A Primer on Social Trading Networks – Institutional Aspects and Empirical Evidence

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Abstract

Social trading networks provide access to an innovative type of delegated portfolio management. We discuss institutional aspects of these platforms and point out that, as an intermediary, they are able to reduce information asymmetries between investors and portfolio managers. Using a unique dataset comprising transactions from the four major network providers, we show that the users on these platforms yield non-normal returns and exhibit a relatively high tail risk. We then apply return-based style analysis and find that they deploy dynamic trading strategies and follow directional approaches. Hence, they bear substantial systematic risk within any short-term period. Throughout the article, we illustrate that social trading networks provide access to hedge funds-like returns, but in contrast offer a high transparency, liquidity and accessibility.

Keywords: social trading networks, delegated portfolio management, dynamic trading, style analysis, hedge funds, CFD trading

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The financial industry is experiencing an ongoing transformation. Besides the challenges induced by regulatory changes, traditional providers face an increasing competition by innovative finance startups ("fintechs") that allow investors to demand conventional services bypassing financial intermediaries in the classical sense. One of these latest innovations is the emergence of social trading networks that allow making investment decisions based upon information gathered in online communities.

The recent financial crisis led to a growing willingness for self-education and communication about investment opportunities. While, as a result of a loss of trust, initially mainstream social networks like Facebook and Twitter were increasingly used to share investment ideas, entrepreneurs recognized the commercial potential of a direct interface to the user's brokerage accounts as of 2008. Startups – with eToro, ZuluTrade, ayondo and Currensee among the first – developed specialized social trading networks and made the generation of trading volume for selected partner brokers to their business model. Since then, a large variety of brokerage firms launched their own platforms which are solely accessible for customers.

Consequently, the main feature of these networks is the so-called "copy trading" that allows for an automated execution of user-generated investment ideas. Basically, there are two user groups: signal providers and signal followers. Signal providers share investment ideas within the respective network that they either execute in a virtual or brokerage account. Investors are given the opportunity to become a signal follower by subscribing to one or more signal providers. Subsequently, all signals published by the subscribed users are automatically executed into the follower's brokerage account proportionally and in real-time.[1] Signal providers receive a platform-specific fee for publishing trading signals. Existing subscriptions can be canceled at any time.

Although followers do not transfer capital to the signal provider's accounts, the latter de facto act as portfolio managers. Hence, social trading networks provide an innovative framework for del-

[1]Note that some platforms as well offer a manual replication, i.e. allow signal followers to manually approve the execution of incoming trading signals. Manual replication can be considered as investment advisory and was the primary service initially offered by the pioneer platforms. However, the automated "copy trading" is the predominant form of signal execution now.

egated portfolio management. Recently, the Financial Conduct Authority (FCA)[2] also stated that it considers the automated execution of trade signals within social networks as portfolio management and therefore requires the platform operators for a respective authorisation.

While social trading platforms initially targeted retail investors, they are increasingly getting institutional investors on board on both the buy and the sell side. On the one hand, digital natives reach adulthood and become a relevant target group for asset managers. Hence, social trading networks provide a suitable sales channel for asset management services. For example, wikifolio as one of the younger platforms already counts roughly 60 institutional asset managers acting as signal providers. On the other hand, institutional investors may use the platforms to screen and derive new investment strategies.

The aim of this paper is to provide an introduction to social trading networks, making them more tangible for practitioners and researchers likewise. Besides a discussion of the institutional aspects, we draw quantitative insights on this innovative type of delegated portfolio management. In more detail, the contribution of this paper is threefold.

First, we theoretically outline the role of the platform operator as an intermediary, aiming to reduce agency problems, and highlight the regulatory guidelines imposed. We argue that, while the platforms are able to reduce both the ex ante and ex post resulting information asymmetry, they are faced with a relatively high probability of charlatanry. Second, using a unique dataset covering the signals published on the major platforms during the year 2012, we analyze the return characteristics and investment strategies employed. We find that, in contrast to common asset classes, subscribing to a user within a social trading network typically yields non-normal returns and leads to a relatively high tail risk. Additionally, in our sample solely the top 50% of signal providers are able to keep up with mutual funds net of fees. In order to identify the investment strategies prevailing in social trading networks, we perform a return-based style analysis according to Sharpe [1992]. We utilize the Lipper Average indices as a benchmark for buy-and-hold strategies and find that signal providers rather deploy dynamic trading than buy-and-hold strategies. More precisely,

[2]The FCA regulates financial service providers that focus on retail investors in the United Kingdom. It aims to ensure the integrity of Britain's financial markets.

we find that they typically follow a directional approach and, in this light, argue that they may exhibit substantial market risk at any point in time. Hence, far more than 25% of the signal providers in our sample can be assumed to bear systematic risk.

Third, we highlight the suitability of social trading networks to adress research questions related to dynamic trading strategies. Throughout the article, we will outline that the returns offered by these networks yield characteristics that are similar to those of hedge funds. However, in contrast to hedge funds, the platform operator ensures an obligatory and standardized disclosure of returns in a transaction-based frequency. This allows us, for example, to illustrate the suitability of a return-based style regression for dynamic trading strategies in more detail as Fung and Hsieh [1997]. We provide further evidence that traditional style analysis according to Sharpe [1992] should solely be applied to portfolio managers who primarily trade a single direction (long/short) and use no or a largely constant leverage.

The remainder of this paper is organized as follows. In the following section, we describe the institutional framework of social trading networks. We outline how the platform operator acts as an intermediary and explain how they are regulated. Subsequently, we first examine the return charateristics and trading strategies accessible by subscribing to a signal provider. We then analyze the systematic risk and directionality involved with these strategies. The last section summarizes our results and provides concluding remarks.

Institutional Aspects of Social Trading Networks

Agency Problems and Remuneration

While signal providers de facto manage the follower's brokerage accounts, an immediate legal relationship solely exists between the two user groups and the social trading network as an intermediary: besides routing trading signals, the platforms attempt to diminish the resulting agency problems (see [Bhattacharya and Pfleiderer, 1985]). On the one hand, they reduce the ex ante and ex post information asymmetry by providing standardized real-time track records for each signal provider, based on historical trade signals. These are supplemented by screening instruments such as rankings and search functions. After an investor subscribed to a signal provider, he can besides track the trading activities as these are mirrored into his brokerage account. In comparison to conventional delegated portfolio management settings, the installation of a social trading platform therefore leads to a higher transparency. However, investors can still not assess whether a good performance is attributed to skill or a lucky coincidence (Huddart [1999]). Since basically any internet user is eligible to join such a network and begin publishing trading signals, we assume this to be particularly difficult on social trading platforms: as Huddart [1999] points out, charlatans that aim to build a solid track record by solely betting on lucky chances are more likely on markets with low entry barriers. From a theoretical point of view, it is therefore unclear whether social trading networks as an intermediary are able to reduce the risk of an adverse selection, compared to conventional forms of delegated portfolio management. In addition, though the high transparency of social trading networks may reduce the risk of a hidden action (moral hazard) by the signal provider, signal follower's can still not control the extent to which a provider reacts to a trading opportunity, i.e., the risk he takes, after subcribing to him (see Dow and Gorton [1997]).

On the other hand, the platforms therefore aim to reduce moral hazard by aligning both the signal providers' and followers' interests by the choice of compensation structure. Prior research emphasized the vital role of the remuneration scheme on the effort a money manager expends and the risk he takes. Though a signal compensation scheme that is typical for social trading was not able to prevail yet, a fundamental distinction can be drawn between follower-based models, profit-based models containing a "high-water mark" and volume-based models.

A *follower-based* model compensates signal providers by a fixed remuneration, determined by the number of followers. The largest provider by users, "eToro", pays a fixed sum depending on the number of relevant followers, limited to a monthly payment of 20,000 USD.[3] Obviously, as signal providers are incentivized to maximize the number of investors, a follower-based fee is comparable to the asset-based fee regularly charged by mutual funds. Here, the manager is payed a periodical

[3]eToro defines a follower as relevant if he assigned at least 100 USD to the respective signal provider.

share of assets under management. According to Sirri and Tufano [1998] and Chevalier and Elison [1997], this incentivizes for excessive risk-taking by virtually providing the manager with limited liability. They find that mutual fund flows are much more sensitive towards relatively good than bad historical returns, leading to a de facto asymmetric and convex compensation scheme. A convex payoff can also arise from the compensation contract explicitly, i.e. from a profit-based fee.

In a standard agency setting, a *profit-based* compensation model has been found to be the optimal approach when information is asymmetrically distributed before and after contracting (see e.g. Holmstrom and Milgrom [1987] and Sappington [1991]). However, it is not considered to be optimal in a delegated portfolio management setting (see Stracca [2006] for a good survey). As a profit-based fee rewards fund managers for gains without requiring them to rebate fees to investors in case of losses, they have only limited liability, which leads to a payoff function similar to a call option. As emphasized by Carpenter [2000], this induces fund managers to take excessive risk when they are out of the money. Therefore, it became a popular practice among hedge funds investors, who are typically charged a substantial performance fee, to tie their payment to a "high-water mark" (henceforth: HWM). Among social trading networks, especially recently founded platforms like "wikifolio" and "United Signals" follow this approach. A HWM can constrain excessive risk-taking by signal providers if their time horizon is long-dated, because they are then faced with a sequence of options. Investing in risky assets affects the future intrinsic value of the option: on the one hand, the signal provider increases the probability of crossing the HWM and therefore gaining money; on the other hand, he also increases the risk of having even less moneyness in future options (see Panageas and Westerfield [2009]).

With the emergence of social trading networks, a compensation model that is unusual in traditional delegated portfolio management settings arose: *volume-based* fees. Here, signal providers receive a rebate on the overall generated trading volume, i.e. a share of the respective bid-ask spread. Thus, they are able to lever their compensation by increasing assets under management and trading frequency. For example, "ZuluTrade" approximately pays a share of 0.005 percent of the generated trading volume. Therefore, ZuluTrade rewards signal providers for both profitable and non-profitable trades.[4] Initially introduced to prevent them from holding on to losing positions for too long in order to maintain their chance for receiving a fee, such a compensation scheme may intuitively increase the risk of churning by randomly opening and closing out positions. Therefore, some networks like, e.g., “ayondo” scale this share by the (risk-adjusted) performance the respective signal provider achieved.

Though a compensation scheme that can be considered optimal from a theoretical point of view has not been found for a delegated portfolio management framework yet, there is empirical evidence for contracts containing a HWM to reduce excessive risk-taking (see e.g. Aragon and Nanda [2012]). Note that the choice of compensation scheme is of particular relevance for the commercial success of the network operators: as talented signal providers attract additional investors and vice versa, social trading platforms are a two-sided market – both user groups induce positive external effects (see Rochet and Tirole [2003]). Hence, on one hand, the compensation scheme must attract good signal providers. On the other hand, it should discourage charlatans from engaging with the platform in order to ensure investor satisfaction.

Traded Instruments

Typically, social trading platforms solely offer over the counter (OTC) trading with so-called “contracts for difference” (CFD). A CFD is a short term total return swap on the returns of an underlying asset versus an interest rate, i.e. the buyer of such a swap receives the difference between the current value of an underlying asset and its value at contract time and pays a (fixed) interest to the seller. Note that it is possible to hold short positions in CFDs as well. In this case, the buyer realizes a profit if the value of the underlying asset decreases after contracting. Since CFDs are traded on margin, the buyer of a CFD solely deposits a cash collateral and therefore participates price movements of the underlying asset disproportionately. Unlike futures, CFDs do not have a fixed

[4] To be more precise, ZuluTrade pays 0.5 pips per lot of generated trading volume. A “pip” (percentage in point) is the last decimal point of a currency pair, while a “lot” refers to 100,000 units of the numerator currency. If a signal provider trades EURUSD and an amount of 2 standard lots (2 x 100,000 = 200,000) is following, he receives a fee of 10 EUR.

expiry date or contract size. The high flexibility in terms of contract sizes allows for a fractional mapping and hence to ensure an exact proportionality between the signal provider's and followers' accounts (Doering et al. [2013]). Since the counterparty usually closes out the position once the initial margin is used up, CFDs are solely offered on underlyings with an appropriate market depth and liquidity (Alexander [2008]). Thus, the investment universe on social trading platforms is constrained to foreign exchange (forex), equity indices and major single stocks, commodities and bond indices. The set of assets tradable by signal providers is therefore solely a subset of the total investment universe accessible by established forms of delegated portfolio management (such as mutual or hedge funds).

Regulatory View

For member states of the European Union (EU), the European Securities and Markets Authority (ESMA) announced in 2008 that it considers the operator of a social trading network to exercise "investment discretion by automatically executing the trade signals of third parties" and therefore requires it for an authorisation in relation to portfolio management as per Markets in Financial Instruments Directive (MiFID). Hence, within the EU, the platform operators themselves instead of the signal providers are assumed to be portfolio managers from a regulatory point of view. The FCA recently announced that it supports this view.[5] Note that these are solely legally non-binding interpretations by now.

In order to conduct business in the USA, platform operators are regulated by the Commodity Futures Trading Commission (CFTC) and are required to register as an introducing broker at the National Futures Association (NFA). However, CFD trading is not permitted to US residents due to restrictions by the Securities Exchange Commission (SEC) on OTC financial instruments. US residents are solely able to trade foreign exchange in virtually the same way as non-US residents via traditional margin trading. Hence, as the US business of network operators is limited to forex

[5] See ESMA Reference 2012/382 and FCA's One Minute Guide "Copy trading in the contract for difference (CFD) retail market", 12/01/2015.

trading, social trading networks are less popular in the US up to now.

Empirical Analysis

Data

Our dataset comprises the 2012 track records of signal providers operating on one of the four major platforms, namely eToro, ZuluTrade, ayondo and Currensee. The lack of entry barriers may however lead to charlatanry. For this reason, we restrict our dataset to signal providers with at least 50 followers as of 31 December 2011. The track records provide a full history of published trade signals, including the traded underlying, trade direction, leverage, price, exit price as well as the date and time for each signal.

This allowed us to calculate weekly returns. However, the track records show the profit/loss of a position solely when it is closed out. In contrast, the returns of an investment fund typically include unrealized gains/losses, as the net asset value accounts for price movements in open positions. In order to ensure comparability to traditional asset managers, we thus need to artificially close all open positions at the end of a trading week and reopen them at the beginning of the subsequent trading week. To compute returns of pending trades, we obtained the opening and closing prices of the underlying assets by Thomson Reuters Datastream. Since the bid-ask spread charged by social trading platforms does not only account for trading fees, but also for signal provider compensation and the platform operators' profit margin, the calculated returns are net of all fees.

This results in a final sample of 150 signal providers, with 52 for eToro, 76 for ZuluTrade, 14 for ayondo and 8 for Currensee. As we use weekly returns, there are 52 returns for each signal provider, leading to 8,200 observations in total.

For the return-based style analysis, we follow the asset class selection of Fung and Hsieh [1997] and employ three equity classes: MSCI US equities, MSCI non-US equities, and MSCI emerging market equities. We use three bond classes: iBoxx eurozone sovereign bonds, iBoxx eurozone corporate bonds, and Datastream US government bonds. For cash we use the 3-month Euro Interbank

Offered Rate (Euribor) and for commodities the price of gold (LBMA fixing). Finally, currencies are represented by the Euro Currency Index. We retrieved the total returns of all asset classes by Thomson Reuters Datastream. In addition, for purposes of comparison with established forms of delegated portfolio management, we also apply the respective models on mutual funds, for which we use the total returns of the 35 Lipper Average indices, representing the major mutual funds investment styles. These indices are calculated in such a way that they are net of management and performance, but gross of trading fees. We obtained the weekly total returns for the Lipper Average indices by Thomson Reuters Datastream.

Summary Statistics and Downside Risk

Summary statistics for the signal providers, mutual funds and asset classes are presented in Exhibit 1. Obviously, with a weekly mean return of 0.07% for the full sample and a standard deviation of 1.79%, the median signal provider did not outperform the median mutual fund or any other asset class during 2012. However, to further deal with charlatanry, we additionally divided the overall sample into two return quantiles. While the worst 50% of signal providers generated a zero return, the upper half achieved a return that is merely twice that of mutual funds. Nonetheless, the standard deviation of the weekly returns achieved by the top 50% is also roughly twice that of mutual funds. Hence, though the top signal providers did not outperform mutual funds on a weekly basis, they at least achieved a similar risk-adjusted return.

EXHIBIT 1: Descriptive Statistics and Normality

This exhibit shows descriptive statistics and the Jarque-Bera test results for signal providers, mutual funds and the asset classes used for the later style regressions. The figures reported for signal providers and mutual funds are median values. The columns *Signal Providers (lower)* and *Signal Providers (upper)* show the median values of the 50% of signal providers with the highest and lowest returns, respectively. The last row reports the p-value for the Jarque-Bera test on normality (see Bera and Jarque [1980]).

	Median											
	Signal Providers (full)	**Signal Providers (lower)**	**Signal Providers (upper)**	**Mutual Funds**	**Non-US equities**	**US equities**	**EM equities**	**Euro Gov Bonds**	**Euro Corp Bonds**	**US Gov Bonds**	**EUR index**	**Gold**
Mean [%]	0.07	0.00	0.48	0.27	0.32	0.27	0.35	0.20	0.25	0.09	0.02	0.18
Std. deviation [%]	1.79	0.58	3.51	1.76	2.04	1.65	2.00	0.57	0.40	0.96	0.91	2.16
Skewness	-0.21	-0.47	-0.04	-0.48	-0.35	-0.35	-0.53	-0.03	0.54	-0.18	0.11	0.42
Excess kurtosis	1.98	1.96	2.14	0.29	0.16	0.06	1.29	0.46	0.77	-0.09	-0.52	-0.27
Min [%]	-4.60	-1.69	-10.79	-5.25	-5.87	-4.33	-6.42	-1.27	-0.62	-2.27	-2.00	-3.97
Max [%]	4.11	1.51	10.33	3.69	4.73	3.74	4.72	1.70	1.34	2.58	2.16	5.58
JB, p-value	0.00	0.00	0.00	0.29	0.52	0.54	0.03	0.68	0.10	0.86	0.78	0.43

The results of the Jarque-Bera test show that, in contrast to mutual funds and any other asset class shown, the majority of signal providers generate returns that are non-normally distributed (Bera and Jarque [1980]). This holds true for both the full and sub samples. In fact, they achieve returns that are characterized by a negative skewness and a, compared to mutual funds and other asset classes, substantial excess kurtosis of roughly 2. Hence, care should be taken when applying mean-variance analysis to evaluate signal providers: the assumption of normally distributed returns may lead to an overestimation of true performance (see e.g. Lamm [2003]).

It is widely accepted that such a combination is the opposite of what investors favor. For example, Scott and Horvath [1980] show that investors have a preference for high (i.e., positive) skewness and low kurtosis. Since a negative skewness as well as a positive excess kurtosis indicate a high probability of a large loss, the combined characteristic of both implies a relatively high tail risk, compared to normally distributed returns (Kat [2003]). Exhibit 2 illustrates the tail risk resulting from following signal providers by different downside risk measures.

EXHIBIT 2: Downside Risk Measures

This exhibit reports selected downside risk measures for signal providers and mutual funds. The columns *Signal Providers (lower)* and *Signal Providers (upper)* show the median values of the 50% of signal providers with the highest and lowest returns, respectively. *VaR* refers to value-at-risk, *CVaR* to conditional value-at-risk.

	Median			
	Signal Providers (full)	**Signal Providers (lower)**	**Signal Providers (upper)**	**Mutual Funds**
VaR (0.95, historical) [%]	-2.78	-0.87	-4.25	-2.46
CVaR (0.95, historical) [%]	-3.85	-1.41	-7.09	-3.59
Maximum Drawdown [%]	9.60	3.57	14.25	10.29
Average Drawdown [%]	3.50	1.48	5.14	4.04
Average Drawdown Length (weeks)	6.69	9.20	5.57	9.20
Average Drawdown Recovery (weeks)	3.15	4.20	2.71	4.55

Obviously, solely the worst 50% of signal providers (that achieved a zero-return, see Exhibit 1) show a lower tail risk compared to mutual funds. The upper and full sample expose a relatively higher (conditional) value-at-risk: with a probability of 95%, the median signal provider did not suffer a weekly loss exceeding 2.78%. If he did, however, the losses averaged to 3.85%. In comparison, the median mutual fund exhibits a VaR (CVaR) of solely 2.46% (3.59%). With regard to the maximum and average drawdown suffered, solely the upper half of signal providers exceeds the figures realized by mutual funds. Note that signal providers – regardless of the subsample – offer relatively favorable drawdown and recovery durations. 50% of all signal providers suffer a drawdown period of less than approximately 7 weeks and only need about 3 weeks to make up all prior losses, i.e. reach a historical high-water mark again. In contrast, the average duration of a mutual funds' drawdown amounts to roughly 9 and the time until recovery to 4.5 weeks.

Within the framework of delegated portfolio management, non-normal return distributions are frequently attributed to dynamic trading strategies, i.e. strategies that, in comparison to buy-and-hold, additionally make use of short sales and regularly lever their bets by margining and/or derivatives (see e.g. Agarwal and Naik [2004] and Gregoriou and Gueyie [2003]). In fact, portfolios managed using these strategies typically exhibit option like return patterns (see Glosten and Jagannathan [1994], Mitchell and Pulvino [2001] and Fung and Hsieh [2001]).

Return Determinants and Trading Strategies

A statistical technique frequently used to analyze the investment strategy of a portfolio manager is the return-based style analysis introduced by Sharpe [1992], who proposed an asset factor model to identify the investment strategy of a fund by estimating its exposures to a variety of asset classes. In order to assess return determinants and to answer the question whether signal providers rather deploy dynamic trading than buy-and-hold strategies, we follow Sharpe [1992] and estimate the model

$$r_t^m = \alpha + \sum_{k=1}^{K} \beta_k r_t^k + \epsilon_t \qquad t = 1, 2, ..., T \tag{1}$$

where r_t^m are the historical returns of mutual fund respectively signal provider m and $r_t^1, r_t^2, ..., r_t^K$ the returns on the $K = 8$ asset classes as explained above. The estimations of the slope coefficients $\beta_k, ..., \beta_K$ then represent the average exposures among the different asset classes. We also apply the following constraints according to Sharpe [1992]:

$$\sum_{k=1}^{K} \beta_k = 1 \tag{2}$$

$$\beta_k > 0 \quad \forall k \tag{3}$$

Equation (2) and (3) constrain for the use of leverage and short selling. In order to analyze whether short sales and leverage are indeed important drivers for signal provider returns, we removed the constraints defined in equation (2) and (3) step-by-step. Thus, we first performed a regression with the restriction that $0 < \beta_k \leq 1$. Note that the estimation of such a model requires quadratic programming (see Sharpe [1992]). We then carry out a regression that allows for leverage, but still constrains for short sales. Finally, we ran a completely unconstrained regression, i.e. estimated the model in equation (1) without the constraints imposed by equation (2) and (3). In order to show the differences compared to managed buy-and-hold portfolios, we also performed these regressions for mutual funds returns. Exhibit 3 presents R^2 quantiles for the regressions for both mutual funds and signal providers.

EXHIBIT 3: R-Squareds for Quadratic Programming and Regressions

This exhibit reports R^2 quantiles of three different style regressions for both mutual funds and signal providers. Column *QP* shows the results for quadratic programming, while column *constr* presents R^2s for a regression that is solely constrained for short sales. Column *unconstr* reports the fit for a completely unconstrained regression. Negative values are not reported and indicated by a dash ("-").

	Mutual Funds			**Signal Providers**		
	QP	**constr**	**unconstr**	**QP**	**constr**	**unconstr**
Min	0.55	0.52	0.58	-	0.00	0.06
0.25 quantile	0.80	0.81	0.83	-	0.04	0.18
Median	0.90	0.90	0.92	0.02	0.07	0.26
0.75 quantile	0.95	0.94	0.96	0.09	0.17	0.35
Max	0.98	0.98	0.98	0.42	0.63	0.69

The R^2s for mutual funds remain almost unchanged when removing leverage or short selling constraints – the model estimated by quadratic programming fits the data as good as a completely unconstrained regression. These results are very similar to those of Sharpe [1992]. However, the results substantially differ for signal providers: estimating a model with a leverage and short selling constraint leads to negative R^2s for at least 25% of the signal providers, i.e. the model fits the data worse than a horizontal line.[6] Allowing for short sales slightly increases the fit, but R^2s are still below 0.20 for at least 75% of signal providers. However, if we additionally remove the leverage constraint, R^2 values significantly increase. For example, the median R^2 changes by a factor of 13 from 0.02 to 0.26.

Since the stepwise removal of trading limitations does virtually not increase the fit for mutual funds, their returns evidently are largely driven by the asset allocation choice. Leverage and short sales at best are subordinated return drivers. Hence, a mutual funds' strategy is similar to buy-and-hold – *where* and much less *how* they invest is the key driver of their returns (Fung and Hsieh [1997]). In contrast, as the fit to signal provider returns considerably increases, leverage and short sales seem to be integral parts of the strategies prevailing in social trading networks. However, unlike for mutual or hedge funds, the high transparency of these platforms reflected in our comprehensive data set allows us to analyze the direction and leverage used for each trade executed by a signal provider. This enables us to analyze whether the majority of signal providers really makes use of margining and short sales frequently. Exhibit 4 provides descriptive statistics on the trading behavior of signal providers for the respective networks.

Obviously, as the mean share of long trades ranges roughly between 50 and 60% across all four platforms, the majority of signal providers bets on both rising and falling markets dynamically. Note that, as the maximum long share for eToro and ayondo is close to 100%, there are a few traders that can be considered as long-only traders. Though the average leverage between 1.55 and 9.06 indicates that signal providers typically lever their exposures by margining, the results

[6] Note that, while a negative *adjusted* R^2 is not rare in regressions, the simple R^2 can solely be negative for constrained regressions. This is the case if constraints enforce an estimation that fits the data worse than a horizontal line, i.e. the mean of the dependent variable provides a better explanation for the outcomes than the estimated model. Then, the residual sum of squares exceeds the total sum of squares and the coefficient of determination totals to a negative value (see Cameron and Windmeijer [1997], for example).

EXHIBIT 4: Descriptive Trading Statistics

This exhibit presents descriptive statistics on the signal providers' trading behaviour. *Long[%]* is the share of long positions a signal provider holds. *Leverage* is the average leverage a signal provider uses. *Trades/week* is the average number of trades a signal provider executes. *Std. Dev.* is the standard deviation.

Panel A: eToro

	Long[%]	Leverage	Trades/week
Mean	58.82	1.55	10.97
Min	23.18	0.00	1.75
Max	96.12	26.41	48.85
Std. Dev.	16.49	4.77	9.68

Panel B: ZuluTrade

	Long[%]	Leverage	Trades/week
Mean	47.85	3.38	14.43
Min	15.07	0.01	1.17
Max	77.54	17.96	44.27
Std. Dev.	15.14	4.18	10.49

Panel C: ayondo

	Long[%]	Leverage	Trades/week
Mean	58.87	9.06	18.59
Min	16.25	1.86	4.38
Max	98.95	22.21	49.52
Std. Dev.	28.62	6.77	14.57

Panel D: Currensee

	Long[%]	Leverage	Trades/week
Mean	47.87	1.82	11.30
Min	32.85	0.51	2.25
Max	70.59	3.65	39.06
Std. Dev.	12.85	1.14	12.87

differ across the platforms. One potential explanation is that the volume-based fee signal providers are payed on ayondo and ZuluTrade induces them to use a, in comparison to the other platforms, higher leverage: as they receive a share of the gross trading volume generated by their signals, they are able to increase their compensation by choosing a higher leverage.[7] The average number of trades per week ranging from approximately 11 to 19 reveals a high trade frequency, i.e., signal providers frequently adjust their exposure. Altogether, the data highlights that the majority of signal providers indeed rather deploys dynamic trading than buy-and-hold strategies.

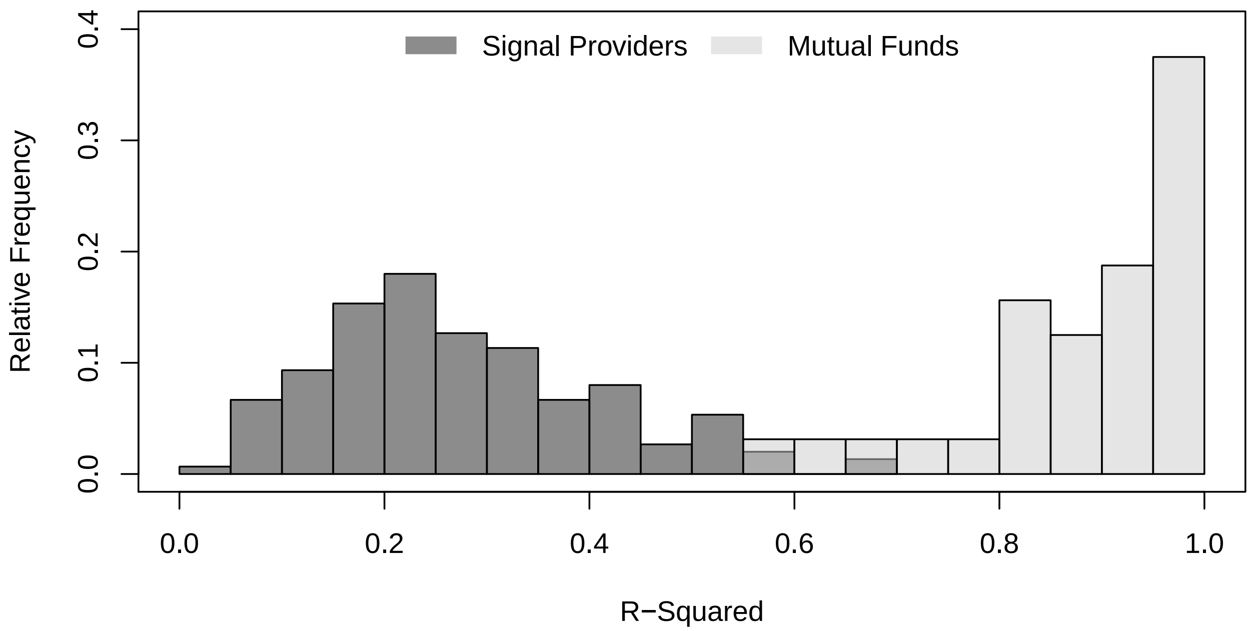
According to Fung and Hsieh [1999], there are two main approaches of dynamic trading strategies: directional and non-directional approaches. *Non-directional* approaches aim to exploit market anomalies by being long and short comparable securities at the same time in order to eliminate systematic risk, while *directional* approaches bet on the direction of markets dynamically by being either long or short. As Fung and Hsieh [1999] point out, non-directional approaches frequently require the holding of complex securities such as convertible bonds. However, signal providers are obliged to trade CFDs (see above). Hence, they are unable to access securities that may be essential to realize non-directional approaches. We thus assume that the majority of signal providers follows directional approaches. We will examine this within the next chapter.

Note that despite the removal of trading limitations, the overall fit for signal providers is still low compared to the buy-and-hold portfolios offered by mutual funds. The results of the unconstrained regression for both signal providers and mutual funds are illustrated in more detail in Exhibit 5. As Exhibit 5 shows, the R^2s for the majority of signal providers are below 0.4, while mutual funds concentrate above 0.6. Such a low fit implies that signal providers typically achieve market neutral returns.

[7] On eToro, signal providers are compensated with a fixed remuneration, determined by the number of followers and limited to 10,000 US dollar per month. We assume the compensation cap to provide an incentive for "locking in" a given income level and hence reduce excessive risk taking. Signal providers operating on Currensee receive a performance-based fee including a high-water mark and therefore solely participate net profits, i.e. are paid only for exceeding the historical maximum value of assets under management. Panageas and Westerfield [2009] outline that such a contract can constrain excessive risk-taking.

EXHIBIT 5: Distribution of R-Squareds

This exhibit shows the distribution of R^2s for the unconstrained regression for both mutual funds and signal providers.



Market Neutrality and Directionality of Returns

Market neutrality is an often cited favorable feature of dynamic trading strategies (see e.g. Agarwal and Naik [2004] and Goetzmann et al. [1999]). In fact, the diversification benefits of hedge funds, who are typically associated with a deployment of these strategies, are their major selling point (Patton [2009]). In order to examine whether social trading networks offer market neutral returns, we first performed an overall F-test (Wald test) on the unconstrained regression discussed above, i.e., we tested on the joint irrelevance of all eight asset classes used. Exhibit 6 shows p-value quantiles for both mutual funds and signal providers. The results imply that, while the hypothesis of market neutrality cannot be rejected for a single mutual fund in our sample, for all common levels of significance, at least 50% of signal providers generate returns that are not exposed to market risk.

Exhibit 7 presents the distribution of asset classes that are significant according to the t-Test on a level of significance of 99%. The majority of mutual funds is exposed to US and non-US

EXHIBIT 6: F-Test for the Unconstrained Regression

This exhibit shows p-value quantiles of the overall F-test for the unconstrained regression.

	Mutual Funds	**Signal Providers**
Min	0.000	0.000
0.25 quantile	0.000	0.016
Median	0.000	0.129
0.75 quantile	0.000	0.440
Max	0.000	0.986

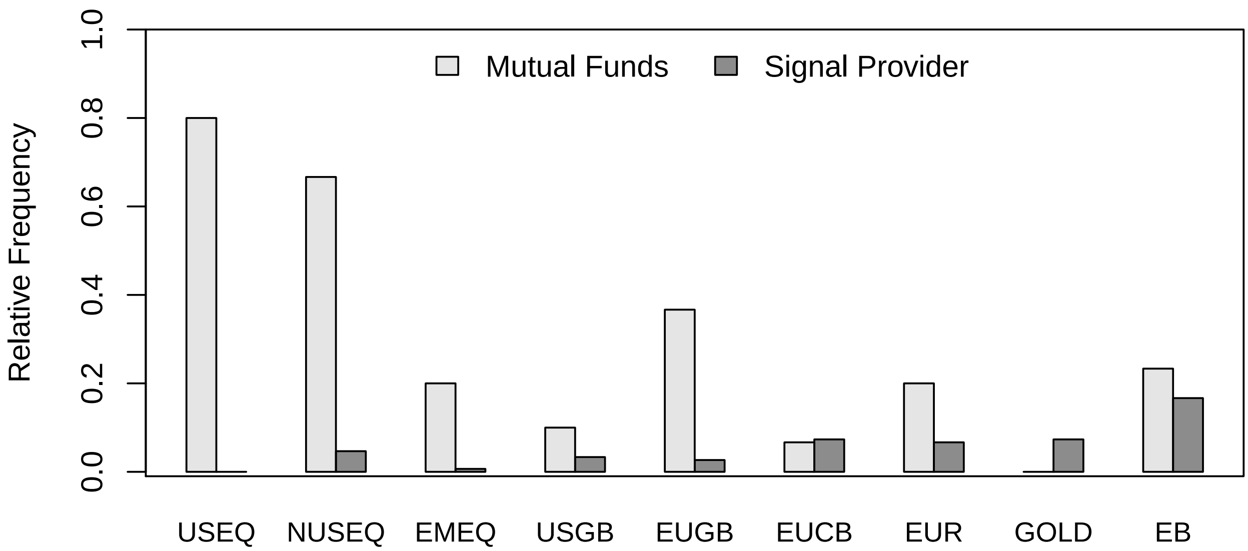
equities. A large share of 37% also exhibits a significant exposure in European government bonds. In contrast, there is not a single asset class that signal providers are typically exposed to: across all markets, the share with a significant exposure does not exceed 20%. Altogether, social trading networks offer returns that are largely market neutral.

However, a large strand of the more recent hedge fund literature questioned the extent to which dynamic trading strategies really generate market neutral returns (see e.g. Ennis and Sebastian [2003] and Patton [2009]). Among others, Fung and Hsieh [1997], Agarwal and Naik [2004] and Mitchell and Pulvino [2001] find a relationship between hedge fund and mutual fund returns that is very similar to our results. Fung and Hsieh [1997] conclude that, as basically both mutual and hedge funds transact in the same asset classes, differences in statistic return properties are due to the dynamic nature of hedge funds trading strategies. In a later paper, Fung and Hsieh [1999] argue that investment style should be thought of in two dimensions: the choice of asset classes to invest in and trading strategy. Trading strategy refers, on the one hand, to the direction (long/short) – i.e. the sign of β_k – and, one the other hand, to the leverage that affects the absolute value of β_k. Hence, the actual returns are the products of location choice and trading strategy (see Fung and Hsieh [1997]).

Regarding the location choice, signal providers and mutual funds differ since the assets tradable for signal providers are solely a subset of the total investment universe accessible by mutual funds. Note that both have in common that they are virtually constrained to transact only in liquid asset classes. However, they strikingly differ in terms of the possible direction of positions and leverage. Since mutual funds typically deploy unlevered long-only (buy-and-hold, see above) strategies,

EXHIBIT 7: Distribution of Significant Asset Classes

This exhibit shows the share of mutual funds and signal providers with significant exposures in different asset classes (according to the t-test at a 99% level of significance). *USEQ*, *NUSEQ* and *EMEQ* refer to US, non-US and emerging markets equities, respectively. *USGB*, *EUGB* and *EUCB* relate to US government, European government and European corporate bonds, respectively. *EUR* denotes the Euro Currency Index and *EB* the Euribor.



their returns relate to market returns in a *linear* pattern, with a positive factor, i.e., the portfolio weight, that varies between 0 and 1 (see Fung and Hsieh [1999]). In addition, as mutual funds are restricted to a principal investment objective and a relative return target (i.e. their performance is measured relatively to a benchmark index) as defined in their prospectus, there will be only a slight intermediate variation of portfolio shares. Mutual funds returns can hence be expressed as a linear combination of asset class returns. A style analysis according to Sharpe [1992] as a linear regression is therefore able to find reliable average exposures.

In contrast, signal providers neither face leverage or short selling constraints, nor investment guidelines (except the universe of tradable underlyings). As a result, portfolio weights are not constrained to lie between 0 and 1 – theoretically, as the platform providers usually require a minimum margin of 1%, the weights can be anywhere between -99 and +99. Thus, as this allows to generate returns that have a *non-linear* relationship to asset class returns, care should be taken when applying traditional style analysis to a portfolio manager that may deploy a dynamic trading strategy.

To illustrate this point, Fung and Hsieh [1997] consider a manager solely trading S&P500 futures contracts. In a mutual fund (buy-and-hold) setting, a "fully invested position of being consistently long one futures contract" will result in a coefficient of +1 on the S&P500 index. Conversely, a fully invested short position will lead to a coefficient of -1. If he however alternates between being completely long and short each day, the style analysis will indicate an exposure that is close to zero, even though substantial market risk is taken at any point in time. Simultaneously, the R^2 of the performed regression will be low. Note that a variation of the leverage used, i.e. a variation of portfolio weights, additionally contributes to a low R^2. To illustrate this weight-induced impact on the R^2, consider the following example. Assume the above manager as a long-only trader. On day one, he is fully invested in S&P500 futures contracts, resulting in a beta of +1. On day two, he adjusts his position by buying another contract on margin, which leads to a coefficient of +2 for day two. Finally, on day three, he buys a third contract on margin, leading to a coefficient of +3. As his returns relate to the market in an exponential manner, a linear regression can only partially explain the manager's returns and is likely to underestimate the true market risk taken.

For such a directional approach, a (linear) style regression leads to incorrect inference. As Fung and Hsieh [1999] point out, traditional style analysis solely draws a realistic picture for non-directional approaches: while these attempt to achieve market neutrality by their style of investing, i.e. by delivering a "steady stream of returns over a wide range of market conditions", directional approaches deliver returns that are solely seemingly uncorrelated to the market by betting on the markets trend. If, as outlined before, the majority of signal providers indeed follows directional approaches, one would thus expect an U-shaped relationship between the R^2s of a traditional style analysis and the share of long trades: style regressions should exhibit a high fit for both long- and short-only signal providers, but a relatively low one for those who frequently vary the direction of trades. If, in contrast, signal providers typically follow non-directional approaches, one would expect a horizontal when plotting the R^2s against the share of long trades. Additionally, one can expect a higher goodness of fit for signal providers who use an almost constant leverage compared to those with a large variation in leverage.

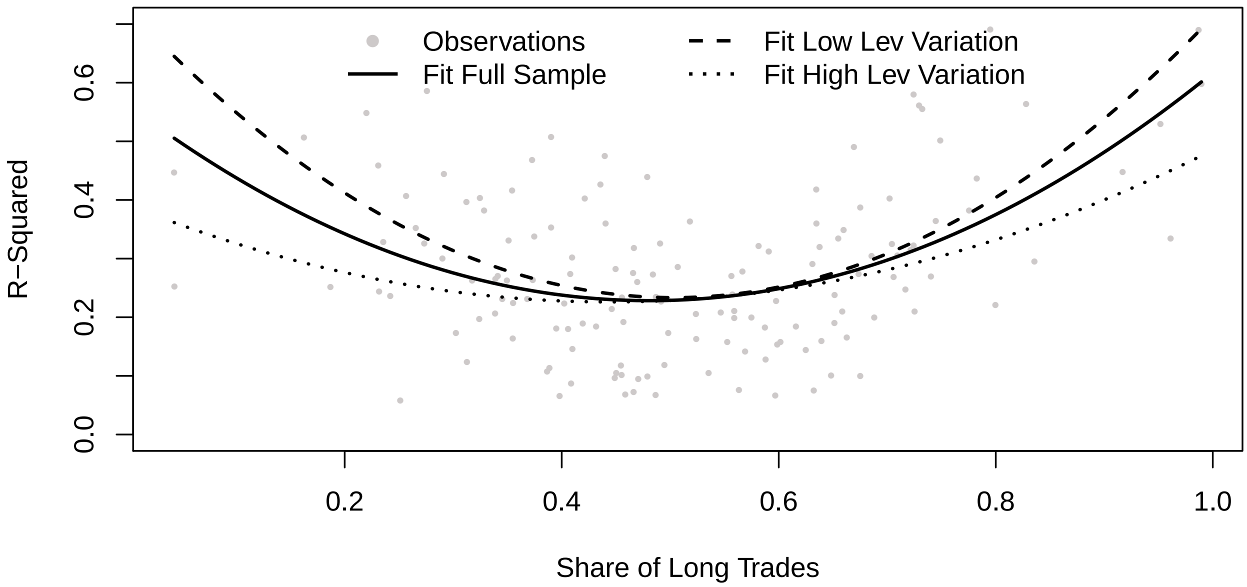
The disclosure of detailed information on each single trade such as the direction and leverage used allows us to carry out the above regression and visualize the behaviour outlined above and initially described by Fung and Hsieh [1997]. For this purpose, we first regress the R^2s of the unconstrained model to the share of long trades of the respective signal provider. We do this by performing a 2nd degree polynomial regression, i.e. we model the R^2s as a 2nd degree polynomial of the long share. In order to assess whether a higher variation of the leverage used contributes to a lower fit, we additionally divide the data into subsamples. Since the simple standard deviation is affected by the mean leverage, but the level of leverage used does not influence a style regression's fit, we need to transform it to a dimensionless measure. We therefore use the median of the variation coefficient, that is the ratio of the standard deviation to the mean, as a cut-off value for classification of signal providers into the two groups.

Exhibit 8 shows the results for this regression. The solid black line shows the estimated curve for the full sample, while the dashed respectively dotted line plots the curve for signal providers with a low respectively high variation coefficient for the leverage used. We find evidence for the U-shaped pattern as described above: the unconstrained regression leads to R^2s that are relatively high for signal providers that primarily trade a single direction and are minimal for those with a balanced ratio of long and short exposures. As the estimated curves for the subsamples show, there is an inverse relationship between leverage variation and regression fit: the higher the variation, the lower the R^2. However, the impact of leverage variation is negliligble for signal providers who frequently vary the direction anyway.

In order to highlight the relation between market neutrality, long share and leverage variation, we performed the same regression with the p-value of the overall F-test as dependent variable. The results are illustrated in Exhibit 9. Correspondingly, as Exhibit 9 shows, there is an inverse U-shaped relationship between the p-value of the overall F-test and the share of long trades. This suggests that signal providers who frequently vary the direction of their trades achieve market neutral returns. Like for the R^2, this is boosted by a high variation of the leverage used. Surprisingly, the latter effect is diminishing with an increasing long share. Hence, the results of the overall F-test

EXHIBIT 8: R-Squareds vs. Share of Long Trades and Leverage Variation

This exhibit plots the R^2s of the unconstrained regression for signal providers against their share of long trades. Additionally, it shows the estimated curve of a 2nd order polynomial regression, whereby the R^2 is regressed to the long share. The solid black line shows the results for the full sample regression. The dashed and dotted lines show the results for this regression when using solely the 50% of signal providers with the lowest and highest leverage variation, respectively. Leverage variation is measured by its variation coefficient, i.e. the cut-off value for a classification into the subsamples is the median of the ratio of leverage standard deviation to the mean leverage.



presented in Exhibit 6 seem to be substantially affected by the long share and leverage variation.

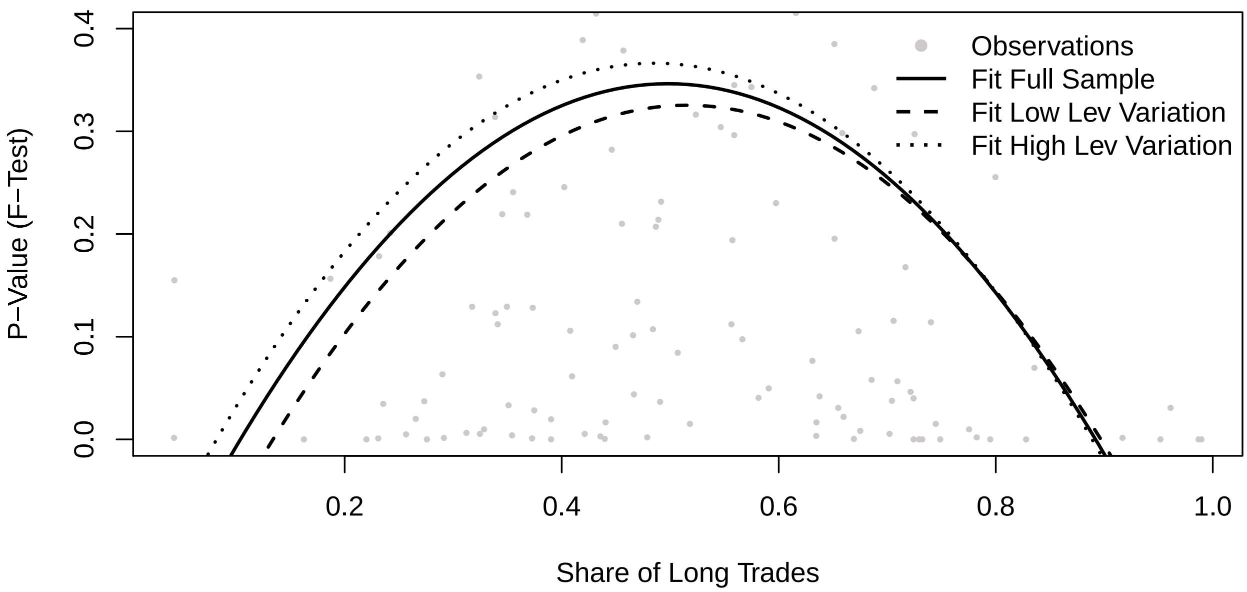
Altogether, this allows to conclude that the majority of signal providers utilizes their access to dynamic trading strategies by a directional approach. Hence, the share of market neutral signal providers discussed above must be interpreted with caution. It is reasonable to assume that a large portion solely exhibits market neutrality, because varying exposures over time average out to zero at the observation date. The share of signal providers offering "truly" market neutral returns can be expected to be much smaller.

Conclusion

Social trading networks allow investors to subscribe one or more signal providers, whose trading signals are then executed within the investor's brokerage account proportionally and in

EXHIBIT 9: Overall F-Test vs. Share of Long Trades and Leverage Variation

This exhibit plots the p-value of the overall F-test for the unconstrained regression for signal providers against their share of long trades. Additionally, it shows the estimated curve of a 2nd order polynomial regression, whereby the p-value of the overall F-test is regressed to the long share. The solid black line shows the results for the full sample regression. The dashed and dotted lines show the results for this regression when using solely the 50% of signal providers with the lowest and highest leverage variation, respectively. Leverage variation is measured by its variation coefficient, i.e. the cut-off value for a classification into the subsamples is the median of the ratio of leverage standard deviation to the mean leverage.



real-time. Hence, social trading networks provide an innovative framework for delegated portfolio management. They experience an increasing popularity among retail and most recently also institutional investors.

Besides providing the technology for trade mirroring, the platforms act as an intermediary between investors and signal providers, reducing the ex ante and ex post information asymmetry by providing detailed real-time track records, rankings and search functions. For sharing their trading ideas, signal providers are paid a fee by the platform provider. However, because there are virtually no barriers to enter such a network and share trading signals, we assume a higher occurence of charlatans (Huddart [1999]). The majority of platforms solely offers CFD trading, as this is a simple solution to ensure a fractional mapping between signal provider and follower accounts. Since CFDs usually are only available for liquid underlyings, signal providers face a limited investment universe. Within the European Union and United States, the platform operator, but not the users acting as signal providers are required to authorize with regulatory bodies.

Using a sample of signals published on major social trading networks during 2012, we show that the returns achievable by subscribing a signal provider follow a significantly non-normal distribution and exhibit a, in comparison to mutual funds, relatively high tail risk. We find that a traditional return-based style analysis according to Sharpe [1992] and with an asset class selection following Fung and Hsieh [1997] results in a high fit for mutual funds, even if we constrain for leverage and short sales. In contrast, R^2s significantly increase for signal provider returns when we remove these constraints step-by-step. By analyzing the direction and margin used for each signal published, we show that signal providers indeed deploy dynamic trading strategies. On average, between 40 and 50% of the signals executed are short trades. Additionally, signal providers typically lever their bets by a factor roughly ranging from 2 to 9.

However, with a median R^2 of 0.26, the explanatory power of an unconstrained style-regression is still low for signal providers compared to mutual funds. Along with the low fit we find that, according to the overall F-test, at least half of the signal providers achieve market neutrality, while all mutual funds in our sample are exposed to systematic risk. Among others, Fung and Hsieh [1997] find a very similar relationship between hedge funds and mutual funds. They argue that, while market neutrality is the major selling point for hedge funds, solely funds following non-directional approaches offer "true" market neutrality. In contrast, directional approaches only yield zero correlation to market returns because time-varying exposures – that may be substantial over a short period of time – average out to zero. This context together with the high transparency of social trading data allows us to analyze whether signal providers follow directional or non-directional approaches. By illustrating the relationship described by Fung and Hsieh [1997], we show that the fit relates to the trading strategy in a U-shaped pattern: it is high for long- or short-only signal providers and relatively low for those frequently changing the direction of trades. In addition, we find evidence for a lower fit for those that considerably vary the leverage used in contrast to those who apply a merely constant leverage. We conclude that at least the majority of signal providers indeed follows directional approaches and thus assume the true share of those achieving market neutrality to be substantially lower than the previous reported 50%. Beyond, this provides further evidence that traditional style analysis according to Sharpe [1992] should solely be applied to portfolio managers who primarily trade a single direction (long/short) and use no or a largely constant leverage. Otherwise, it is important to allow for a non-linear relationship between manager and market returns (see e.g. Agarwal and Naik [2004]).

Altogether, social trading networks allow to realize hedge funds-like returns, even to retail investors, plus offer a substantially higher degree of transparency and liquidity (see Doering et al. [2013] for a more detailed discussion).

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