Hedge Funds and Herding Behaviour

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Abstract

This chapter examines whether hedge funds herd, how this herding occurs and any potential market wide effects. Bringing together the mainstream finance literature and that from a more management and sociological perspective, it is shown that hedge funds herd, although there is some evidence this is less than other large institutional investors. Mechanistically, such consensus trades occur because hedge firms communicate within tight knit clusters of trusted and smart managers, who share and analyse trading positions together. This industry structure is a function of the hyper decision-making environment faced by hedge fund managers, coupled with a desire for legitimisation and to maintain reputation. Finally, note that hedge fund herding can have market wide effects either directly via network risk and indirectly, as follower institutional investors amplify hedge fund trading patterns.

1. Introduction

The volatile prices often generated by financial markets are typically viewed as imposing an adverse impact on the real economy and consequently, society at large. In a recent example, the global financial crisis (GFC) of 2007 to 2008 saw large run-ups in all manner of asset prices including housing, equities and commodities as diverse as copper and wheat. Of course, in the latter half of 2008 and first quarter of 2009, prices fell dramatically. Figure 1 shows the S&P500 index registered a cyclical high of 1565 on October 9th 2007, whilst falling to a low of 677 on March 9th 2009.[1] This enormous loss in value had serious implications for US GDP growth which fell -2.78 percent in 2009.

[Insert Figure 1 about here]

There are several competing and complementary explanations for the misevaluations that result in asset price bubbles and crashes (Stein, 2015). Amongst these, herding of market participants is frequently mentioned in both the academic literature and popular press, defined by Kellard *et al*. (2017) as:

"*In the context of markets, herding commonly refers to several actors making the same investment decision either at the same time or in close succession, leading to high concentration of similar market orders and higher risks.*" (p.84)

Theoretically, herding can emerge via a variety of processes. The mainstream finance literature commonly examines prices and trades suggesting mechanisms such as information cascades as investors observe other's trades (Sias, 2004), access to the same public information (Froot, Scharfstein and Stein, 1992), momentum trading (Nofsinger and Sias, 1999), reputational concerns and benchmarking (Boyson, 2010), and trading related to fads (Barberis and Shleifer, 2003) or asset characteristics (Bennett *et al.*, 2003). Within this sphere of literature, social connections are little mentioned although it could be argued given the empirical findings that geographical proximity (Hong *et al*., 2005) and shared college education (Cohen *et al*., 2010) of market participants increases correlated trading behaviour, there is some *prima facie* evidence of a link between herding and communication between investors.

[1] The movement in other prices was even more dramatic – on July 11th 2008, the benchmark Brent Crude oil price stood at $147 a barrel; by Christmas Eve that year, the price had collapsed to $43.

On the other hand, overlapping organisational, management and social studies of finance literature primarily stresses the underlying operational similarities or social ties between investment firms which may facilitate herding. For example, operationally, firms may employ the same quantitative models, computer software (Zaloom, 2003; Callon and Muniesa, 2005) or heuristic approaches to valuation which serve to narrow the range of investor opinions (MacKenzie, 2003; Beunza and Stark, 2012) and lead to similar trades. Other work, drawing on the view that economic decision making *per se* is embedded in social ties (Baker, 1984; Granovetter, 1985; Uzzi, 1996, 1999), suggests that inter-firm communication can result in herding (Kellard *et al*., 2017). We shall discuss this in more detail during later sections.

This chapter focuses on the herding behaviour of hedge funds. It might be argued that in popular opinion, hedge funds are often regarded as a pejorative symbol of the entire financial sector.[2] However, such funds, are quite different from most other financial institutions and this suggests their herding behaviour may present some distinct characteristics. The U.S. President's Working Group on Financial Markets (1999) defines hedge funds as:

"Any pooled investment vehicle that is privately organised, administered by professional investment managers, and not widely available to the public." (p.1)

Given this lack of exposure to the public, hedge funds are less regulated than other investment structures including mutual and pension funds. As a consequence, hedge fund portfolios tend to be more varied than more traditional funds (Fung and Hsieh, 1999), comprising not just of long equity and fixed income positions but derivatives, short-positions and high leverage. Typically, hedge funds are grouped by the particular investment style they

[2] Such opinion has been reinforced by recent television dramas such as 'Billions.'

primarily adhere to, the most popular including long-short, event-driven, multi-strategy, distressed and macro (Smith, 2011).

Although looming large in the collective imagination, in terms of actual size, the hedge fund industry is a relatively small component of the investment community. Presently, assets under management (AUM) are approximately $3.24 trillion (eVestment, 2019) which is a small fraction of the global asset management industry at $79.4 trillion (Boston Consulting Group, 2018). In a recent study, Yin (2016) employing the Lipper TASS database, shows that the 2563 funds[3] examined had a mean AUM of $244 million with a maximum size of $13 billion. This compactness extends into other areas of operation – hedge funds tend to have a relatively small number of employees of up to 20 people (Kellard *et al*., 2017).

Despite, or perhaps because of their small size, hedge funds have been shown to have an outsized influence on prices and measures of market quality. For example, when examining whether investor trading positions held any predictability for crude oil futures returns, Singleton (2014) showed that those held by hedge funds influenced returns and the shape of the futures term structure. A corollary of this is that such trading will affect the real economy via the effect on energy and fuel prices. Other work suggests that increased correlation between equity and commodity returns, with a consequent reduction in the effectiveness of portfolio diversification, is caused by hedge fund trades (Buyuksahin and Robe, 2011). In any case, other investment vehicles often hold substantial positions in hedge funds. In a 2017 survey (Willis Towers Watson, 2017) showed that an increasing share of hedge fund investors come from pensions funds, insurance companies and sovereign wealth funds.

[3] Some estimate there are around 10,000 active hedge funds.

Given the importance of hedge funds in the financial system architecture, it is crucial to ask (i) theoretically, why hedge funds might herd, (ii) empirically, whether hedge funds herd and this destabilises markets? In particular, as hedge funds employ derivatives, short-selling and leverage, similar trades by several hedge funds concurrently can markedly increase market risk, ultimately leading to greater financial instability.[4] The remaining parts of the chapter are therefore divided into five sections in an attempt to answer the above questions: Section 2 briefly considers the theory on herding in financial markets more generally, whilst also providing a discussion of where hedge funds may differ from other firms. Turning to the empirical evidence, Section 3 covers the literature from quantitative perspective, whilst Sections 4 and 5, the literature using primarily a qualitative and mixed-methods lens respectively. Finally, Section 6 provides a discussion and conclusion.

2. A Brief Theory of Herding

The theory of rational expectations was first suggested by Muth (1961) and implies that whilst agents' forecasts might not be entirely accurate, they do not make systematic errors over time i.e., their forecasts do not typically contain a positive or negative bias and therefore the expected forecast error is zero. Amongst many other things, such work was the basis of the efficient market hypothesis (EMH – see Fama, 1970) whereby stock prices follow a 'random walk' and the expected returns to speculative activity are zero. Of course, as Fama (1970) notes, investor disagreement (see, *inter alia*, Singleton, 2014), transactions costs and differential access to information can be sources of inefficiency.

[4] Kellard *et al*. (2017) discuss a case study event where several hedge funds were short VW stock. In actuality, there was not enough VW stock available to cover all the short positions, and the eventual scramble to purchase what was available drove the price of the car manufacturer to record highs and several hedge funds out of business.

As noted in the introduction, there are a number of theoretical mechanisms rooted in the lack of perfect information and suggested in the extant literature by which herding in financial markets *per se* and between hedge funds more specifically, may emerge. To begin consider the phenomena of 'information cascades' described by Bikhchandani *et al*. (1992) as occurring when:

"...it is optimal for an individual, having observed the actions of those ahead of him, to follow the behaviour of the preceding individual without regard to his information." (p.994)

They stress that at this juncture, the individual's decision is uninformative for future agents in any sequential game. Such agents will therefore glean the same conclusion from the time series of prior decisions and adopt the same action. The information cascades through sequentially future decisions until some information shock occurs.

Banerjee (1992) provides a model based on cascades which explains herding behaviour but notes that the consequence of individual's ignoring their own private information can result in welfare-reducing, inefficient equilibria.[5] Moreover, the equilibria established are likely volatile. This is derived from imperfect information signals which may not be correct and initial decision makers using these signals around which a crowd develops. In the context of financial asset markets, Banerjee (1992) suggest this may provide at least a partial explanation of the common finding of excess volatility. In their model, Bikhchandani *et al*. (1992) also note that cascades are *fragile* and that the type of localized conformity[6] can

[5] Interestingly, Banerjee (1992) suggests that in these circumstances it may be optimal to restrict at least a subset of individuals (i.e., the initial decision makers) to only use their private information.

[6] Such behavioural effects are not limited to asset prices. For example, Bikhchandani *et al*. (1992) note that, "The [recent] rejection of communism began in Poland and later spread rapidly among other Eastern European countries. Religious movements, revivals, and reformations, started by a few zealots, sometimes sweep across

change dramatically in response to quite small innovations. In essence, this transpires because although agents are assumed to have some information, the signal is relatively small compared to the noise. In this case, any new information (or perhaps rumour) has the potential to move the equilibrium markedly with repeated games resulting in social behaviour such as fads or asset price behaviour including bubbles and crashes. Empirical work by authors such as Sias (2004) on financial institutions has provided some support for the hypothesis that herding in financial markets results from information cascades whereby agents deduce information from other's trading positions.

Some theoretical approaches to herding emphasise that financial agents may hold the same or similar information sets on which to base trading decisions. Specifically, so-called 'Investigative herding' occurs when investors' information is cross-sectionally correlated and therefore they trade similar assets. For example, Froot, Scharfstein and Stein (1992)[7] show that speculators with short investment horizons may trade on the basis of one piece of information, rather than an entire information set, particular if they believe others will do so. This type of informational inefficiency, driven by positive information spillovers,[8] can be quite large, with traders herding around low quality or even non-fundamental related data. Froot *et al*. (1992) suggest this may provide a plausible mechanism for how rational bubbles (see, *inter alia*, Tsvetanov *et al*., 2016) occur. Here the investment horizon is all important in the modelling and implications; with a longer-term horizon, prices will revert to fundamental

populations with astonishing rapidity. Addiction to and social attitudes associated with alcohol, cigarettes, and illegal drugs have fluctuated widely." (p.993)

[7] For closely related work, see Hirschleifer, Subrahmanyam and Titman (1994). Perhaps the main difference is that Hirschleifer *et al*. (1994) demonstrate that herding can result without short horizons being exogenously imposed. They note "Our analysis instead demonstrates that risk-sharing considerations alone can lead to inefficient outcomes in information acquisition" (p.1668).

[8] A positive information spillover is one where an investor becomes better off when others trade on the same information she possesses.

values and therefore information spillovers are negative (i.e., investors are better off if they trade only on their information).

Of course, financial agents may observe trades and other relevant information but they will also observe prices. Amongst many others, Nofsinger and Sias (1999), show that institutions are momentum traders. Using U.S. data over a 20-year period, additionally they show that annual changes in institutional share ownership are highly and positively correlated with returns. This empirical finding has two potentially reinforcing explanations. The first is that herding by institutional investors affects prices more than herding by individual investors; second, that intra-year positive feedback trading[9] by institutions outweighs that by individual investors. Furthermore, there seems to be empirical support for both hypotheses; Nofsinger and Sias (1999) stress that after large-scale trading by institutional investors, there is no-evidence of mean-reverting returns, momentum strategies can account for some but not all this continued positive return and therefore, institutional investors appear to possess an informational advantage over individuals.

The above theoretical approaches are not necessarily inconsistent with forms of rationality. On the hand, it's quite possible that certain types of irrationality drive herding behaviour.[10] For example, seminal work by Shiller (1984, 1989) argues that observed excess volatility and mispricing in asset markets has its roots in the psychology of investors, and in particular, the tendency to engage in *fads*. A fad is any wedge between the fundamental and market price of

[9] Positive feedback trading is where returns become a common information signal for momentum traders and therefore herding.

[10] Of course, some agents may possess irrational expectations, as is the case with noise traders (De Long *et al.*, 1990). On the other hand, Simon (1982) proposed that rationality is necessarily bounded given constraints (and differences) on our available information, cognitive ability and tools, and decision-making time. Extending this, Lo (2004) placed Simon's ideas of satisficing within an evolutionary frame (i.e., the Adaptive Markets Hypothesis or AMH) suggesting that this explains behavioural phenomena such as overconfidence, overreaction and loss aversion. One could argue that fight to 'survive' would also draw such agents into following fads or communicating directly with each other.

an asset that is caused by some psychological factor. Shiller (1989) notes that a fad becomes a bubble[11] if:

"...the contagion of the fad occurs through price; people are attracted by observed price increases. Observing past price increases means observing other people becoming wealthy who invested heavily in the asset, and this observation might interest or excite other potential investors" (p.56).

Following Tsvetanov *et al*. (2016), a bubble process can be simply modelled as:

$$S_t = S_t^f + B_t \quad (1)$$

where S_t is the current spot price of an asset, S_t^f represents the fundamental price and B_t is a bubble component. Assuming the bubble is driven by a fad v_t, we could replace (1) with:

$$S_t = S_t^f + v_t \quad (2)$$

where v_t is some autoregressive process such as:

$$v_t = \varphi v_{t-1} + \varepsilon_t \quad (3)$$

If $\varphi = 1 + r$, where r is positive and non-zero, then Summers (1986) notes (3) will represent a speculative bubble.[12] In this sense, fads via the price, can act as an irrational common signal to investors leading to herding and bubble behaviour in particular assets or more latterly, styles (see Barberis and Shleifer, 2003). Of course, bubbles are more likely to periodically collapse and so perhaps an Evans (1991) type process, shown below, is more appropriate:

[11] In October 2017, Shiller referred to Bitcoin as a fad (see https://www.cnbc.com/2017/10/16/nobel-winning-economist-shiller-calls-bitcoin-a-fad.html).
[12] Alternatively, we might characterise the bubble process as mildly explosive by allowing $r = cn^{-\eta}$ and requiring particular restrictions on values of c and η (see Phillips and Magdalinos, 2007a, 2007b).

$$v_t = [(1+r)v_{t-1}I\{v_{t-1} \leq \alpha\}u_t + [\delta + \pi^{-1}(1+r)\theta_t(v_{t-1} - (1+r)^{-1}\delta)]I\{v_{t-1} > \alpha\}]u_t \tag{4}$$

where $0 < \delta < (1+r)\alpha$, u_t is a positive *i.i.d* random variable with $E_t[u_t] = 1$, and $I\{\cdot\}$ is an indicator function that assumes a value of 1 when the condition in parentheses holds and zero otherwise. Note that θ_t is an *i.i.d* Bernoulli process where the probability of $\theta_t = 0$ is $(1-\pi)$ and $\theta_{t+1} = 1$ is π, where $0 < \pi \leq 1$. Given $v_{t-1} \leq \alpha$, then the bubble grows at a mean rate $1 + r$. At some point, when this threshold is breached (i.e., $v_{t-1} > \alpha$), the bubble grows at the quicker rate $(1+r)\pi^{-1}$, however with a probability $(1-\pi)$ that it will collapse to an expected mean level δ.

Of course, the categorisation of assets and trades into particular styles can lead to a further rationale for herding; hedge fund managers in particular, may herd because of reputational concerns (see Boyson, 2010). These can arise given the typical habit of comparing manager performance within a style to some benchmark measure, often related to the average performance of relevant managers. The manager then has a decision whether to (i) ignore benchmarking in portfolio decision-making (ii) attempt to closely track the benchmark or (iii) deviate from the benchmark. Relatively risk-averse managers are likely to attempt tracking, potentially leading to herding in assets thought likely to deliver the benchmark.

Finally, one may posit that the theoretical paradigms outlined above are not mutually exclusive but may act in concert. Consider at time *t*, risk-averse hedge fund manager *m* will jointly observe the trades of others, public information and asset prices whilst potentially holding reputational concerns. Furthermore, assume that the information set possessed by *m* is relatively uninformative and that investment horizons, as opposed to some financial institutions, are relatively short. Under such assumptions, any fad in (2), (3) and (4) and consequently the wedge between market and fundamental prices in (1), is likely to be relatively large in magnitude and volatility.

The theoretical paradigms so far tend to be evaluated in a quantitative context (i.e., statistically analysing relevant data on prices and trading positions), and the related empirical work on hedge funds is discussed in the next section. By contrast, an examination of the ‘sociality’ of herding (i.e., the specific communication mechanisms linking financial agents) has a richer body of work derived from qualitative and mixed-methods approaches. Given the theoretical implications are typically an outworking of the data analysis in these latter methodologies, both their theory and empirical frameworks are presented together in sections 4 and 5.

3. Quantitative Approaches

Within the mainstream finance literature, there have been numerous empirical investigations into the presence of herding in various market participants such as institutional investors (Sias, 2004), mutual funds (Jiao and Ye, 2014) or pension funds (Lakonishok, Shleifer, and Vishny, 1992); however, perhaps less emphasis has been placed on hedge funds. A good starting point is Boyson (2010) who analyses Credit Suisse/Tremont data on 2345 funds, over the period January 1994 to December 2004. Amongst other information, the data contains the name of the hedge fund manager and therefore allows an assessment of whether reputational concerns influence managers’ propensity to herd. The proxies used to measure herding are estimated within a manager’s peer group, which Boyson (2010) identifies as those other funds within the same style. Following Chevalier and Ellison (1999) and Hong, Kubik, and Solomon (2000), the measures employed are:

- tracking error deviation;
- beta deviation;
- standard deviation difference.

Tracking error is the residual standard deviation from a time series asset pricing model of a single fund's returns. Therefore *tracking error deviation* is the absolute difference between a fund's tracking error and the average tracking error of all funds in the same style. Similarly, *beta deviation* represents the absolute difference between a fund's beta from a single index model and the average beta of funds in the same style. Lastly, the *standard deviation difference* is defined as the absolute difference between a fund's return standard deviation and the average standard deviation of the style.

Employing a time-varying proportional hazards model, Boyson (2010) shows that interaction variable comprising of herding, as proxied by the measures above and manager tenure, is a positive and significant determinant of fund failure. This implies that older managers who deviate from the herd are more likely to oversee the liquidation of the fund. Having established the importance of herding in hedge funds outcomes, the question becomes do hedge funds herd more as a manager's tenure increases? Subsequently, a fixed effects panel model is employed to regress the herding measures on a number of potentially explanatory variables including tenure. Strikingly, for a majority of measures, tenure is shown to be significant and negative determinant. In other words, as managers get more senior, they herd more.

As Boyson (2010) emphasises, the findings related to hedge funds, manager tenure and herding are in direct contrast to those found for some other investment vehicles such as mutual funds. Chevalier and Ellison (1999) for example, show that mutual fund managers herd less the more experienced they become, because younger managers are more likely to be dismissed for a given level of poor performance. The herding incentives for hedge fund managers are reversed given fund termination (and hence manager termination) occurs when older managers ignore local benchmarks when trading.

A novel approach is adopted by Jiao and Ye (2014) who assess not only whether hedge funds herd but whether this herding encourages mutual funds to follow likewise? As context, they note that several mutual funds have 'copied' hedge funds by setting up in-house funds which adopt analogous investment styles to the latter. The data on hedge funds is obtained from Thomson Financial's CDA/Spectrum 13F database[13], is sampled over the period 2000:Q1 to 2007:Q2, and comprises of 401 fund holding companies which Jiao and Ye suggest correspond to at least 1000 individual funds. Their primary measure of herding is taken from Lakonishok, Shleifer and Vishny (1992)[14] and is the following:

$$H_{it} = |f_{it} - E[f_{it}]| - E|f_{it} - E[f_{it}]| \tag{5}$$

where H_{it} represents herding within a particular investor grouping, f_{it} corresponds to the proportion of funds purchasing equity i at time t, E is an expectations operator and $E[F_{it}]$ is proxied by the average proportion of purchases across all equities at time t, and finally, $E|f_{it} - E[f_{it}]|$ is a correction term to allow for random variation. In other words, (5) reflects whether an investor grouping are trading the same stock, and in a similar direction, more than would be expected under the null hypothesis of independent and random trading. Building on this work, Wermers (1999) constructs a further two conditional measures of herding that

[13] Quarterly 13F filings are required for all institutional investors who have AUM of greater than $100 million and US equity holdings of either $200,000 or 10,000 shares. As Jiao and Ye (2014) note, this means the hedge funds in their sample are likely to be those that attribute a significant weight to their equity strategies.
[14] This herding measure is also employed in work such as Grinblatt, Titman and Wermers (1995). Amongst others, Wylie (2005) and Frey, Herbst and Walter (2012) outline some of the issues with such measures. The latter paper provides an alternative, non-directional measure of herding.

reflect the tendency of funds to herd when buying or selling stocks. These measures are labelled BH_{it} and SH_{it} respectively:

$$BH_{it} = H_{it} | f_{it} > E[f_{it}] \tag{6}$$

$$SH_{it} = H_{it} | f_{it} < E[f_{it}] \tag{7}$$

Finally, Brown, Wei and Wermers (2014) provide an adjusted measure of herding ($adjH_{it}$) which for a buy herding stock is defined as:

$$BH_{it} - \min(BH_{it}) \tag{8}$$

and for a sell herding stock is:

$$-[SH_{it} - \min(SH_{it})] \tag{9}$$

where $\min(BH_{it})$ and $\min(SH_{it})$ represent the minimum value of BH_{it} and SH_{it} in time period *t*. Therefore measures (8) and (9) capture how heavily a stock is bought or sold by herding funds.

Using the data and measures above, Jiao and Ye (2014) find a number of interesting results. Firstly, they note that although measures (5), (6) and (7) show that *on average* hedge funds herd less than mutual funds, examining the whole distribution reveals that hedge funds tend to herd heavily but in a smaller number of stocks. Moving on, to test whether mutual funds herd by following hedge fund herding, they run the following regression:

$$adjH_{M,it} = \mu + \gamma_1 adjH_{H,it-1} + \gamma_2 adjH_{H,it-2} + \theta X_{it} + u_{it} \tag{10}$$

where subscript *M* denotes mutual funds and *H*, hedge funds, whilst X_{it} is a group of relevant control variables. Perhaps the key result of the paper is that $\hat{\gamma}_1$ and $\hat{\gamma}_2$ are positive and statistically significant, indicating that in a herding context, mutual funds follow hedge funds.[15]

What is the market wide effect of mutual funds following hedge funds? To investigate the possible price impact, Jiao and Ye (2014) estimate the regression[16] below:

$$R_{it+k} = \mu + \gamma_1 D^C adjH_{M,it} + \gamma_2 D^{NC} adjH_{M,it} + \theta X_{it} + u_{it} \qquad (11)$$

where R_{it+k} is the characteristic-adjusted stock return for firm *i* (see Daniel *et al.*, 1997) at time $t + k$, D^C is a dummy variable equal to unity when stock *i* is in the group of stocks held by mutual funds closely following hedge funds and 0 otherwise, and D^{NC} is an analogous dummy variable but for when stock *i* is not in the group held by follower mutual funds. In particular, results show that $\hat{\gamma}_1$ is positive and significant when $k = 0$ but becomes significantly negative when $k = 1$. In other words, mutual funds' following of hedge funds provides an initial mispricing of stocks which leads to a later price reversal and therefore additional volatility.[17] It would appear as if the market wide implications of hedge fund herding are considerably amplified via the lagged actions of larger mutual funds.

Why do mutual funds follow hedge funds? A potential rationale, Jiao and Ye (2014) suggest, is that mutual fund managers do so for reputational reasons. To test this, they develop a so-called 'intensity measure' to capture how much a mutual fund adjusts their equity holdings conditional on last period's herding by hedge funds. Specifically, the new measure I_{jt} for each mutual fund *j* is:

$$I_{jt} = \sum_{i=1}^{k} (w_{j,it} - \widehat{w}_{j,it-1})\, adjH_{H,it-1} \qquad (12)$$

[15] Note that conversely, there is no evidence that hedge funds follow mutual fund herding.
[16] Similarly regressions have been estimated by Brown, Wei and Wermers (2014) and Gompers and Metrick (2001).
[17] Jiao and Ye (2014) also examine whether such behaviour, rather than being explained by mutual funds following hedge funds, is due to (i) mutual funds continually herding or by (ii) hedge and mutual funds herding on common information signals. Both hypotheses are rejected.

where $w_{j,it}$ is fund j's portfolio weight on stock i, $\widehat{w}_{j,it-1}$ is an adjustment factor to control for passive weight changes and therefore I_{jt} is a quasi-covariance measure between last period's herding of hedge funds and this period's active changes in portfolio weights by fund j. Following work such as Chevalier and Ellison (1999) and associating reputation with performance, Jiao and Ye (2014) then regress measures of performance[18] on I_{jt} and a number of control variables. Strikingly, performance/reputation is shown to be a positive and significant determinant of mutual funds following of hedge fund herding. This implies that mutual funds (and their managers) with a high reputation, follow hedge funds to safeguard their reputation.

A related study to Jiao and Ye (2014) is Sias, Turtle, and Zykaj (2016). Similarly, this latter work uses quarterly 13F filings over the period 1998 to 2011, with the final sample containing the U.S. equity long-only position of over a thousand hedge funds. Methodologically, four pair-wise measures are applied to assess portfolio overlap (i.e., the number of securities held in common by both funds, the Bray and Curtis (1957) independence measure, and two cosine similarity measures) and results suggest that hedge funds have relatively independent portfolios.[19] Moreover, hedge fund demand shocks are shown to be positively correlated with lagged equity returns, potentially suggesting that hedge funds possess superior information about mispricing upon which they trade.

[18] Specifically, they use the estimated alpha from a 4-factor model again following work such as Chevalier and Ellison (1999) and Brown, Wei and Wermers (2014). Assuming reputation is a longer-term concept, the alpha is calculated over the past 60 months.

[19] Interestingly, although Sias *et al.* (2016) show that these crowds have grown over the sample period, this is due to an increased number of funds as opposed to more similar trading behaviour.

Other recent quantitative work on the propensity of hedge funds to herd assesses evidence from futures markets. Specifically, Boyd, Buyuksahin, Haigh and Harris (2016) employ data from the U.S. Commodity Futures Trading Commission (CFTC) over the period 2004 to 2009, which provides information on those considered large traders in thirty markets. Using the Lakonishok, Shleifer and Vishny (1992) measure of herding discussed earlier, Boyd *et al*. (2016) show evidence of substantial herding amongst managed money (i.e., hedge fund) traders but suggest that such behaviour does not notably "destabilize" futures market prices. Interestingly, they further suggest that the levels of herding observed are rooted in (i) analogous trading strategies (ii) analogous benchmarks and (iii) information deficiencies. In support of this latter rationale, it is shown that herding is higher in open-outcry markets relative to electronic alternatives, coupled with the assumption that as electronic venues contain higher numbers of traders and volumes, they present higher information content.[20]

Finally, recent work by Caglayan, Celiker and Sonaer (2019) examines whether hedge fund herding occurs specifically at an industry level?[21] To do so, again institutional holdings come from Thomson-Reuters 13F filings and these are matched with hedge funds names from Lipper TASS. Employing the Lakonishok, Shleifer and Vishny (1992) and Sias (2004) measures of herding, Caglayan *et al*. (2019) show that hedge funds herd less than other institutions over the period 1994 to 2013. However, when considerable hedge fund herding in a specific industry does occur, this industry typically undergoes a return reversal in the long-run. It is suggested this occurs because (i) other institutions (in a similar manner to Jiao and Ye, 2014) follow hedge fund herding, particularly on the sell-side and (ii) these institutions

[20] Although note that Snaith *et al*. (2018) show that open outcry futures markets can be relatively more efficient (compared to electronic markets) when volatility is high and/or time to maturity is low.

[21] Work such as Choi and Sias (2009) and Celiker, Chowdhury and Sonaer (2015) show institutional/mutual fund herding in industries but demonstrate that such herding does not significantly affect industry returns.

are subsequently slow to react to positive industry news implying the reversal is itself is delayed.

In summary then, the extant literature employing a quantitative empirical approach finds that hedge funds herd, although perhaps less than other institutions, and that they do so due to common trading strategies, benchmarking and reputational reasons, particularly as hedge fund managers become more senior. Although hedge funds herding may not influence prices directly, this herding actually has market wide effects on prices and volatility via an ‘amplification’ channel whereby larger mutual funds follow hedge fund herding. Of course, as Kellard *et al*. (2017) note, whilst such quantitative approaches can assess whether herding occurs, they have limited ability to uncover the mechanism behind herding. In particular, a qualitative approach is more likely to be able to identify the existence and form of social connections, organisational practices and communication between market participants which may lead to similar trades. It is this area of research we turn to next.

4. Qualitative Approaches

As noted earlier, there have been some attempts to uncover not just *if* but *how* herding occurs in financial markets? Within an operational context, it is plausible that similar trading strategies emerge from the use of the same or similar quantitative models or underlying software. For example, Zaloom (2003) conducted fieldwork[22] at both an open outcry trading pit at Chicago Board of Trade (CBOT) and an electronic trading room[23] in a London futures dealing firm. In particular, the aim was to assess whether new technology had significant

[22] Interestingly, this fieldwork was carried out whilst the author was employed by each organisation.
[23] Callon and Muniesa (2005) stress that whilst trading rooms and trading screens can be analysed as calculative spaces, the calculative form of each will be different.

implications for "forms of sociality and knowledge" (p. 259). One finding noted that screen-based technologies in the trading room reduced the range of information available, particularly the bodily cues that derive from observing others in pit trading.[24] It could be argued, *ceteris paribus,* a smaller information set will increase the propensity of similar trades and herding.

To further develop the above ideas, Beunza and Stark (2012) examine the quantitative models that traders employ in derivative trading rooms. Specifically, they undertook a three-year ethnographic study at a merger arbitrage desk of an investment bank, showing that arbitrageurs use models to compare their estimates of important variables to those of their competitors. Beunza and Stark term this "reflexive modelling" and suggest that while providing individual funds with access to the pricing insights of others, such practices inculcates a "cognitive interdependence" which can magnify trading errors.

Moving into a specific a hedge fund context, MacKenzie (2003) examines the case of Long-Term Capital Management (LTCM) and the related financial crisis in 1998. As is well known, the proximate cause of the crisis was a Russian default on Rouble-denominated bonds, leading to a 'flight-to-quality' and sharp falls in several asset prices. LTCM was highly leveraged, price movements bringing it close to bankruptcy before being recapitalized by a consortium overseen by the Federal Reserve Bank of New York. Mackenzie (2003) posits that the prior success[25] of LTCM led to extensive copying or 'imitation' of their trading positions. Several market participants were holding correlated positions and this

[24] Snaith *et al*. (2018) note that such bodily 'cues' might actually aid efficiency when markets are relatively volatile and provide some necessary transparency in benchmark pricing.

[25] LTCM was well-known from its inception given it was led by John Meriwether, a renowned bond trader and Nobel Laureates, Merton and Scholes were partners. Adding to this fame, before 1998, the fund was exceptionally successful. For example, in 1996 as Perold (1999) shows, LTCM's gross returns were 61.5%. After fees, they were 40.8%.

resulted in a *superportfolio* whereby systemic risk increased given a higher probability that market movements would be amplified. Therefore, in addition to the proximate cause of the crisis, the falls in asset prices begun by the Russian default were magnified by the existence of the superportfolio, worsening the trading position of LTCM and other similarly positioned funds.

To assess the hypothesis of imitation, Mackenzie (2003) adopted a primarily interview-based approach. Specifically, a number of market participants were interviewed both (i) partners and employees of LTCM and (ii) other market actors from outside LTCM but who traded in the same markets. These interviews revealed that investment banks and other hedge funds were under pressure to run, and subsequently adopted, analogous arbitrage strategies to LTCM. How did other funds learn about LTCM's positions? Here Mackenzie (2003) provides an interesting quote from a hedge fund manager external to LTCM:

"…the arbitrage community…are quite a bright lot, so if they see a trade happening – and the market gets to find out about these trades, even if you're as secretive as Long-term Capital Management – they'll analyse them and realise there's an opportunity for themselves" (p.360).

This method of analysis was greatly aided by the relatively small size of the arbitrage community and consequently, competing funds or banks would often be counterparty to an LTCM trade. Another interviewee noted that this process led to many of LTCM's strategies becoming "consensus trades." What happened next illustrates the stark dangers inherent in herding amongst hedge funds, as Mackenzie (2003) notes:

"As arbitrageurs began to incur losses, they almost all seem to have reacted by seeking to reduce their positions, and in doing so they intensified the price pressure that had caused them to make the reductions" (p.363).

This intensification of price pressure, further reinforced by the internet leaking of a private memo to LTCM investors, threatened LTCM with bankruptcy and as noted above, a rescue package was assembled. As rationale for coordinating the recapitalization, William McDonough (President, Federal Reserve Bank of New York) noted in his statement to the Committee of Banking and Financial Services (1998):

"By Friday, September 18, with the efforts to raise new capital still unsuccessful--and with an increasing number of people now aware of Long-Term's plight because of the efforts to bring in new investors - events seemed to come to a head. With market conditions particularly unsettled that day, I made a series of calls to senior Wall Street officials to discuss overall market conditions. Let me take a moment to put those calls in context. One important objective of the Federal Reserve is to ensure financial stability. Particularly in times of stress, it is essential that the Federal Reserve continue to take the pulse of the market. One way to do that is through candid and open communication with key market participants. Everyone I spoke to that day volunteered concern about the serious effect the deteriorating situation of Long-Term could have on world markets."

Amongst other things, Mackenzie (2003) concludes that: (i) the process of trading and investment is embedded in networks of social ties, as others have suggested for other economic activity (Baker, 1984; Granovetter, 1985; Uzzi, 1996, 1999) (ii) within the scope of sociality is imitation and, under certain conditions, this can be perilous for markets and consequently, the real economy and (iii) conflation of the *financial* and *social* can be broadly conceptualised by appealing to the existence of a ‘global microstructure’ (see Knorr Cetina and Bruegger, 2002), whereby although markets (enabled by modern technology) have a global framing but inherent within them are connections that are locally social.

These socio-technical explanations of herding wherein hedge funds observe others behaviour and analytically deduce their trades is clearly part of the story of hedge fund herding. However, are there other forms of sociality exhibited and if so, what underpins and maintains these connections? One line of research by Choi (2011) suggests that senior hedge fund managers commonly provide support and advice to new managers when they begin their own fund. The mentoring ‘lineage’ configuration enables strong connections among ‘generations’ of hedge fund managers, enabling the proliferation of analogous trading ideas.

5. A Mixed-Methods Approach

In an attempt to deepen the understanding about the types of communication used by hedge funds, Kellard *et al*. (2017) [hereafter KMSE] adopt a mixed-methods approach. Ex-ante they provide several theoretical props for likely existence of *direct and potentially frequent* communication between competing hedge funds and their managers. At first this may appear surprising – why would competitors communicate in this manner? However, in a non-hedge fund context, both theoretical (see Stein, 2008) and empirical (see Ingram and Roberts, 2000) support is provided for competitor communication.

Let’s take Stein’s model as a starting point. Note here that the central proposition relates to whether the expected (financial) payoff of communication between two firms is greater than the payoff derived from any prior competitive advantage. Given a positive expected value for both firms, communication will occur. KMSE extend this argument to non-financial remuneration, arguing that for hedge funds, external legitimization of a particular trading action or confirmation of the 'correctness' of analysis, are significant drivers for communication. In doing so they draw on work such as (i) Hong *et al*. (2000), who propose that inexperienced analysts seek to legitimize their work to co-workers and supervisors by providing price forecasts close to the mean forecast of all analysts and (ii) Boyson (2010), who as we noted earlier, shows the increased likelihood of senior hedge fund managers herding and thus KMSE posit that mechanistically this occurs via competitors using a pool of trusted connections to confirm that a potential trade is suitable.

It might also be added that the relatively small employee size of hedge funds, certainly compared to investment banks, makes the occurrence of communication with those external to the fund more likely. As theorised by KMSE, this implication of scale is compounded given hedge funds face what they term a "hyper-decision making environment" (p.87). Specifically, hedge fund managers encounter a global and computerized financial market that contains thousands of assets. Strategies around trading these assets can be configured in innumerable positions, particularly given hedge funds ability to sell short, leverage and employ derivatives and structured products. Moreover, unlike an industrial process, whereby firms decide to purchase or sell a particular good and then deliver on this promise at some agreed and static point in the future, hedge fund trading is dynamic in the sense that they face further decisions at least daily about whether to maintain a trade, change its size or exit. This high potential frequency of trading generates the requirement for more frequent information, analysis, legitimisation and confirmation.

KMSE's fieldwork and interviews took place over a period that included the events of the GFC (i.e., from December 2007 to June 2009). The research primarily focuses on hedge funds involved in long-short or event-driven strategies.[26] These are two of the most popular 'styles', employ techniques representative of hedge funds (i.e., short-selling, leverage and derivatives use) and commonly involve positions held for reasonable time periods (e.g., several weeks) and therefore are more likely to encourage communication between hedge fund managers. Interviews[27] following a semi-structured approach were conducted with 36 hedge fund professionals and 24 brokers[28], adopting a purposive and snowball method of sampling. This resulted in a sample that covered funds with approximately 15 percent of hedge fund AUM worldwide. Questions were designed, amongst other things, to assess communication with contacts external to the firm, obtain biographical information and understand the process by which investment decisions were taken.

The interviews with hedge fund managers were revealing in terms of communication practice with managers in other funds. For example, one respondent commented:

"You try to share information and ideas. It is reciprocity, actually. You will not keep those people as friends if you don't have something else to offer" (p. 92).

And another:

[26] A long-short trade involves a long position in one asset, funded by selling another asset short. Event-driven trades are based around the expected future announcement and occurrence of mergers, acquisitions or other events with pricing implications.
[27] Interviews took place with market actors in London, New York, Hong Kong, Geneva and Madrid.
[28] Brokers execute trades for hedge funds, provide some initial market research and market context known as 'flow information', and occasionally organise additional capital. Aside from direct hedge-fund to hedge-fund connections, brokers may indirectly inform hedge funds as to the possible activities of other funds.

"I trust their opinion about stocks. I have had recently a situation where we were short one stock and the guy at [name of a competing hedge fund] was long. So we met up inside our offices with him to discuss why we had different opinions about the stock. He is very smart, so I wanted to pick his brains and share my views to see who was missing what" (p. 92).

These two quotes capture much of the essence of hedge fund communication identified by KMSE – in particular, reciprocity and the desire for relationship longevity with 'smart' investors. To further assess these connections and their strength, KMSE constructed a network encompassing all the documented relationships between hedge fund managers and brokers and this is reproduced in Figure 2.

[Insert Figure 2 about here]

Coupled with the interview-based evidence, the network demonstrates that communication in the hedge fund ecosystem relies on a two-tiered structure of connections where (i) brokers have multiple links to hedge fund managers whilst (ii) by contrast, the managers themselves preserve closer-knit connections with only a few trusted peers. Importantly, KMSE subsequently demonstrate that these dense connections between managers are underpinned by previously working together, common language, smartness and mentoring. For example, focusing on a single triad of managers (labelled H6, H9 and H16), reproduced in Figure 3, they note that whilst these actors now work in different hedge funds, they used to be employed at the same firm and still often converse about professional issues and socialise together.

[Insert Figure 3 about here]

During fieldwork, KMSE observed this triad discussing investment ideas and even though they had known each other for eight years or more, H6 and H16 still mentored H9. This reinforces Choi (2011) proposition that a mentoring 'lineage' configuration exists in the hedge fund industry.

What are the consequences of the type of communication structures described above? KMSE provide both interview and case study evidence that herding will arise. One interviewed manager noted:

"It is a small village. What is interesting is at the end of the day, we all come from a similar background, we probably studied very similar things and often have worked together doing valuations or what have you together, using the same models. You probably have a big chance that you are going to look at similar things in a similar way, so you come to the same conclusion in a similar timeframe" (p. 96).

whilst a prime broker commented:

"Yes, there are many people that have similar kind of trades. There is a certain universe of consensus trades, everyone has those trades... Because if one hedge fund manager knows that something is cheap he is likely to let another hedge fund manager know it is cheap. People share information, especially among hedge funds" (p. 96).

However, such herding can have dangerous implications for financial stability given potential effects on market prices and risk. For instance, KMSE observed several hedge funds in 2008 who were involved in a long-short trade involving Porsche (the long leg) and Volkswagen (the short leg). In late 2008, it became apparent that there was not enough Volkswagen equity available to cover all the short positions held by hedge funds. In the resulting scramble for shares, the price of Volkswagen stock jumped six-fold over a matter of days and some hedge funds even closed. To add to the cautionary tale, ironically, it emerged that hedge funds had ignored early warnings from broker analysts about potential stock shortages.

6. Discussion and Conclusions

There is certainly empirical evidence that hedge funds herd and that this herding matters in the sense of triggering wider market implications. Using measures such as tracking error deviation, beta deviation and standard deviation difference, quantitative approaches have found herding amongst funds in the same style or investor grouping and this behaviour of hedge funds itself acts a common signal for mutual funds to herd, amplifying mispricing effects including volatility. This evidence is reinforced by qualitative work; interview data revealing hedge fund managers knowingly hold consensus trades.

Why do hedge funds herd? *A priori*, one might assume that such funds, with an image as exceptionally skilled investors, would have less incentive to act collectively. Of course, there are several theoretical explanations for herding in financial markets generally. Amongst several plausible rationales, earlier work suggested information cascades, cross-sectionally correlated information sets amongst investors, positive feedback trading, and fads or characteristic trading.[29] However, in terms of hedge funds, some recent work has highlighted herding for reputational reasons, particularly as managers become senior.

Work in the social studies of finance literature has arguably provided a richer explanation of hedge fund trading and herding. Mackenzie (2003) argues that trading of hedge funds is rooted in a 'Granovetterian sociology of market embedding' and KMSE provide further

[29] In a more contemporary sense, one might legitimately ask whether the growth of factor analysis and investing amongst hedge funds and others will lead to factor-based herding?

theoretical and empirical evidence for this notion. They construct an argument whereby the 'hyper-decision making environment' facing funds, coupled with a relatively small average firm size and specialised analysis required for trading decisions, leads to managers forming small clusters of perceived quality[30] actors. Such reasoning corresponds to Podolny (2001), who conceptualises network linkages as *pipes* which transmit information and resources, and *prisms,* in which separate network nodes gauge each other's quality; and it's the cooperation between these tightly-knit nodes that KMSE show generates similar positions or what they term 'expertise-based' herding.

This expertise-based herding can be conceptualised as nesting, combining and augmenting other forms. For example, expertise-based herding in the hedge fund industry involves what one might call quasi-information cascades, as managers observes others actions via information from brokers or direct communication. Additionally, it involves a more developed type of 'investigative herding' where managers not only have similar information sets as they have access to the same public information but because tight-knit clusters of hedge funds share private information and work on analysis together. Finally, expertise-based hedging incorporates a type of reputational hedging, where those perceived as trusted and smart are more likely to form and maintain the cooperative clusters.

It was suggested in the earlier theory section that the theoretical paradigms described in the extant literature may not be mutually exclusive but may, in fact, act together in concert. Expertise-based herding encapsulates this togetherness notion. However, in this earlier section, it was also stated that under such conditions, the wedge between market and fundamental prices in (1) may become large and volatile. Expressed another way, the

[30] Quality in the sense of both trust and smartness.

cooperation demonstrated by expertise-based hedging can be dangerous. For example, whilst clearly important for generating the type of industry structure observed for hedge funds, the adaptive process of building up and maintaining quality relationships can generate new risks. KMSE suggest managers in close groupings can discuss, analyse and action a progressively narrow set of trading ideas, whilst increasingly disregarding those ideas originating from outside the trusted frame. This, they argue, explains hedge fund managers ignoring the advice of broker analysts in the Porsche-Volkswagen trade described above. In sociological terms, hedge fund communication practices can engender a type of over-embeddedness (Uzzi, 1996; Uzzi and Lancaster, 2003) and in financial terms, this leads to a new 'network' risk: the risk of underweighting germane market information that emanates externally to the cluster of densely connected managers.

The presence of 'network' risk has a number of implications for hedge funds and policy makers. For example, KMSE suggest that regulators could mandate firms to record and submit details on their social networks[31], permitting the generation of a map of industry vulnerabilities. When superimposed on trading and position data, this might allow a useful assessment of current and future network risk.[32] Additionally, at a firm or micro level, this novel type of social accounting might be able to alert individual hedge fund to latent over-embeddedness, allowing reflection on whether clustered relationships should be reconfigured.

[31] This could be considered similar to the requirement of firms to report on operational risk under Basel II and III.

[32] Given detection, KMSE posit that regulators might even be able to intervene in such networks.

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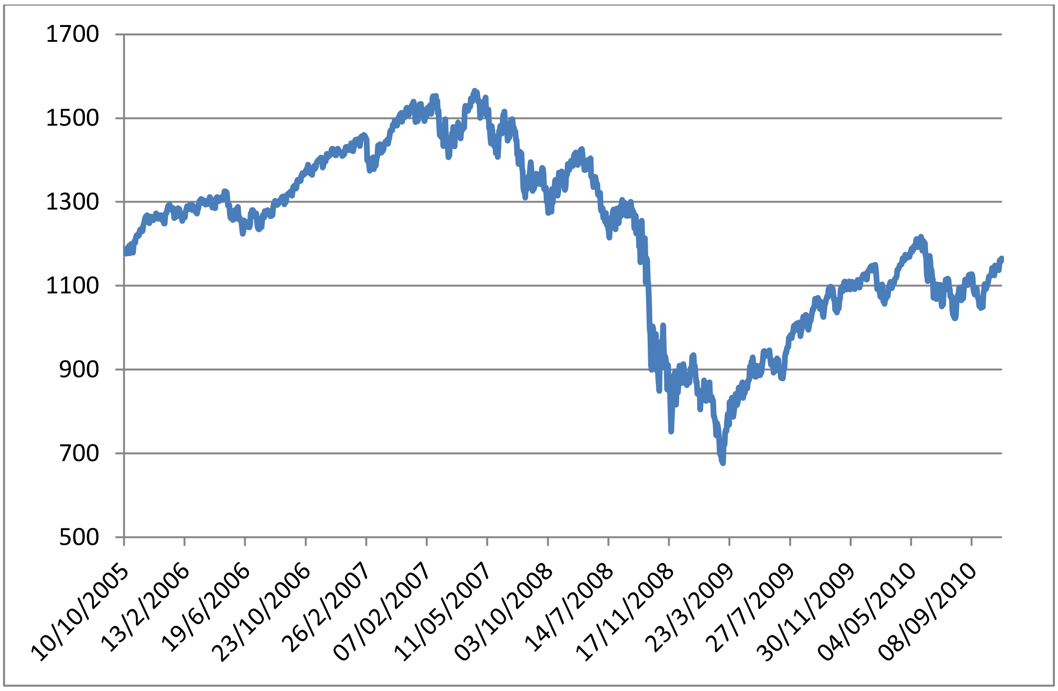
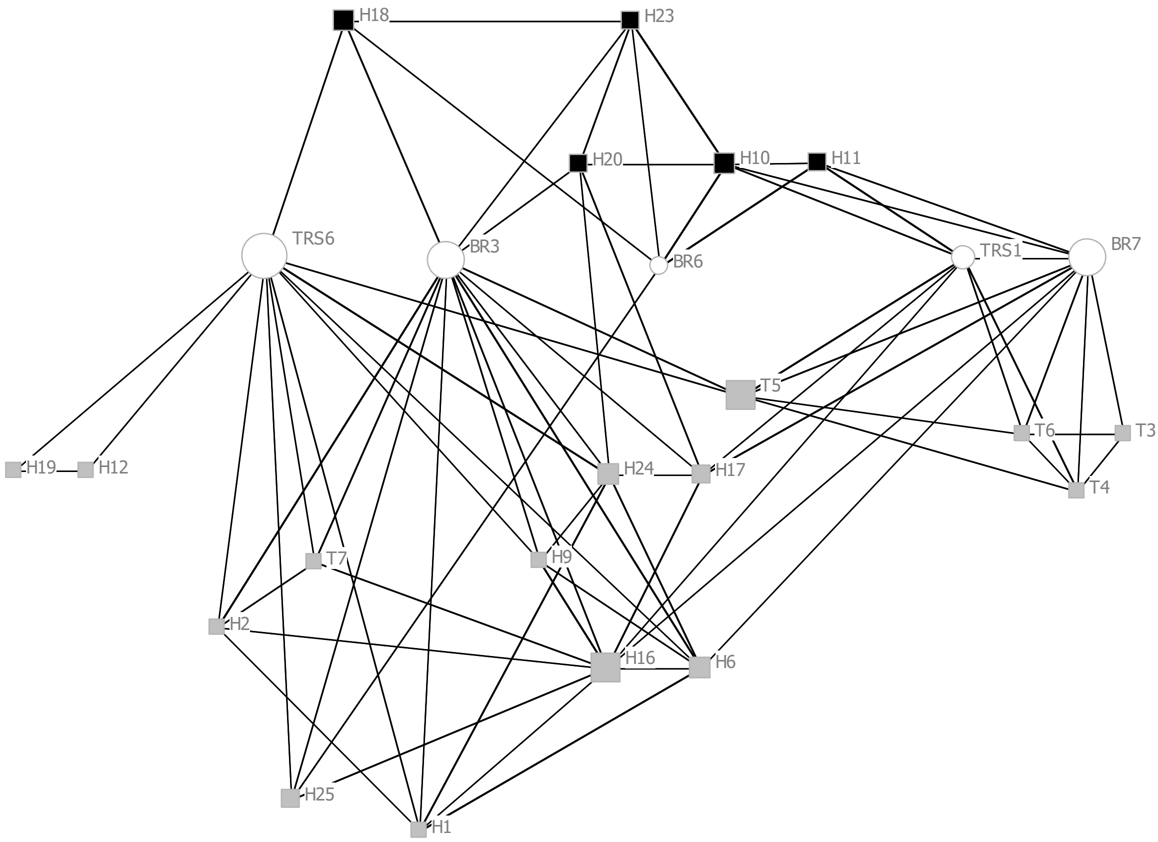
Figure 1: S&P500 index – October 2005 to October 2010



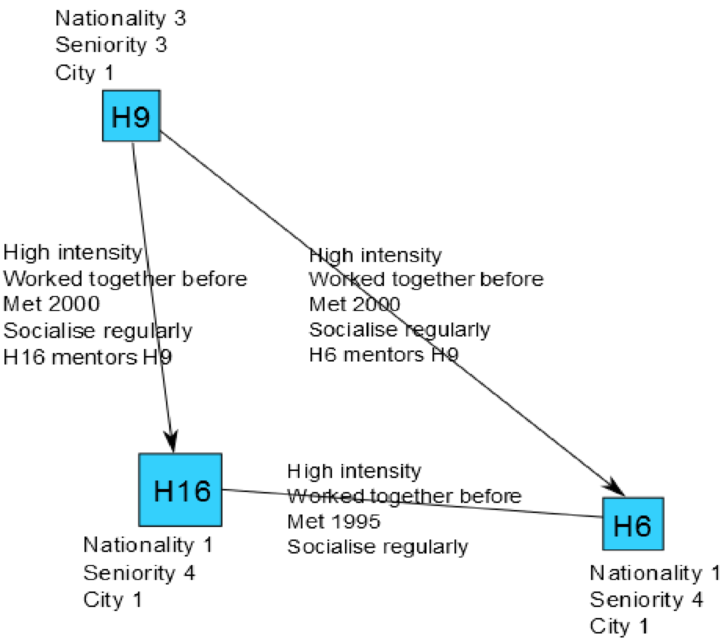
Source: DataStream

Figure 2: Network of hedge fund managers and brokers



Notes: Reproduced from Kellard *et al*. (2017: p.93). The node's shape represents its role (e.g., circles are brokers and squares are hedge fund managers). The node's colour represents its dominating strategy (e.g., grey is long-short and black is event driven). The node's size represents its betweeness centrality.

Figure 3: Mentoring triad



Notes: Reproduced from Kellard *et al*. (2017: p.95).