Buy}_{i,t}$, and $D\Delta Acc^{Sell}_{i,t}$ as *wikifolio* account buy pressure indicators.

2.3. Regression model

We use pooled OLS regressions with Driscoll-Kraay standard errors[8] to assess the relation between trades on the *wikifolio* platform and aggregate changes in private sector holdings. The Driscoll-Kraay error structure is assumed to be heteroskedastic, autocorrelated, and possibly correlated between the stocks. We employ this method since untabulated Woolridge (2002) tests for autocorrelation in panel data with the implementation of Drukker (2003) indicate autocorrelation in some subsamples. Moreover, we employ quantile regressions of which the estimated variance–covariance matrix of the estimators is obtained via bootstrapping. The quantile

[7] Admittedly, thresholds for retail investors to take short positions became much lower in recent years. However, the majority of retail investors still does not consider taking a short position to bet against a company. Hence, we assume it is still reasonable to differentiate between sell and buy transactions.

[8] Our results stay stable when we use pooled OLS regressions with Newey-West standard errors, pooled OLS regressions with time-fixed effects and robust standard errors, and panel regressions with random- or stock-fixed and/or time-fixed effects.

Table 6
Quantile regressions with $D\Delta SHS^{h}_{i,t}$ as dependent variable and *wikifolio* transaction buy pressure indicators of the previous month as independent variable.

	Net buy transactions on *wikifolio*; $\Delta Trans_{i,t} > 0$			Net sell transactions on *wikifolio*; $\Delta Trans_{i,t} < 0$		
	25th-percentile	50th-percentile	75th-percentile	25th-percentile	50th-percentile	75th-percentile
$D\Delta Trans^{Buy}_{i,t\ \ 1}$	.229***	.463***	.148***			
	(0.025)	(0.039)	(0.026)			
$D\Delta Trans^{Sell}_{i,t\ \ 1}$				.000	.089	.190***
				(0.038)	(0.075)	(0.045)
$Ret_{i,t\ \ 1}$	0.030***	0.096***	0.019***	0.045***	0.081***	0.005
	(0.006)	(0.011)	(0.007)	(0.010)	(0.031)	(0.006)
$MaxRet_{i,t\ \ 1}$	.375***	.970***	365**	.127	.988***	.326
	(0.119)	(0.225)	(0.121)	(0.216)	(0.330)	(0.219)
$MCap_{i,t\ \ 1}$	1.06***	.055	0.951***	.970***	.302**	1.19***
	(0.032)	(0.091)	(0.033)	(0.058)	(0.125)	(0.063)
$IVol^{t\ \ 1}_{i,\ t\ \ 6}$	0.001	0.007	.005	.006	0.003	0.015
	(0.017)	(0.023)	(0.013)	(0.089)	(0.285)	(0.067)
$ISkew^{t\ \ 1}_{i,t\ \ 6}$	0.003	0.216**	0.160***	.002	.014	0.127
	(0.051)	(0.108)	(0.053)	(0.050)	(0.126)	(0.093)
$Trans_{i,t}$	0.454***	.559***	.897***	0.622***	0.373***	.454***
	(0.061)	(0.105)	(0.048)	(0.063)	(0.139)	(0.080)
α	26.74***	6.64***	20.10***	23.42***	7.63***	27.55***
	(0.654)	(1.97)	(0.791)	(1.40)	(2.80)	(1.59)
Pseudo R^2	.059	.026	.072	.053	.007	.075
N	11,234	11,234	11,234	4,273	4,273	4,273
#stocks	435	435	435	425	425	425

Notes: We provide coefficients of quantile regressions with time-fixed effects, their standard errors (in parentheses) and the respective R^2 for the regression model of *Equ. 1* with the aggregate private transaction indicator $D\Delta SHS^{h}_{i,t}$ as dependent variable. The variance–covariance matrix of the estimators is obtained via 50 bootstrap replications. The symbols ***, **, and * respectively denote statistical significance at the one, five, and ten percent level. Example: Regressing $D\Delta SHS^{h}_{i,t}$ on the social trading transaction buy pressure indicator $D\Delta Trans^{Buy}_{i,t}$ with 25th-percentile regressions yields a coefficient of 0.229 with statistical significance at the one percent level (corresponding to a bootstrapped standard error for the coefficient estimate of 0.025).

regressions include month dummies to cover time-fixed effects. The quantile regressions are employed to address a possible non-linear relationship between our dependent and independent variables. The baseline regression model is as follows:

$$D\Delta SHS^{h}_{i,t} = \beta_1 \times IV_i + \beta_2 \times Ret_{i,t\ \ 1} + \beta_3 \times MaxRet_{i,t\ \ 1} + \beta_4 \times MCap_{i,t\ \ 1} + \ \beta_5 \times IVol^{t\ \ 1}_{i,\ t\ \ 6} + \beta_6 \times ISkew^{t\ \ 1}_{i,t\ \ 6} + \beta_7 \times Trans_{i,t} + \beta_8 \times Acc_{i,t} + \ \alpha. \tag{1}$$

$D\Delta SHS^{h}_{i,t}$ is the aggregate private transaction indicator. IV_i is a stand-in for the independent variable of interest represented by $D\Delta Trans^{Buy}_{i,t}$, $D\Delta Trans^{Sell}_{i,t}$, $D\Delta Acc^{Buy}_{i,t}$, or $D\Delta Acc^{Sell}_{i,t}$ for regressions that analyze whether transactions of signal providers proxy aggregate transactions of the private sector in the same month. In further regressions, we use the respective lagged variables $D\Delta Trans^{Buy}_{i,t\ \ 1}$, $D\Delta Trans^{Sell}_{i,t\ \ 1}$, $D\Delta Acc^{Buy}_{i,t\ \ 1}$, and $D\Delta Acc^{Sell}_{i,t\ \ 1}$ as IV_i for regressions that analyze whether transactions of signal providers predict aggregate transactions of the private sector in the following month. $Ret_{i,t\ \ 1}$ depicts the monthly return, $MaxRet_{i,t\ \ 1}$ is the maximum of the absolute values of the daily returns of stock *i* during the previous month ($t\ \ 1$). $MCap_{i,t\ \ 1}$ is the market capitalization of stock *i* in month $t\ \ 1$. $IVol^{t\ \ 1}_{i,\ t\ \ 6}$ and $ISkew^{t\ \ 1}_{i,t\ \ 6}$ respectively depict idiosyncratic volatility[9] and idiosyncratic skewness[10] of stock *i* measured using daily return data over the previous six months ($t\ \ 6$ to $t\ \ 1$).

Idiosyncratic volatility and idiosyncratic skewness are included as control variables as they capture private sector preferences for lottery-like returns (Kumar, 2009).[11] Extreme positive and negative daily price movements capture the attention of private investors, and consequently have an impact on trading decisions (Barber and Odean, 2008; Bali et al., 2011). Thus, we include a control variable mirroring absolute maximum daily return. Furthermore, we include $Trans_{i,t}$ and $Acc_{i,t}$ as control varibales to capture overall trading

[9] Idiosyncratic volatility is measured as the standard deviation of the residuals obtained by fitting the Carhart (1997) four-factor model to a time-series of daily stock returns of the previous six months.

[10] Idiosyncratic skewness is measured in accordance with Harvey and Siddique (2000) and Kumar (2009). Thus, idiosyncratic skewness is third moment of the residuals obtained when regressing daily stock returns covering the previous six months on a two factor-model where the market excess return and the square of the market excess return are employed as the respective factors.

[11] In untabulated results we also included the third lottery-stock feature, i.e., the stock price. However, the stock price was collinear with market capitalization and not statistically significant, i.e. skewed the results. We thank an anonymous referee for pointing this issue out.

Table 7
Panel regressions with $D\Delta SHS_{i,t}^{h}$ as dependent variable and *wikifolio* transaction/account buy pressure indicators of the same month as independent variable (stocks with market capitalization >= 10 billion Euros).

	Net buy transactions on *wikifolio*; $\Delta Trans_{i,t} > 0$ (models (1) and (2)) and $\Delta Acc_{i,t} > 0$ (models (3) and (4))				Net sell transactions on *wikifolio*; $\Delta Trans_{i,t} < 0$ (models (5) and (6)) and $\Delta Acc_{i,t} < 0$ (models (7) and (8))			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$D\Delta Trans_{i,t}^{Buy}$	.503***	.478***						
	(0.042)	(0.040)						
$D\Delta Trans_{i,t}^{Sell}$					.037	.200**		
					(0.134)	(0.093)		
$D\Delta Acc_{i,t}^{Buy}$			.529***	.486***				
			(0.047)	(0.045)				
$D\Delta Acc_{i,t}^{Sell}$							0.090	.045
							(0.078)	(0.086)
$Ret_{i,t-1}$		0.151***		0.128***		0.083*		0.098**
		(0.015)		(0.015)		(0.047)		(0.037)
$MaxRet_{i,t-1}$		1.16***		1.01***		.313		0.169
		(0.318)		(0.290)		(0.452)		(0.735)
$MCap_{i,t-1}$		0.377		0.395*		0.544		0.769**
		(0.231)		(0.218)		(0.390)		(0.341)
$IVol_{i,t-6}^{t-1}$		1.75***		1.48**		0.759		0.841
		(0.568)		(0.626)		(0.814)		(0.580)
$ISkew_{i,t-6}^{t-1}$		0.443***		0.470***		0.583*		0.230
		(0.159)		(0.150)		(0.291)		(0.321)
$Trans_{i,t}$		.628***				0.451		
		(0.226)				(0.278)		
$Acc_{i,t}$				.897***				0.473
				(0.217)				(0.283)
α	1.77***	4.95	1.72***	4.66	1.51***	14.77	2.05***	20.06
	(0.318)	(5.24)	(0.367)	(5.12)	(0.451)	(8.95)	(0.365)	(7.81)
R^2	.075	.191	.087	.192	.000	.072	.003	.104
N	1,479	1,479	1,479	1,479	244	244	244	244
#stocks	46	46	46	46	43	43	43	43

Notes: We provide coefficients of pooled OLS regressions with Driscoll-Kraay standard errors (in parentheses) and the respective R^2 for the regression model of *Equ. 1* with the aggregate private transaction indicator $D\Delta SHS_{i,t}^{h}$ as dependent variable. The symbols ***, **, and * respectively denote statistical significance at the one, five, and ten percent level. Example: Regressing $D\Delta SHS_{i,t}^{h}$ on the social trading transaction buy pressure indicator $D\Delta Trans_{i,t}^{Buy}$ without controls yields a coefficient of 0.503 with statistical significance at the one percent level (corresponding to a Driscoll-Kraay standard error for the coefficient estimate of 0.042).

activity regarding stock *i* (Barber and Odean, 2008; Welch, 2022; Barber et al., 2022). The control variables $MaxRet_{i,t-1}$, $MCap_{i,t-1}$, $Trans_{i,t}$, and $Acc_{i,t}$ are positively skewed and thus transformed using the natural logarithm. The respective descriptive statistics are presented in Table 1.

Pearson correlations displayed in Table 2 show a positive correlation between the aggregate private transaction indicator $D\Delta SHS_{i,t}^{h}$ and the buy pressure indicators $D\Delta Trans_{i,t}^{Buy}$ and $D\Delta Acc_{i,t}^{Buy}$ with a statistical significance at the one percent level. The sell pressure indicators $D\Delta Trans_{i,t}^{Sell}$ and $D\Delta Acc_{i,t}^{Sell}$ are weaker correlated with the transactions of the aggregate private sector. Furthermore $Trans_{i,t}$ and $Acc_{i,t}$ are positively correlated with $D\Delta SHS_{i,t}^{h}$, i.e. stocks that are frequently traded by many accounts are stronger bought/weaker sold by the private sector.

3. Results

3.1. Full sample

The results of the regression analysis presented in Table 3 show that transactions on the *wikifolio* platform are significantly related to the aggregate private sector stock transactions. More specifically, for stocks that are net bought on *wikifolio*, the social trading transaction buy pressure indicator as well as the social trading account buy pressure indicator are positively related to the aggregate private transaction indicator with a statistical significance at the one percent level. Hence, stocks that are strongly bought by signal providers are also strongly bought by the aggregate private sector. Moreover, in the regression specification (8) we find a positive relation between the social trading account sell pressure indicator and the aggregate private transaction indicator that is significant at the one percent level for stocks that are net sold on the *wikifolio* platform. Furthermore, stocks that are frequently traded by many accounts on the *wikifolio* platform are stronger bought/weaker sold by the private sector. Because of these significant relations, we state that the transactions on the *wikifolio* platform are a good proxy for the aggregated transactions of the private sector.

We perform regressions with lagged *wikifolio* buy pressure indicators to analyze whether the transactions on the *wikifolio* platform

Table 8
Panel regressions with $D\Delta SHS_{i,t}^{h}$ as dependent variable and *wikifolio* transaction/account buy pressure indicators of the previous month as independent variable (stocks with market capitalization >= 10 billion Euros).

	Net buy transactions on *wikifolio*; $\Delta Trans_{i,t\ \ 1} > 0$ (models (1) and (2)) and $\Delta Acc_{i,t\ \ 1} > 0$ (models (3) and (4))				Net sell transactions on *wikifolio*; $\Delta Trans_{i,t\ \ 1} < 0$ (models (5) and (6)) and $\Delta Acc_{i,t\ \ 1} < 0$ (models (7) and (8))			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$D\Delta Trans_{i,t\ \ 1}^{Buy}$	.379***	.282***						
	(0.051)	(0.049)						
$D\Delta Trans_{i,t\ \ 1}^{Sell}$					0.025	0.014		
					(0.106)	(0.101)		
$D\Delta Acc_{i,t\ \ 1}^{Buy}$			.372***	.310***				
			(0.044)	(0.042)				
$D\Delta Acc_{i,t\ \ 1}^{Sell}$							0.043	.035
							(0.092)	(0.089)
$Ret_{i,t\ \ 1}$		0.112***		0.121***		0.198***		0.208***
		(0.019)		(0.017)		(0.031)		(0.024)
$MaxRet_{i,t\ \ 1}$		1.12***		.932***		1.30***		.746
		(0.299)		(0.284)		(0.452)		(0.485)
$MCap_{i,t\ \ 1}$		.128**		.026		0.326		0.366
		(0.218)		(0.229)		(0.342)		(0.319)
$IVol_{i,\ t\ \ 6}^{t\ \ 1}$		1.19**		1.03*		1.37		1.70*
		(0.502)		(0.559)		(0.974)		(0.878)
$ISkew_{i,t\ \ 6}^{t\ \ 1}$		0.414***		0.354***		1.06**		0.769**
		(0.146)		(0.129)		(0.470)		(0.307)
$Trans_{i,t}$		.210				0.014		
		(0.217)				(0.290)		
$Acc_{i,t}$				.524**				0.233
				(0.233)				(0.247)
α	1.36***	5.03	1.26***	3.74	1.28**	7.68	1.35***	10.16
	(0.320)	(4.93)	(0.364)	(5.49)	(0.554)	(7.24)	(0.423)	(7.34)
Adj. R^2	.043	.109	.043	.123	.000	.180	.001	.189
N	1,470	1,470	1,470	1,470	252	252	252	252
#stocks	46	46	46	46	42	42	42	42

Notes: We provide coefficients of pooled OLS regressions with Driscoll-Kraay standard errors (in parentheses) and the respective R^2 for the regression model of *Equ. 1* with the aggregate private transaction indicator $D\Delta SHS_{i,t}^{h}$ as dependent variable. The symbols ***, **, and * respectively denote statistical significance at the one, five, and ten percent level. Example: Regressing $D\Delta SHS_{i,t}^{h}$ on our *wikifolio* transaction buy pressure indicator $D\Delta Trans_{i,t\ \ 1}^{Buy}$ without controls yields a coefficient of 0.379 with statistical significance at the one percent level (corresponding to a Driscoll-Kraay standard error for the coefficient estimate of 0.051).

predict aggregate private sector transactions. The results of this regression analysis are presented in Table 4 and provide empirical support for the conjecture that transactions on the social trading platform in month $t\ \ 1$ are a good predictor for the aggregate private stock transactions in month *t*. For stocks that are net purchased on the *wikifolio* platform, both the transaction and account buy pressure indicator in month $t\ \ 1$ are significantly positively related to the aggregate private transaction indicator. For stocks that are net sold, we also find a significant positive relation between the social trading transaction and account buy pressure indicators and the aggregate private transaction indicator in the following month, but only when the full regression model is applied and with smaller effect size. Moreover, among stocks that are net purchased on the *wikifolio* platform, those that are traded more frequently and on more accounts are stronger bought by the household sector in the following month.

Quantile regressions with the social trading transaction indicators as independent variables provide further support for the significant positive relation between the social trading transaction buy pressure indicators and the aggregate private transaction indicator in the same month (see Table 5). However, for stocks that are net purchased on the *wikifolio* platform, the effect size is more than twice as high for the 50th-percentile than for the 25th- and the 75th-percentile of the distribution. For stocks that are net sold, the relation is only significant at the one percent level in the 75th-percentile regression. This means that the relation is significant particularly for stocks with higher values of $D\Delta SHS_{i,t}^{h}$, i.e. stocks that are weaker sold/stronger bought by the aggregate private sector. Put differently, the relation between the social trading transaction buy pressure indicators and the aggregated transactions of the private sector becomes statistically more significant and larger in effect size when we look at stronger bought/weaker sold stocks. Stocks that are strongest sold by private households, however, are significantly more frequently traded on the social trading platform. In addition, we observe a significant change in the relation between stocks market capitalization and $D\Delta SHS_{i,t}^{h}$ from significantly positive (25th-percentile) to significantly negative (75th-percentile) for both stocks that are net sold and stocks that are net purchased by *wikifolio* traders. These patterns are also observed when we analyze the relation between transactions on the social trading platform in month $t\ \ 1$ and transactions of private households in month *t* (see Table 6). We dig deeper on the role of stocks' market capitalization by analyzing respective subsamples.

Table 9

Panel regressions with $D\Delta SHS_{i,t}^{h}$ as dependent variable and *wikifolio* transaction/account buy pressure indicators of the same month as independent variable (stocks with market capitalization < 10 billion Euros).

	Net buy transactions on *wikifolio*; $\Delta Trans_{i,t} > 0$ (models (1) and (2)) and $\Delta Acc_{i,t} > 0$ (models (3) and (4))				Net sell transactions on *wikifolio*; $\Delta Trans_{i,t} < 0$ (models (5) and (6)) and $\Delta Acc_{i,t} < 0$ (models (7) and (8))			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$D\Delta Trans_{i,t}^{Buy}$	.091***	.201***						
	(0.020)	(0.025)						
$D\Delta Trans_{i,t}^{Sell}$					0.057	.046		
					(0.042)	(0.045)		
$D\Delta Acc_{i,t}^{Buy}$			.086***	.228***				
			(0.023)	(0.037)				
$D\Delta Acc_{i,t}^{Sell}$							0.019	.131***
							(0.040)	(0.044)
$Ret_{i,t-1}$		0.042***		0.039***		0.000		0.013
		(0.008)		(0.006)		(0.006)		(0.010)
$MaxRet_{i,t-1}$		.346***		.458***		.477***		.281*
		(0.099)		(0.092)		(0.165)		(0.156)
$MCap_{i,t-1}$		0.102		0.104		0.157*		0.121
		(0.076)		(0.063)		(0.086)		(0.080)
$IVol_{i,t-6}^{t-1}$		.009***		.006***		.004		0.008***
		(0.003)		(0.002)		(0.007)		(0.003)
$ISkew_{i,t-6}^{t-1}$		0.109*		0.128**		0.121		0.037
		(0.064)		(0.052)		(0.084)		(0.077)
$Trans_{i,t}$		.527***				0.147		
		(0.087)				(0.102)		
$Acc_{i,t}$				.685***				0.364***
				(0.115)				(0.084)
α	0.271	1.13	0.239***	1.51	1.29***	1.98	1.10***	2.55
	(0.188)	(1.43)	(0.229)	(1.14)	(0.310)	(1.85)	(0.313)	(1.76)
R^2	.002	.021	.001	.021	.001	.009	.000	.010
N	9,921	9,921	9,921	9,921	4,107	4,107	4,107	4,107
#stocks	413	413	413	413	397	397	397	397

Notes: We provide coefficients of pooled OLS regressions with Driscoll-Kraay standard errors (in parentheses) and the respective R^2 for the regression model of *Equ. 1* with the aggregate private transaction indicator $D\Delta SHS_{i,t}^{h}$ as dependent variable. The symbols ***, **, and * respectively denote statistical significance at the one, five, and ten percent level. Example: Regressing $D\Delta SHS_{i,t}^{h}$ on the social trading transaction buy pressure indicator $D\Delta Trans_{i,t}^{Buy}$ without controls yields a coefficient of 0.091 with statistical significance at the one percent level (corresponding to a Driscoll-Kraay standard error for the coefficient estimate of 0.020).

3.2. Sample split

We split the sample in stocks with a market capitalization smaller than 10 billion Euros and remaining stocks with higher market capitalization per month. The latter stocks by and large are the (temporarily included) constituents of the most popular German blue-chip index DAX30. We repeat the pooled OLS regressions with Driscoll-Kraay standard errors for both samples individually.

Results for the about 45 stocks with at least 10 billion Euros of market capitalization are presented in Table 7 and Table 8. For stocks net purchased on *wikifolio*, again, the social trading buy pressure indicators are positively related to the aggregate private transaction indicator in the same (see Table 7) and in the following month (see Table 8) with a statistical significance at the one percent level. However, the respective coefficients are at least two times higher than in Table 3 and Table 4, indicating a larger effect size for the DAX30 stocks. A comparison of the coefficient in columns (1) – (4) of Table 7 and Table 8 also indicates a smaller effect for transactions of the private households in the following month than in the same month. Regarding sell transactions on the *wikifolio* platform, we do not find a convincingly significant relation anymore.

Table 9 and Table 10 show the results for stocks with a market capitalization of less than 10 billion Euros. The statistically significant positive relation between the social trading buy pressure indicators and households' stock holding changes in the same and following month for net bought stocks on *wikifolio* is confirmed again, however, with smaller coefficients. This indicates that the effect size is smaller for stocks with lower market capitalization. We also find that stocks, which are sold by many accounts on the *wikifolio* platform, are stronger sold by private households in the same month with a statistical significance at the one percent level. In addition, we find that both buy pressure indicators are related to stock sales of households in the following month with a statistical significance at the five percent level. Hence, stock sales on the *wikifolio* platform only work as good predictors for private households' sales for stocks with small market capitalization. Nevertheless, it is important to note that the explanatory power, measured as R^2 of the regression models, is considerably smaller for stocks with lower market capitalization (<=2.2 % vs. up to 19 % for stocks with high market capitalization). It seems possible that the higher news coverage and higher awareness level of DAX30 companies among the population causes this effect, i.e. households and social traders are more aware of these stocks with high market capitalization. Although these stocks represent only 10 percent of the listed companies, they represent about 80 percent of the market capitalization of

Table 10
Panel regressions with $D\Delta SHS^{h}_{i,t}$ as dependent variable and *wikifolio* transaction/account buy pressure indicators of the previous month as independent variable (stocks with market capitalization < 10 billion Euros).

	Net buy transactions on *wikifolio*; $\Delta Trans_{i,t-1} > 0$ (models (1) and (2)) and $\Delta Acc_{i,t-1} > 0$ (models (3) and (4))				Net sell transactions on *wikifolio*; $\Delta Trans_{i,t-1} < 0$ (models (5) and (6)) and $\Delta Acc_{i,t-1} < 0$ (models (7) and (8))			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$D\Delta Trans^{Buy}_{i,t-1}$	.111***	.199***						
	(0.021)	(0.026)						
$D\Delta Trans^{Sell}_{i,t-1}$					.020	.102**		
					(0.047)	(0.048)		
$D\Delta Acc^{Buy}_{i,t-1}$			.105***	.198***				
			(0.024)	(0.021)				
$D\Delta Acc^{Sell}_{i,t-1}$							.053	.115**
							(0.042)	(0.045)
$Ret_{i,t-1}$		0.030***		0.028***		0.016*		0.039***
		(0.007)		(0.007)		(0.009)		(0.013)
$MaxRet_{i,t-1}$		.549***		.659***		.452***		.174
		(0.155)		(0.169)		(0.149)		(0.204)
$MCap_{i,t-1}$		.095		.096		0.169**		0.073
		(0.062)		(0.071)		(0.074)		(0.070)
$IVol^{t-1}_{i,t-6}$		.002		.002		0.003		.064
		(0.007)		(0.004)		(0.003)		(0.100)
$ISkew^{t-1}_{i,t-6}$		0.122*		0.124*		0.035		0.104
		(0.066)		(0.073)		(0.087)		(0.087)
$Trans_{i,t}$		.233***				0.044		
		(0.085)				(0.102)		
$Acc_{i,t}$				.282***				0.082
				(0.099)				(0.110)
α	0.513**	4.45***	0.475**	4.60***	0.607*	2.55	0.498*	1.09
	(0.222)	(1.16)	(0.219)	(1.42)	(0.341)	(1.71)	(0.277)	(1.63)
Adj. R^2	.002	.013	.002	.013	.000	.007	.001	.009
N	9,794	9,794	9,794	9,794	4,027	4,027	4,027	4,027
#stocks	408	408	408	408	395	395	395	395

Notes: We provide coefficients of pooled OLS regressions with Driscoll-Kraay standard errors (in parentheses) and the respective R^2 for the regression model of *Equ. 1* with the aggregate private transaction indicator $D\Delta SHS^{h}_{i,t}$ as dependent variable. The symbols ***, **, and * respectively denote statistical significance at the one, five, and ten percent level. Example: Regressing $D\Delta SHS^{h}_{i,t}$ on our *wikifolio* transaction buy pressure indicator $D\Delta Trans^{Buy}_{i,t-1}$ without controls yields a coefficient of 0.111 with statistical significance at the one percent level (corresponding to a Driscoll-Kraay standard error for the coefficient estimate of 0.021).

the German stock market, which makes the relation between transactions on the social trading platform and households' transactions economically meaningful. However, it is beyond the scope of this paper to analyze the role of DAX30 membership in more detail.

4. Discussion and conclusion

Our results show that the transactions of signal providers on a social trading platform are a good proxy for the aggregate transactions of the private sector in the same month. More specifically, net purchases of stocks with higher market capitalization by many accounts on the *wikifolio* platform are related to high net purchases of the same stocks by the households in the same month. The effect size of this relation varies, depending on stocks' market capitalization and whether we look at the edges or the center of the distribution, between 0.2 and 0.5. Hence, if the buy pressure on the social trading platform of a stock with high market capitalization increases, e.g. from the 3rd to the 7th decile, the stock will on average move by two vingtiles in the distribution of households' monthly holding changes, e.g. from the 15th to the 17th vingtile. This can be considered economically meaningful. However, the effect is not even half as large for smaller stocks. Regarding stock sales, we sporadically find a significant relation and with smaller effect size. We interpret this finding as further evidence that most private investors use the same signals to identify stocks to be bought, e.g. are subject to attention induced trading (Barber and Odean, 2008; Barber et al., 2022). However, identifying the drivers of the transactions of signal providers is beyond the scope of this paper. Hence, we leave it to further research to identify the determinants of signal providers' decisions.

Furthermore, we find that, although with a bit smaller effect sizes between 0.1 and 0.5, the transactions of signal providers are a good predictor for the aggregate transactions of the private sector in the following month. This finding might be interpreted as indication for herding behavior induced by social trading platforms that spills over from the social trading network. Thus, we provide indications that virtual social trading transactions impact real-world asset markets. Hence, our findings complement Tang et al. (2017) stating that a small number of leaders produces the majority of market sentiment (Pelster, 2017). However, we cannot rule out that the latter finding is driven by some unobserved factors that simultaneously influence the transactions of signal providers in month $t-1$

and investors of the private sector in month *t* (see Barber et al., 2009, who observe a similar pattern). Further studies applying event study approaches could provide further support on potential spill-over effects. Moreover, we only find a significant relation between sales on the *wikifolio* platform and sales by the private sector in the following month for stocks with lower market capitalization. Further studies could dig deeper to identify the reason for this asymmetric effect.

Our findings have important implications for regulators, investors, and researchers. The aggregate market behavior of the private sector is not directly observable in real-time. The *SHS-base* is the only database we are aware of that covers all stock holdings of the private sector of an entire country – and it is published with a time lag. Having a proper, immediately and freely available proxy of the aggregate market behavior of the private sector at hand can help regulators to detect market frictions early-on. Investors can use this information to avoid stocks that are pumped up by the crowd of private investors (for example when there are exceptionally high net purchases with regard to single stocks) or join the crowd when it is wise and steadfast in times of financial turmoil (Welch, 2022, see also Barber et al., 2009). Researchers can use the findings of our study as indication that patterns observed regarding the trading behavior of signal providers on social trading platforms, particularly regarding buy transactions of stocks with high market capitalization, may also be observed in a representative sample of private investors.

CRediT authorship contribution statement

Matthias Horn: Writing – review & editing, Writing – original draft, Validation, Methodology, Formal analysis, Data curation, Conceptualization. **Julian Schneider:** Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Andreas Oehler:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

References

Bade, M., Flory, J., Gomolka, M., Schönberg, T., 2017. Securities Holdings Statistics Base plus, Data Report 2017-08 - Metadata Version 1-0. Deutsche Bundesbank, Research Data and Service Centre.
Bali, T.G., Cakici, N., Whitelaw, R., 2011. Maxing out: stocks as lotteries and the cross-section of expected returns. J. Financ. Econ 99, 427–446.
Bali, T., Hirshleifer, D., Peng, L., Tang, Y., 2021. Attention, Social Interaction, and Investor Attraction to Lottery Stocks. Working Paper.
Barber, B., Huang, X., Odean, T., Schwarz, C., 2022. Attention-induced trading and returns: evidence from robinhood users. J. Financ. 77 (6), 3141–3190.
Barber, B.M., Odean, T., 2008. All that glitters: the effect of attention and news on the buying behavior of individual and institutional investors. Rev. Financial Studies 21 (2), 785–818.
Barber, B.M., Odean, T., Zhu, N., 2009. Do retail trades move markets? Rev. Financial. Studies 22 (1), 151–186.
Blaschke, J., Sachs, K., Yalcin, E., 2022. Securities Holdings Statistics Base plus, Data Report 2022-05 - Metadata Version 5-0. Deutsche Bundesbank, Research Data and Service Centre.
Bonaparte, Y., Cooper, R., 2009. Costly Portfolio Adjustment, NBER Working Paper 15227.
Brunnermeier, M.K., Nagel, S., 2008. Do wealth fluctuations generate time-varying risk aversion? Micro-Evidence on Individuals' Asset Allocation. Am. Econ. Rev. 98 (3), 713–736.
Carhart, M.M., 1997. On persistence in mutual fund performance. J. Finance 52 (1), 57–82. https://doi.org/10.1111/j.1540-6261.1997.tb03808.x.
Deng, J., Yang, M., Pelster, M., Tan, Y., 2023. Social trading, communication, and networks. Inf. Syst. Res.(forthcoming). https://doi.org/10.1287/isre.2021.0143.
Döring, P., Neumann, S., Paul, S., 2015. A Primer on Social Trading Networks –Institutional Aspects and Empirical Evidence. Working Paper, Bochum.
Drukker, D.M., 2003. Testing for serial correlation in linear panel-data models. Stata J 3 (2), 168–177.
Erdős, S., Papp, T., Vörös, Z., 2022. The effects of community-based signals on investment decisions in copy trading. J. Behavioral Experimental Econ. 97, 101847.
Fecht, F., Hackethal, A., Karabulut, Y., 2018. Is proprietary trading detrimental to retail investors? J. Finance. 72 (3), 1323–1361.
Gemayel, R., Preda, A., 2018a. Does a scopic regime erode the disposition effect? Evidence from a social trading platform. J. Econ. Behav. Organ 154, 175–190.
Gemayel, R., Preda, A., 2018b. Does a scopic regime produce conformism? Herding behavior among trade leaders on social trading platforms. Eur. J. Financ 24 (14), 1144–1175.
Glaser, F., Risius, M., 2018. Effects of transparency: analyzing social biases on trader performance in social trading. J. Inf. Technol. 33 (1), 19–30.
Han, B., Hirshleifer, D., Walden, J., 2022. Social transmission bias and investor behavior. J. Financ. Quant. Anal. 57 (1), 390–412.
Harvey, C.R., Siddique, A., 2000. Conditional skewness in asset pricing tests. J. Finance 55 (3), 1263–1295. https://doi.org/10.1111/0022-1082.00247.
Herberger, T., Horn, M., Oehler, A., 2020. Are intraday reversal and momentum trading strategies feasible? An analysis for German blue chip stocks. Financial Markets and Portfolio Manag. 34, 179–197.
Horn, M., Oehler, A., Wendt, S., 2020. FinTech for Consumers and Retail Investors: opportunities and Risks of Digital Payment and Investment Services. In: Walker, T., Gramlich, D., Bitar, M., Fardnia, P. (Eds.), Ecological, Societal, and Technological Risks and the Financial Sector, pp. 405–421.
Kromidha, E., Li, M.C., 2019. Determinants of leadership in online social trading: a signaling theory perspective. J. Bus. Res. 97, 184–197.
Kumar, A., 2009. Who gambles in the stock market? J. Finance 64, 1889–1933.
Lee, W., Ma, Q., 2018. Discovering expert traders on social trading services. J. Adv. Computat. Intell. Intellig. Inf. 22 (2), 224–235.
Liêu, L., Pelster, M., 2020. Framing and the disposition effect in a scopic regime. Q. Rev. Econ. Finance 78, 175–185.
Oehler, A., Horn, M., Wendt, S., 2016. Benefits from social trading? Empirical evidence for certificates on wikifolios. Int. Rev. Financial Anal. 46, 202–210.
Oehler, A., Schneider, J., 2022. Gambling with lottery stocks? J. Asset Manag. 23, 477–503.
Oehler, A., Schneider, J., 2023. Social trading: do signal providers trigger gambling? Rev. Manager. Sci. 17, 1269–1331.

Oehler, A., Wendt, S., Horn, M., 2017. Are investors really home-biased when investing at home? Res. Int. Bus. Finance 40, 52–60. https://doi.org/10.1016/j.ribaf.2016.12.003.
Pelster, M., 2017. 2017. I'll Have What S/he's Having: a Case Study of a Social Trading Network. In: Proceedings of the International Conference on Information Systems.
Pelster, M., Breitmayer, B., 2019. Attracting attention from peers: excitement in social trading. J. Econ. Behav. Organ 161, 158–179.
Pelster, M., Hofmann, A., 2018. About the fear of reputational loss: social trading and the disposition effect. J. Bank. Financ 94, 75–88.
Röder, F., Walter, A., 2019. What drives investment flows into social trading portfolios? J. Financ. Res. 42 (2), 383–411.
Schneider, J., Oehler, A., 2021. Competition for Visibility: when do (FX) signal providers employ lotteries? Int. Rev. Financ. Anal 78, 101892.
Tang, S., Liu, Q., McQueen, M., Counts, S., Jain, A., Zheng, H., Zhao, B.Y., 2017. Echo Chambers in Investment Discussion Boards. In: The 11th International Conference on Web and Social Media, ICWSM (Eds.). AAAI Press, Montreal, pp. 240–249.
Welch, I., 2022. The wisdom of the robinhood crowd. J. Finance 77 (3), 1489–1527.
Wohlgemuth, V., Berger, E.S., Wenzel, M., 2016. More than just financial performance: trusting investors in social trading. J. Bus. Res 69 (11), 4970–4974.
Wooldridge, J.M., 2002. Econometric Analysis of Cross Section and Panel Data. MIT Press, Cambridge, MA.