Fluctuations of Social Influence: Evidence from the Behaviour of Mutual Fund Managers during the Economic Crisis 2008/09[☆]

Frederik König

Faculty of Business Administration and Economics
Goethe-University
Frankfurt/Main
fkoenig@wiwi.uni-frankfurt.de

Abstract

In this paper, I analyse the reciprocal social influence on investment decisions within an international group of roughly 2000 mutual fund managers that invested in companies of the DAX30. Using a robust estimation procedure, I provide empirical evidence that in the average a fund manager puts 0.69% more portfolio weight on a particular stock, if other fund managers increase the corresponding position by 1%. The dynamics of this influence on portfolio weights suggest that fund managers adjust their behaviour according to the prevailing market situation and are more strongly influenced by others in times of an economic downturn. Analysing the working locations of the fund managers, I conclude that more than 90% of the magnitude of influence is due to pure observation. While this form of influence varies much in time, the magnitude of influence resulting from the exchange of opinion is more or less constant.

Keywords: Mutual Fund Managers, Social Interaction, Herding, Word-of-Mouth
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1. Introduction

As of September 30^{th} 2011, mutual funds worldwide had \$ 9,043 billion equity assets under management.[1] This corresponds to one third of the global investable equity opportunity set.[2] Hence, mutual fund managers' overall investment behaviour might have a considerable impact on the dynamics of stock prices, if they simultaneously make similar investment decisions, such that prices are driven into a specific direction. In this context, it is important to distinguish how parallel decisions arise. The group of fund managers is homogenous, such that it is likely that they independently make the same decisions. However, fund managers might also influence each other such that investment decisions are aligned.

There is large body in the financial literature that provides empirical evidence in favour of the latter explanation, i.e. social influence[3] among mutual fund managers. There are two strands separating how social influence takes place. Influence through observation is generally stated by the large body of the literature that deals with herding behaviour. In this context it is generally assumed that a fund manager is homogenously influenced by all other fund managers. A pioneer work of this herding literature has been presented by Lakonishok et al. (1992). With their empirical measure, which has been applied in many studies since then,[4] they provided weak empirical evidence for herding behaviour among US pension fund managers. For the German market, Oehler and Wendt (2009) find that fund managers show herding behaviour when they face market-wide cash inflows or cash outflows. Walter and Weber (2006) also detect herding behaviour among German fund managers. However, they show that a large portion of this behaviour is unintentional due to changes in benchmark index compositions. Hence, identified herding patterns are rather spurious caused by correlated signals. Regarding

[1] See statistics of the Investment Company Institute on www.ici.org/research/stats/worldwide/ww_09_11.

[2] As of November 30^{th} 2011, MSCI reports a market capitalisation of \$ 30,057 billion for the MSCI ACWI All Cap Index that covers approximately 98% of the global equity investment opportunity set. Index fact sheets are available on www.msci.com/resources/.

[3] Social influence refers to the situation where fund managers directly influence each other. This is opposed to indirect influence that for instance takes place via market price mechanisms.

[4] See Frey et al. (2006) for a brief survey of studies that used the measure of Lakonishok et al. (1992).

the impact on stock prices, they conclude that herding behaviour has neither a stabilising nor a destabilising effect. Pomorski (2009) deviates from the classical herding literature that assumes a homogeneous reciprocal influence of all participants in the market. He analyses how mutual fund managers with outstanding past performance influence other fund manager. It is provided evidence that influence on fund managers that performed poorly in the past is greater than on fund managers with moderate past performance.

The other strand of empirical literature that deals with the influence by the exchange of opinion, also known as word-of-mouth effect[5], among mutual funds managers is much sparser. First evidence has been provided by the survey data of Shiller and Pound (1989) indicating that the word-of-mouth effect among institutional investors plays a considerable role. The empirical survey of Arnswald (2001) also reveals the existence of the exchange of opinion among German mutual fund managers. A milestone is represented by the work of Hong et al. (2005) who provide empirical evidence that portfolios of fund manager in the same city are more similar than of those working in other cities. This still holds true after controlling for the city specific effect of local preferences, which means that fund manager in the same city all tend to put more weight on the same local companies. It is concluded that fund managers exchange their opinion within a city based network and adjust their investment decisions accordingly. Pareek (2011) relaxes the assumption of city based homogeneous networks by assuming that fund managers holding a large portion of a specific stock maintain an informational network link irrespective their working location. This assumption is justified by correlated trading behaviour that cannot be explained by style investing or geographic locations. The density of the underlying network is then related to stock price dynamics and it is provided empirical evidence that prices of stocks are less volatile if that are held by fund managers that maintain more network links to other fund managers.

With this paper, I contribute to both strands of literature by determining the whole magnitude of social influence among fund managers and dividing it into observational influence and influence from the exchange of opinion afterwards. Irrespective how the influence takes place, I allow it to be heterogeneous among fund managers. This means I do not assume that a single

[5] I use the term "exchange of opinion" in order to emphasise, that information is not only transmitted, but also discussed.

fund manager is equally influenced by all other fund managers. As a major contribution, I relate both, the absolute magnitude of influence as well as the number of fund managers by whom a single fund manager is influenced to the prevailing market environment.

My first hypothesis is that social influence among fund managers represents a substantial effect. The theoretical literature about the behaviour of mutual fund managers offers a wide range of explanations in favour of this hypothesis.[6] In his famous book "Irrational exuberance", Shiller states that fund managers' action are driven by human greed and fear (see Shiller (2000)). However, there exist several rational foundations. From the perspective of a single fund manager, other fund managers might have or at least be assumed to have a better set of information, which is revealed by the observation of their investment decisions (Welch, 1992; Ellison and Fudenberg, 1993, 1995; Avery and Zemsky, 1998; Bala and Goyal, 1998; Bikhchandani et al., 1998). Equivalently, other fund managers might be perceived to have a better ability to process available pieces of information, such that observing and copying their decisions is beneficial (Banerjee, 1992; Bikhchandani et al., 1992). Moreover, imitating fund managers with a high reputation has less severe consequences in the case of a failure (Scharfstein and Stein, 1990; Dasgupta and Prat, 2008). Furthermore, fund managers are remunerated according to their relative performance within a certain period of time which usually equals one year. If they already outperformed other fund managers in the first part of this period, they have an incentive to copy investment behaviour of other fund managers such that relative performance is fixed on the prevailing level (Maug and Naik, 1996). Eren and Ozsoylev (2006); Stein (2008); Gray (2010) among others give a rationale for the exchange of opinion among participants in financial markets. Although they are competitors, fund managers can profit by sharing their methods of information elaboration that are then reciprocally enriched by the opinion and views of the counterpart.

With my second hypothesis, I put the magnitude of fund managers' social influence as well as the number of fund managers by whom a single fund manager is influenced into a perspective. I state that they vary both over time according to the prevailing market environment and are lower (higher)

[6] See e.g. Bikhchandani and Sharma (2000); Hirshleifer and Teoh (2003) for a survey of theoretical and empirical research on herd behaviour on financial markets or **?** for a more recent survey about general social influence on financial markets.

during an economic upturn (downturn). The theoretical foundation for this hypothesis is as follows. In a bull market fund managers rather try to distinguish themselves from their competitors in order to "stand out of the crowd" and to get a higher remuneration (Zwiebel, 1995). In times of a bear market, fund managers fear the loss of reputation (Scharfstein and Stein, 1990) and compensation (Maug and Naik, 1996), such that they are more strongly influenced by other fund managers.

Looking at the different kinds of influence, my third hypothesis is that only the magnitude of observational influence varies as a function of the prevailing market situation, while the influence from the exchange of opinion stays constant. This can be justified by the fact that the number of social contacts does not alter with the state of the market. However, afore cited aspects of reputation and remuneration induce fund managers to align their decisions with a greater (smaller) number of other not personally known competitors during an economic downturn (upturn).

My dataset consists of portfolio holdings of roughly 2000 equity mutual funds that had invested at least \$ 10 million in companies of the DAX30 index as of December 31^{st} 2010. For these funds, I retrieved all available portfolio holdings in the period from 2002 to 2010. This time period offers the possibility to analyse different market environments, namely the economic upturn until from 2002 to 2006 as well as the financial and economic crisis starting in 2007. Unlike almost all empirical studies in this domain before, my dataset contains international investors such that the analysis of influence is not limited to country borders. This is an important aspect, because today's media make global influence possible. A further advantage of considering funds that invest into companies of the DAX30 is that I obtained a quite homogenous group of fund managers whose behaviour can be related to price dynamics of the main stock index of Germany which is one of the most important economies in the world.

For the empirical strategy, I borrow from the literature of social interaction (see e.g. Manski (1993); Brock and Durlauf (2001); Moffitt (2001); Bramoullé et al. (2009); Blume et al. (2010); Lee et al. (2010)). The dependent variable is given by the portfolio weight a fund manager assigns to a particular stock at a particular point of time. The choice is motivated by the fact that the portfolio composition represents the entirety of a fund manager's current believes. Unlike quite all empirical studies before, trades of fund managers are not considered. The reason is given by the fact, that they would have to be inferred by portfolio changes. However, portfolio holdings in the dataset

are only available on a quarterly or semi-annually basis and Elton et al. (2010) showed that this introduces a great sample bias, because round trip trades cannot be captured and the point of time, when the trade actually took place also remains uncertain. A further and even more important argument in favour of portfolio weights is their relative nature. They always sum up to 100% and thus are not affected by the prevailing market environment that could for instance lead to market wide cash in or outflows of equity assets. This is a crucial aspect for the verification of my second hypothesis. I determine the underlying network of influence among fund managers endogenously. Therefore, every possible link between two fund managers is examined. One drawback of the herding measure proposed by Lakonishok et al. (1992) is that one cannot directly distinguish between true and spurious influence. I intend to overcome this by controlling for several factors that are decisive for portfolio selection. These control variables comprise the average historic return, the volatility, as well as the analysts' consensus price target, earnings forecast and price earnings ratio of every particular stock a fund manager holds in his portfolio. I furthermore account for the index weight of a single stock, if it is included in one of the major global indexes. Finally, I also control for the working location of a fund manager and the headquarters of the company that has emitted the particular stock. The database of portfolio holdings has been enriched by all these control variables and results to be unique for the quantity of portfolio weights amounting to 6 million, which have been matched with stock specific data of about 17,000 companies. After having determined the underlying influential network, the overall average magnitude of influence can be estimated. Thereafter, I separate the observational influence and the influence from the exchange of opinion by the working locations of the fund managers. Using the empirical evidence provided by Hong et al. (2005), an intra-city link between two fund managers is defined as influence trough the exchange of opinion while all inter-city links are considered to be observational influence.
In the average, a fund manager puts 0.69% more portfolio weight on a particular stock, if other fund managers increase the corresponding position by 1%. This magnitude of social influence reaches its maximum during the economic crisis 2008/09, which suggests that fund managers are more strongly influenced by others in times of an economic downturn. More than 90% of the magnitude of influence is due to pure observation. While the magnitude of this observational influence varies much in time, the magnitude of influence resulting from the exchange of opinion stays more or less constant.

The remainder of the paper is organised as follows. In chapter 2, I present the empirical model and introduce a robust estimation procedure. Chapter 3 serves to present the dataset used for the empirical analysis in chapter 4. Chapter 6 concludes.

2. Methology

For the empirical analysis, I make use of the standard linear model to identify social interactions based on network structures (e.g. Bramoullé et al. (2009); Lee et al. (2010)):[7]

$$w_{ict} = \delta_t \sum_{j \neq i} \gamma_{ijt} w_{jct} + \mathbf{x}_{ict} \beta_{\mathbf{t}} + \epsilon_{ict}, \tag{1}$$

where w_{ict} is the portfolio weight fund manager i puts on the stock of company c at time t. The row vector $\mathbf{x}_{ict}$ contains exogenous control variables that are decisive for the portfolio decision. The coefficient δ_t captures the magnitude of average contemporaneous influence that fund managers have on each other. The influence of a single fund manager j on fund manager i is weighted by $\gamma_{ijt} \geq 0$.[8] The weighting coefficients are normalised, such that

$$\sum_{j \neq i} \gamma_{ijt} = \begin{cases} 1 & \text{if fund manager i is influenced by at least one other fund manager} \\ 0 & \text{otherwise} \end{cases} . \tag{2}$$

This ensures, that δ_t captures the total magnitude of social influence. As it is usual in the social interaction literature, I consider strategic complementarities, i.e. $\delta_t \geq 0$. This is the only assumption imposed on the coefficients of the model and can be justified as follows. Consider two fund managers, where one acts as a net buyer while the other is a net seller. Their portfolio weights are thus negatively related, which could be expressed by a negative value of δ_t. This relationship, however, does not represent a form of social

[7] Contrary to the social interaction literature, I do not consider contextual effects, i.e. the influence of an individual's characteristics on the outcome of an other individual, as it is unlikely that a mutual fund manager's decisions are influenced by the background of another fund manager.

[8] More general than in the social interaction literature, I do not assume that a fund manager is equally influenced by other fund managers. This means, the values of γ_{ijt} do not have to be equal for fixed i and t.

influence the fund managers have on each other.
Regarding the error term of the model, I assume that ϵ_{ict} is heteroskedastic, which might come up by the exogenous variables $\mathbf{x}_{ict}$ but is also due to the boundedness of the dependent variable w_{ict} between zero and one. Moreover, I assume that the values of ϵ_{ict} are correlated for fixed i and t, because by definition portfolio weights of one fund manager at one point of time have to sum up to one. However, unlike in other social interaction settings (e.g. Lee et al. (2010)), I do not assume that ϵ_{ict} is correlated in between different fund managers, i.e. for varying i. This is justified by the fact, that the group of analysed fund managers can be considered to be homogeneous enough, such that the bias induced by individual (unobserved) characteristics can be neglected.
For notational convenience, equation 1 can be rewritten in a matrix form

$$\mathbf{w}_t = \delta_t \mathbf{\Gamma_t} \mathbf{w}_t + \mathbf{X}_t \beta_\mathbf{t} + \epsilon_t. \tag{3}$$

If $\mathbf{\Gamma_t}$ is known, then identification of the coefficients δ_t and $\beta_\mathbf{t}$ is possible. However, they cannot be consistently estimated by OLS, because from the reduced form of equation 3

$$\mathbf{w}_t = \left(\mathbf{I} - \delta_t \mathbf{\Gamma_t}\right)^{-1} \left(\mathbf{X}_t \beta_\mathbf{t} + \epsilon_t\right). \tag{4}$$

it follows that

$$\mathrm{E}(\mathbf{\Gamma_t} \mathbf{w}_t, \epsilon_t) = \mathrm{E}(\mathbf{\Gamma_t} \left(\mathbf{I} - \delta_t \mathbf{\Gamma_t}\right)^{-1} \left(\mathbf{X}_t \beta_\mathbf{t} + \epsilon_t\right), \epsilon_t) = \sigma^2_{\epsilon_t} \, tr(\mathbf{\Gamma_t}((\mathbf{I} - \delta_t \mathbf{\Gamma_t})). \tag{5}$$

Hence, the regressor $\mathbf{\Gamma_t} \mathbf{w}_t$ is correlated with the error term. The problem can be illustrated as follows. Regressing w_{ict} on w_{jct} yields the influence fund manager j has on fund manager i plus the influence fund manager i has on fund manager j. Hence, the estimates of the influence are upward biased.[9]
In order to overcome this problem, Kelejian and Prucha (1998) proposed a three step procedure that has been refined by Lee (2003). As stated above, I do not assume that the error term is correlated across fund managers. In this case, the three step procedure reduces to a two step procedure and I proceed like in Bramoullé et al. (2009). In the first step, equation 3 is estimated by

[9] Lee (2002) has shown that this bias vanishes, if the overall influence of an individual is very small. My results however suggest that the influential network of fund managers is sparse, such that the influence of a single fund manager indeed is not neglectible.

a 2SLS estimator using the instruments $\mathbf{Z} = [\mathbf{\Gamma_t X}_t, \mathbf{X}_t]$. In the appendix, it is shown that these instruments can be used, if $\mathbf{X}_t$ is uncorrelated with the error term and if the spectral radius of $\delta_t \mathbf{\Gamma_t}$ is smaller than one. While the first condition is assumed to be generally fulfilled, the second will have to be verified after having obtained the results. The resulting estimates of the coefficients $\lambda_t = [\delta_t, \beta_{\mathbf{t}}{}']'$ are given by

$$\hat{\lambda}_t = (\mathbf{QZ}(\mathbf{Z}'\mathbf{Z})^{-1}\mathbf{ZQ})^{-1}\mathbf{QZ}(\mathbf{Z}'\mathbf{Z})^{-1}\mathbf{Zw}_t, \tag{6}$$

with $\mathbf{Q} = [\mathbf{\Gamma_t w}_t, \mathbf{X}_t]$. The second step, also consists of a 2SLS estimator. This time the instruments $\tilde{\mathbf{Z}} = [\mathbf{\Gamma_t} \hat{\mathbf{w}}_t, \mathbf{X}_t]$ are used, where $\hat{\mathbf{w}}_t$ is the consistent estimate of portfolio weights from the first step and results by plugging in $\hat{\delta}_t$ and $\hat{\beta}_{\mathbf{t}}$ into equation 4. Since the 2SLS estimator of the second step is just identified, the estimates of the coefficients λ_t from the second step are given by

$$\hat{\hat{\lambda}}_t = (\tilde{\mathbf{Z}}\mathbf{Q})^{-1}\tilde{\mathbf{Z}}\hat{\mathbf{w}}_t \tag{7}$$

In order to account for the assumed heteroskedasticity and within portfolio correlated error term (clustered errors), the variance of the coefficients is estimated by

$$V(\hat{\hat{\lambda}}_{\mathbf{t}}) = (\tilde{\mathbf{Z}}\mathbf{Q})^{-1}\tilde{\mathbf{Z}}'\Omega\tilde{\mathbf{Z}}(\tilde{\mathbf{Z}}\mathbf{Q})^{-1}, \tag{8}$$

with the block matrix Ω that contains the estimates of the error variance and the within portfolio correlation obtained by the second step.

As stated above, identification of δ_t and $\beta_{\mathbf{t}}$ is possible if $\mathbf{\Gamma_t}$ is known. If $\mathbf{\Gamma_t}$ is not given, it is still possible make assumptions about its structure. Hong et al. (2005) for instance assume that γ_{ijt} is only unequal zero if fund manager i and j work in the same city. This is reasonable, because they are only interested in word-of-mouth effects that are stronger expressed, if fund managers work near by and can regularly meet each other. Pomorski (2009) is more concerned with the influence that results from observing fund managers with high past performance. He assumes that γ_{ijt} only takes values unequal zero if fund manager i showed poor past performance while fund manager j performed well. With my paper, I intend to capture both, the influence form the exchange of opinions as well as from pure observation. For this reason, I do not impose any assumptions on the structure of $\mathbf{\Gamma_t}$, but determine it endogenously. Therefore, I estimate equation 3 for every possible combination[10] of fund manager i^* and j^* by setting

$$\gamma_{ijt} = \begin{cases} 1 & \text{if } i = i^* \text{ and } j = j^* \\ 0 & \text{otherwise} \end{cases} . \tag{9}$$

The influence of fund manager j^* on fund manager i^* is then given by δ_t. As stated above, equation 3 cannot be consistently estimated by OLS, because the estimates of the influence from fund manager j^* on fund manager i^* also contain the influence in the opposite direction. The problem does not even vanish if influence is unidirectional. This is due to the fact that imposing constraint 9 introduces an omitted variable problem, because the influence of fund managers $j \neq j^*$ is neglected. A solution consists in also applying the procedure of Kelejian and Prucha (1998) and Lee (2003). However, the second step is not feasible, because it is made use of the estimated weights $\hat{\mathbf{w}}_t$ that can only be obtained if the influence of all fund managers on a particular fund manager is considered. Nevertheless, the first step can be conducted and although Lee (2003) stated that the estimates of the first step[11] are not optimal, they are still consistent. With the estimates of the first step, the matrix $\mathbf{\Gamma_t}$ is then constructed as follows. If fund manager j^* does not have a positive influence on investor i^* on a 5% level significance, then $\gamma_{i^*j^*t}$ is set equal to zero. Otherwise, the magnitude of influence is normalised through the division by the summed influence of all other fund managers $j \neq j^*$ on fund manager i^* and is assigned to $\gamma_{i^*j^*t}$.

One remaining important question is how to deal with "zero weights". Portfolios weights of stocks that are not held by a fund manager are implicitly equal to zero. Considering every stock in the world, most of the elements of the vector $\mathbf{w}_t$ would be zero. This leads to two problems. First, it has to be accounted for a censored dependent variable. This could either be done by applying a likelihood technique or for instance by using the estimator proposed by Honoré and Leth-Petersen (2007) that does not rely on any

[10] In order to ensure enough degrees of freedom for the empirical analysis, I require two fund managers to hold at least 30 stocks in common at a particular point of time, such that a social influence might be considered. Otherwise, γ_{ijt} is set to zero. This is a reasonable approach, because a fund manager cannot be influenced by other fund managers who hold completely different portfolios.

[11] Actually, Lee (2003) showed that the estimators of the third step in the three step procedure proposed by Kelejian and Prucha (1998) are not optimal. However, assuming that the error term is not correlated across fund managers, the first and the third step in Kelejian and Prucha (1998) are equal.

assumption regarding the error distribution. While the first problem thus is solvable, there is another which is more crucial, because it induces the risk of false inference regarding fund managers' reciprocal influence. It arises from the fact that fund managers will have a lot of zero weights in common. This could erroneously be interpreted as empirical evidence for strong social influence that prevents fund managers from holding particular stocks, while in truth these fund managers might just be restricted by their investment policies not to buy these stocks. Hong et al. (2005) try to solve this problem by restricting the "universe" of potential investment opportunities to the stocks of the 2000 largest companies. This reduces the problem. But the risk of false inference still is high, if fund managers rather hold stocks of small companies, which leads to a lot of zero weights regarding the stocks of the larger companies. I confront this problem by only analysing non zero portfolio weights on the left hand side of equation 3. This has to be kept in mind for the interpretation of the results, because it means that the magnitude of influence only represents the influence for holding a stock and putting a specific weight on it. The influence for not holding a particular stock is not captured. This might be a little drawback of my approach. Nevertheless, it ensures robust results, because the magnitude of influence is rather underestimated. Note, that on the right hand side of equation 3, the resulting vector of $\mathbf{\Gamma_t w}_t$ still may contain zeros, if a fund manager holds a stock that is not held by any other fund manager at a specific point of time. This can be illustrated by having a closer look to the structure of $mathbf\Gamma_t$, which is given by

$$\mathbf{\Gamma_t} = \left[\begin{array}{cccc} \mathbf{0}_{C_{1t}\times C_{1t}} & \gamma_{12t}\mathbf{M}_{C_{1t}\times C_{2t}} & \dots & \gamma_{1Nt}\mathbf{M}_{C_{1t}\times C_{Nt}} \\ \gamma_{21t}\mathbf{M}_{C_{2t}\times C_{1t}} & \mathbf{0}_{C_{2t}\times C_{2t}} & \dots & \gamma_{2Nt}\mathbf{M}_{C_{2t}\times C_{Nt}} \\ \vdots & \vdots & \ddots & \vdots \\ \gamma_{N1t}\mathbf{M}_{C_{Nt}\times C_{1t}} & \gamma_{N2t}\mathbf{M}_{C_{Nt}\times C_{2t}} & \dots & \mathbf{0}_{C_{Nt}\times C_{Nt}} \end{array} \right], \qquad (10)$$

where $\mathbf{0}_{C_{it}\times C_{it}}$ is a $C_{it} \times C_{it}$ matrix of zeros and C_{it} stands for the number of stocks fund manager i holds at time t. $\mathbf{M}_{C_{it}\times C_{jt}}$ is a $C_{it} \times C_{jt}$ matrix that is in principle an identity matrix but the cth column is missing if fund manager i holds the stock of company c and fund manager j does not. Considering two fund managers, where one holds stock 1 and stock 2 and the other only holds stock 1, the vector of portfolio weights on the left hand side of equation

3 is given by

$$\mathbf{w}_t = \begin{bmatrix} w_{11t} \\ w_{12t} \\ w_{21t} \end{bmatrix}. \tag{11}$$

On the right hand side, the matrix $\mathbf{\Gamma_t}$ has the structure

$$\mathbf{\Gamma_t} = \left[\begin{array}{cc|c} 0 & 0 & \gamma_{12t} \\ 0 & 0 & 0 \\ \hline \gamma_{21t} & 0 & 0 \end{array}\right], \tag{12}$$

such that the product

$$\mathbf{\Gamma_t}\mathbf{w}_t = \begin{bmatrix} \gamma_{12t}w_{21t} \\ 0 \\ \gamma_{21t}w_{11t} \end{bmatrix} \tag{13}$$

contains zeros.

3. Data

The data regarding portfolio compositions of mutual funds has been obtained from the ThomsonReuters ownership database. I selected only funds that had invested at least \$ 10 million in companies of the DAX30 as of December 31st 2010. For these funds all obtainable sets of portfolios compositions have been taken in the period from 2002 to 2010. They were available either on a quarterly or on a semi-annually basis. Moreover, I also retrieved information about the particular fund and the engaged fund manager. This set of information contains the orientation (active/passive) of the fund as well as the working location of the fund manager. The final database contains 1943 funds with 5,809,739 portfolio weights.[12] On December 31st 2010, the total money invested by these funds in companies of the DAX30 amounts to approximately one third of the total DAX30 market capitalisation.
In order to properly disentangle the reciprocal influence of fund managers, it is import to find strong exogenous variables that explain their investment behaviour (matrix $\mathbf{X}_t$ in equation 3). Otherwise, spurious correlation might be interpreted as intentional influence. In his survey about the investment

[12]In order to put these numbers into a perspective, note that e.g. Hong et al. (2005) used data of 1635 funds during a two-year period, which leads to less than a quarter of the number of observations used in this paper.

behaviour of fund managers, Arnswald (2001) detects that investment decisions regarding a particular stock are primary based fundamental valuations, past stock returns and a general portfolio optimisation. In order to capture these components, I enriched database of portfolio weights by market data obtained from Bloomberg. For 16,732 companies of those that are held by at least one fund manager at at least one point of time, stock prices and analysts' consensus price targets as well as the mean value of the three consensus earnings forecasts referring to the three fiscal years following a particular date have been obtained. Moreover, the corresponding P/E ratio has been retrieved. Comparability is ensured by converting all quotes to euro with the prevailing exchange rates. This market data has then matched with the portfolio data in the following way. For every point of time where a set of portfolio composition has been available, the average and volatility of daily stock price returns in the preceding quarter has been calculated and matched with the relevant portfolio weight. The same has been done with price targets, averaged earnings forecasts and P/E ratios. The two former have both been normalised by the stock price such that they represent forecasted returns. In order to account for the individual portfolio situation of a fund manager, I relate these four variables to other stocks his portfolio at a specific point of time. Therefore, I take the difference of a particular variable and its average that is weighted with the portfolio weights of all other stocks this fund manager holds at a specific point of time. The resulting variables are DIFF_RET, DIFF_VOLA, DIFF_PT, DIFF_EARN, DIFF_P/E and denote the difference of average daily stock returns, of the volatility of daily stock returns, of normalised price targets, of normalised earnings forecasts and of the price earnings ratio, respectively. In order to illustrate this data preparation, consider a portfolio with four stocks that are weighted with 50%, 25%, 12.5% and 12.5%, respectively. The average of daily stock returns in the preceding quarter shall amount to 2%, 1%, 3% and 5%, respectively. Then the value of DIFF_RET for the first stock is given by $2\% - (0.25 \cdot 1\% + 0.125 \cdot 3\% + 0.125 \cdot 5\%) = 0.75\%$. Turning back to the main determinants of investment decisions, DIFF_PT, DIFF_EARN and DIFF_P/E account for fundamental valuations. Past stock returns are captured by DIFF_RET and it is accounted for portfolio optimisation by both, DIFF_RET and DIFF_VOLA.

Walter and Weber (2006) stated that a large portion of similar behaviour among mutual fund managers can be explained by variations of underlying benchmark indices. Hence, a variable that captures this effect is needed.

Therefore, the underlying benchmark of every fund manager has to known. Among all 1943 fund managers in the database, there are 277 that have a passive orientation. This means these fund managers choose portfolio weights such that they just replicate a particular index. Hence, by definition they cannot by influenced by other fund managers and are excluded for the empirical analysis. However, their portfolio weights can be used as benchmark weights for the remaining 1666 active portfolio managers. Therefore, I regressed the weights of every active fund manager on the weights of every passive fund manager. If the coefficient of this bivariate regression turned out to be positive and significant at a 5% level, I concluded that the weights of the passive fund manager serve as a benchmark for the active fund manager. In case, there are more than one passive fund managers whose portfolio weights can be used as a benchmark for one active fund manager, I considered the average that has been weighted by the magnitude of the regression coefficients. This situation occurs, if there are several passive fund managers that replicate the same index or if an index is included in another index. The resulting variable is denoted BENCHMARK.

Coval and Moskowitz (1999) provided empirical evidence, that fund managers are more likely to invest in the stocks of companies that are located near by. In order to account for this effect, I retrieved information about the location of the headquarters for the afore mentioned 16,732 companies from ThomsonReuters. Thereof, I created two dummy variables. CITY takes the value one if a fund manager works in the city where the headquarters of the company, he invested in, is located. COUNTRY equals one if the headquarter is not located in the same city but in the same country.

In order to illustrate how the group of the analysed 1666 active fund managers is composed, table 1 gives an overview of the families the funds belong to. This list is restricted to fund families with at least 10 funds in the database. Table 2 shows the working locations of the managers of the analysed fund by country and city. Note that the list of cities only contains those cities where at least 10 fund managers work. Removing the portfolios weights of the passive fund managers reduces the dataset to 4,399,889 observations. Table 3 provides summary statistics for the corresponding variable PORT_WEIGHT and all other afore mentioned variables. Please note, that market data has been corrected by outliers (upper and lower 1% percentiles). The mean portfolio weight equals 0.64%. This means, that in the average a fund manager holds 156 stocks at a particular point of time. Table 4 shows how the number of funds and available portfolio weight is distributed over the period from 2002

Table 1: Overview of the fund families of the analysed active funds

Fund Family	Frequency	relative Frequency
Allianz Global Investors Kapitalanlagegesellschaft mbH	82	4.9%
MFS Investment Management	42	2.5%
DWS Investment GmbH	41	2.5%
Union Investment Group	39	2.3%
Fidelity Management & Research	38	2.3%
Deutsche Asset Management Investmentgesellschaft mbH	29	1.7%
AllianceBernstein L.P.	28	1.7%
Fidelity International Limited	28	1.7%
Deka Investment GmbH	27	1.6%
ING Investment Management (Netherlands)	26	1.6%
Amundi Asset Management	23	1.4%
Templeton Investment Counsel, LLC	22	1.3%
JPMorgan Asset Management U.K. Limited	21	1.3%
Wellington Management Company, LLP	20	1.2%
UBS Global Asset Management (Switzerland)	19	1.1%
Swedbank Robur AB	18	1.1%
Newton Investment Management Ltd.	18	1.1%
BNP Paribas Asset Management S.A.S.	16	1.0%
Aberdeen Asset Management (Edinburgh)	15	0.9%
Schroder Investment Management Ltd. (SIM)	15	0.9%
Invesco Advisers, Inc.	14	0.8%
La Banque Postale Asset Management	14	0.8%
AllianceBernstein Ltd. (Value)	13	0.8%
Henderson Global Investors Ltd.	13	0.8%
M & G Investment Management Ltd.	12	0.7%
OppenheimerFunds, Inc.	12	0.7%
Franklin Mutual Advisers, LLC	12	0.7%
BlackRock Investment Management (UK) Ltd.	11	0.7%
Danske Capital	11	0.7%
Dexia Asset Management Belgium S.A.	11	0.7%
Aviva Investors France S.A.	10	0.6%
Natixis Asset Management	10	0.6%

The list of fund families is restricted to those with at least 10 funds in the database.

Table 2: Overview of the working locations of the analysed active funds

Country	Frequency	rel. Frequency	City	Frequency	rel. Frequency
United States	448	26.9%	London	261	15.7%
Germany	332	19.9%	Frankfurt	255	15.3%
United Kingdom	306	18.4%	Boston	136	8.2%
France	147	8.8%	Paris	134	8.0%
Switzerland	65	3.9%	New York	107	6.4%
Sweden	49	2.9%	Stockholm	48	2.9%
Canada	43	2.6%	Zurich	43	2.6%
Netherlands	40	2.4%	Edinburgh	41	2.5%
Belgium	37	2.2%	Brussels	36	2.2%
Italy	37	2.2%	Milan	33	2.0%
Luxembourg	29	1.7%	Toronto	32	1.9%
Denmark	27	1.6%	Luxembourg	28	1.7%
Ireland	22	1.3%	The Hague	26	1.6%
Japan	16	1.0%	Copenhagen	23	1.4%
Spain	16	1.0%	Dublin	22	1.3%
Bahamas	12	0.7%	Cologne	22	1.3%
Norway	9	0.5%	Chicago	22	1.3%
Austria	8	0.5%	Denver	16	1.0%
Australia	4	0.2%	Tokyo	16	1.0%
Portugal	4	0.2%	Geneva	12	0.7%
Finland	3	0.2%	Madrid	12	0.7%
South Africa	2	0.1%	Los Angeles	12	0.7%
Liechtenstein	2	0.1%	Short Hills	12	0.7%
n.a.	2	0.1%	Nassau	12	0.7%
Singapore	2	0.1%	Puteaux	11	0.7%
Hong Kong	1	0.1%	Fort Lauderdale	11	0.7%
Greece	1	0.1%	San Francisco	10	0.6%
Taiwan	1	0.1%	Munich	10	0.6%
Bermuda	1	0.1%			
	1666	**100%**			

The list of cities is restricted to those where at least 10 active fund managers work.

Table 3: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
PORT_WEIGHT	0.006396	0.012125	0.000000	1.000000	4,399,889
DIFF_RET	-0.000364	0.002410	-0.012611	0.007152	3,679,430
DIFF_VOLA	0.000477	0.000790	-0.005347	0.006336	3,679,431
DIFF_PT	-0.018298	0.194100	-0.854410	1.337569	3,109,250
DIFF_EARN	-0.003905	0.035997	-0.152663	0.185215	2,801,973
DIFF_P/E	-0.130618	11.708073	-64.667999	75.106094	2,786,845
BENCHMARK	0.000240	0.001264	0.000000	0.159050	3,724,983
CITY	0.028229	0.165625	0.000000	1.000000	3,796,512
COUNTRY	0.157178	0.363968	0.000000	1.000000	4,399,889

The portfolio weight an active fund manager puts on a specific stock at a particular point time is given by PORT_WEIGHT. DIFF_RET, DIFF_VOLA, DIFF_PT, DIFF_EARN, DIFF_P/E denote the three months average daily stock return, the three months volatility of daily stock returns, the normalised price target, the normalised three years average earnings forecast and the price earnings ratio, respectively, minus the corresponding portfolio specific weighted mean value. BENCHMARK represents the portfolio weight a specific stock receives in the average benchmark portfolio of passive fund managers that is relevant for a particular active fund manager. CITY and COUNTRY are dummy variables. CITY equals one if an active fund managers works in the same city like the company whose stock he holds. COUNTRY is equal to one if an active fund manager does not work in the same city but in the same country like the company whose stock he holds.

to 2010. The average number of analysed funds per half-year equals 1164. This means that not all 1666 fund managers can be examined at the same time. Particularly, the number of fund managers that are observed in the second half-year of 2010 is considerably lower than in the first half-year of 2010. This is due to the fact, that the data has been retrieved at the beginning of 2011, when not all funds had already reported their portfolio weights for the end of 2010. The empirical results, however, are not affected by this variation, because the magnitude of social influence is determined separately for every half-year and because it can be assumed, that errors induced by missing funds are not systematic. In table 5 the cross correlations of all variables are given. As one would expect, PORT_WEIGHT is positively correlated with DIFF_RET, DIFF_EARN, BENCHMARK, CITY and COUNTRY whereas PORT_WEIGHT and DIFF_VOLA are negatively correlated. This suggests that a fund manager puts more weight on stocks with higher average daily returns, with higher analysts' earnings forecasts, with a higher weight in the relevant benchmark portfolio and on those stock where he works near the headquarter of emitting company. Less weight is assigned to stocks with a higher return volatility. Surprisingly, PORT_WEIGHT is negatively correlated with DIFF_PT, which indicates that a high return implied by analysts' price targets leads to a lower portfolio weight of a particular stock. The price earning ratio does not seem to be decisive for fund managers' portfolio selections as the corresponding correlation coefficient is almost zero and not significant on a 10% level.

4. Results

In the following, I test the three hypotheses of the paper. Therefore, I determine the magnitude of social influence among fund managers, divide it into observational influence and influence from the exchange of opinion and relate it to the prevailing market environment. First, I select the variables that are relevant for the portfolio selection. The correlation coefficients provided in the preceding chapter all showed the expected sign, except for DIFF_PT and DIFF_P/E. In order to capture correctly the fundamental component, different specifications with the three fundamental variables are tested within an OLS panel regression with fixed effects on the fund manager level. The results are shown in table 6. It can be seen that DIFF_EARN has the highest relevance, such that I use the variables of the third specification for the analysis of influence.

Table 4: Temporal distribution of the number of funds and portfolio weights

	N	K
2002/I	122,120	851
2002/II	139,790	949
2003/I	144,382	965
2003/II	160,395	1029
2004/I	167,069	1007
2004/II	203,472	1102
2005/I	211,041	1084
2005/II	242,202	1169
2006/I	248,259	1201
2006/II	272,548	1263
2007/I	274,041	1261
2007/II	301,352	1398
2008/I	332,090	1401
2008/II	323,982	1427
2009/I	342,310	1461
2009/II	383,330	1482
2010/I	311,922	1082
2010/II	219,584	824
sum / mean	**4,399,889**	**1164**

N is the number of available portfolio weights per half-year that are provided by K fund managers.

Table 5: Matrix of Cross Correlations

Variables	PORT_WEIGHT	DIFF_RET	DIFF_VOLA	DIFF_PT	DIFF_EARN	DIFF_P/E	BENCHMARK	CITY
DIFF_RET	0.058							
	(0.000)							
DIFF_VOLA	-0.082	0.079						
	(0.000)	(0.000)						
DIFF_PT	-0.018	-0.219	0.191					
	(0.000)	(0.000)	(0.000)					
DIFF_EARN	0.043	-0.114	0.130	0.305				
	(0.000)	(0.000)	(0.000)	(0.000)				
DIFF_P/E	-0.001	0.058	-0.043	-0.127	-0.316			
	(0.199)	(0.000)	(0.000)	(0.000)	(0.000)			
BENCHMARK	0.233	0.009	-0.051	-0.010	0.034	-0.022		
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
CITY	0.075	0.006	0.010	0.004	0.022	-0.000	0.004	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.734)	(0.000)	
COUNTRY	0.037	-0.007	0.004	0.047	-0.030	-0.021	0.026	-0.080
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

The portfolio weight an active fund manager puts on a specific stock at a particular point time is given by PORT_WEIGHT. DIFF_RET, DIFF_VOLA, DIFF_PT, DIFF_EARN, DIFF_P/E denote the three months average daily stock return, the three months volatility of daily stock returns, the normalised price target, the normalised three years average earnings forecast and the price earnings ratio, respectively, minus the corresponding portfolio specific weighted mean value. BENCHMARK represents the portfolio weight a specific stock receives in the average benchmark portfolio of passive fund managers that is relevant for a particular active fund manager. CITY and COUNTRY are dummy variables. CITY equals one if an active fund managers works in the same city like the company whose stock he holds. COUNTRY is equal to one if an active fund manager does not work in the same city but in the same country like the company whose stock he holds. The table contains the correlation coefficients. P-values are reported in parenthesis.

Table 6: OLS panel regression with fixed effects on the fund manager level

	Specification I	Specification II	Specification III	Specification IV
DIFF_RET	0.14133∗∗∗	0.12958∗∗∗	0.15040∗∗∗	0.13368∗∗∗
	(0.00204)	(0.00193)	(0.00187)	(0.00187)
DIFF_VOLA	−0.67585∗∗∗	−0.65888∗∗∗	−0.70066∗∗∗	−0.64053∗∗∗
	(0.00647)	(0.00606)	(0.00597)	(0.00583)
DIFF_PT	−0.00081∗∗∗	−0.00005∗		
	(0.00003)	(0.00002)		
DIFF_EARN	0.01112∗∗∗		0.01130∗∗∗	
	(0.00015)		(0.00013)	
DIFF_P/E	−0.00001∗∗∗			−0.00002∗∗∗
	(0.00000)			(0.00000)
BENCHMARK	1.20364∗∗∗	1.08347∗∗∗	1.21971∗∗∗	1.23161∗∗∗
	(0.00496)	(0.00401)	(0.00482)	(0.00486)
CITY	0.00272∗∗∗	0.00288∗∗∗	0.00269∗∗∗	0.00269∗∗∗
	(0.00003)	(0.00003)	(0.00003)	(0.00003)
COUNTRY	0.00128∗∗∗	0.00121∗∗∗	0.00122∗∗∗	0.00114∗∗∗
	(0.00002)	(0.00002)	(0.00002)	(0.00002)
CONST	0.00556∗∗∗	0.00553∗∗∗	0.00552∗∗∗	0.00545∗∗∗
	(0.00001)	(0.00001)	(0.00001)	(0.00001)
N	2,160,103	2,536,435	2,331,492	2,312,400

The dependent variable is given by the portfolio weight an active fund manager puts on a specific stock at a particular point. DIFF_RET, DIFF_VOLA, DIFF_PT, DIFF_EARN, DIFF_P/E denote the three months average daily stock return, the three months volatility of daily stock returns, the normalised price target, the normalised three years average earnings forecast and the price earnings ratio, respectively, minus the corresponding portfolio specific weighted mean value. BENCHMARK represents the portfolio weight a specific stock receives in the average benchmark portfolio of passive fund managers that is relevant for a particular active fund manager. CITY and COUNTRY are dummy variables. CITY equals one if an active fund managers works in the same city like the company whose stock he holds. COUNTRY is equal to one if an active fund manager does not work in the same city but in the same country like the company whose stock he holds. The table contains the regression coefficients that result by an OLS panel regression with fixed effects on the fund manager level. The significance of coefficients is indicated by stars (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$). The corresponding standard deviations are reported in parenthesis.

I estimate the coefficients of equation 3 for every half-year from 2005 to 2010. The years from 2002 to 2004 are skipped, because the number of available earnings forecasts in the database is too low.[13] For every half-year, I further remove all funds where not at least 30 portfolios weights have been available. This ensures enough degrees of freedom for the empirical analysis. As described in chapter 2, the matrix $\mathbf{\Gamma_t}$ is determined by pair wise regressions. Therefore, PORT_WEIGHT is used for $\mathbf{w}_t$ and the columns of the matrix $\mathbf{X}_t$ consist of the variables DIFF_RET, DIFF_VOLA, DIFF_EARN, BENCHMARK, CITY, COUNTRY as well as of a row vector of ones in order to introduce a constant term. Remind, that the matrix of instruments is given by $\mathbf{Z} = [\mathbf{\Gamma_t X}_t, \mathbf{X}_t]$. If however, some variables are identical for the two fund managers under consideration, then the columns of $\mathbf{Z}$ result to be collinear. This can be demonstrated by the constant term that by definition always is a column vector of ones. The matrix of instruments can be written as

$$\mathbf{Z} = [\mathbf{\Gamma_t}[\mathbf{X}_t^{(1-6)}, \mathbf{c}], [\mathbf{X}_t^{(1-6)}, \mathbf{c}]], \tag{14}$$

with $\mathbf{c}$ being a column vector of ones. The matrix $\mathbf{X}_t^{(1-6)}$ contains the other variables as explained above. Now, equation 14 can be reformulated as

$$\mathbf{Z} = [\mathbf{\Gamma_t X}_t^{(1-6)}, \mathbf{\Gamma_t c}, \mathbf{X}_t^{(1-6)}, \mathbf{c}]. \tag{15}$$

The rows of $\mathbf{\Gamma_t}$ are normalised, such that the single row elements sum up to one. This yields $\mathbf{\Gamma_t c} = \mathbf{c}$. Hence, the 7^{th} and the 14^{th} column of matrix $\mathbf{Z}$ are identical and thus collinear. This problem of colinearity might also occur for the variables BENCHMARK, CITY or COUNTRY, if fund managers have the same benchmark or work in the same city or country, respectively. In order to rule out the potential problem, I use the instruments $\mathbf{Z} = [\mathbf{\Gamma_t X}_t^{(1-3)}, \mathbf{X}_t]$, where the matrix $\mathbf{X}_t^{(1-3)}$ only consists of the variables DIFF_RET, DIFF_VOLA and DIFF_EARN that are guaranteed to be individual for every fund manager as they depend on the specific portfolio compositions. Regarding the timing of possible influence, I assume that fund managers can only be influenced by other fund managers if they published their portfolio weights within the same month and at that time held at least 30 stocks in common. Moreover, I do not examine the reciprocal influence of

[13] Removing the variable DIFF_EARN and including the years 2002 to 2004 qualitatively leads to the same results.

funds that belong to the same fund family, because this does not represent a form of external influence.
After having obtained the matrix $\mathbf{\Gamma_t}$, the two step procedure outlined in chapter 2 can be applied in order to estimate the coefficients δ_t and $\beta_{\mathbf{t}}$ for every half-year. The vector $\mathbf{w}_t$ and the matrix $\mathbf{X}_t$ are defined as explained above for the determination of $\mathbf{\Gamma_t}$. This time however, I use $\mathbf{Z} = [\mathbf{\Gamma_t X}_t^{(1-6)}, \mathbf{X}_t]$ as set of instruments, where $\mathbf{X}_t^{(1-6)}$ contains the same column like $\mathbf{X}_t$ except the vector of ones. This choice is justified by the fact, that not all fund managers neither have the same benchmark, nor work in the same city or country, respectively, such that only the column vector of ones could generate a collinearity. The estimation results are shown in table 7. It can be seen, that all values of δ_t are lower than one. As the matrix $\mathbf{\Gamma_t}$ is row normalised by equation 2, i.e. the single row elements sum up to one, the spectral radius of $\delta_t \mathbf{\Gamma_t}$ is also always lower than one. Hence, the instruments used for the estimation procedure are valid.
The average estimate of the coefficient δ_t equals 0.6878. This means that an average increase of 1% in portfolio weights by the relevant fund managers of the underlying influential network leads to an increase of 0.69% for a particular fund manager. Among the variables that are decisive for the portfolio selection, BENCHMARK has a considerable effect. The corresponding average coefficient of 1.2282 is greater than one, which thus suggests that portfolio managers generally hold fewer stocks than are included in all relevant indices. Therefore, variations in the benchmark portfolio translate into higher variations in an individual portfolio. Moreover, in the average, an increase of DIFF_RET and DIFF_EARN and a decrease of DIFF_VOLA each by one standard deviation leads to an increase in portfolio weights by 0.04%, 0.03% and 0.09%, respectively. Interestingly, the regression coefficients for DIFF_VOLA are considerable smaller in the second half-year of 2008 and the first half-year of 2009, which results from the high volatility most of the stocks experienced during that period of time. Fund managers tend to put 0.02% more portfolio weight on stocks, if they work in the city, where the headquarters of the emitting company is located. 0.01% more portfolio weight is chosen, if not the city but at least the country is equal. The resulting variations appear to be low. However, remind that the average portfolio weight equals 0.64%. The afore presented results show, that although after controlling for the key determinants of the portfolio selection, the effect of social influence among fund managers is statistically and economically sig-

Table 7: Estimation results for the magnitude of social influence δ_t

	δ_t	DIFF_RET	DIFF_VOLA	DIFF_EARN	BENCHMARK	CITY	COUNTRY	CONST	N/K
2005/I	0.6804***	0.1973***	−2.9388***	0.0037***	0.9845***	0.0023***	0.0014***	0.0063***	30,965
	(0.0206)	(0.0250)	(0.1539)	(0.0011)	(0.0760)	(0.0003)	(0.0002)	(0.0001)	415
2005/II	0.7809***	0.1567***	−0.9084***	0.0096***	1.1204***	0.0024***	0.0015***	0.0052***	132,884
	(0.0226)	(0.0119)	(0.1333)	(0.0010)	(0.1502)	(0.0002)	(0.0001)	(0.0001)	901
2006/I	0.6645***	0.0444***	−1.1161***	0.0117***	2.0421***	0.0017***	0.0013***	0.0053***	140,871
	(0.0170)	(0.0140)	(0.0841)	(0.0008)	(0.1782)	(0.0002)	(0.0001)	(0.0001)	895
2006/II	0.6516***	0.1056***	−0.8132***	0.0104***	1.1843***	0.0022***	0.0011***	0.0049***	169,451
	(0.0106)	(0.0077)	(0.0647)	(0.0009)	(0.1183)	(0.0001)	(0.0001)	(0.0000)	967
2007/I	0.6867***	0.1735***	−1.8908***	0.0164***	1.1092***	0.0023***	0.0013***	0.0050***	179,348
	(0.0143)	(0.0104)	(0.0785)	(0.0009)	(0.2454)	(0.0001)	(0.0001)	(0.0001)	961
2007/II	0.6606***	0.2970***	−1.1007***	0.0156***	0.3769***	0.0029***	0.0014***	0.0054***	207,838
	(0.0097)	(0.0058)	(0.0327)	(0.0007)	(0.0649)	(0.0001)	(0.0001)	(0.0000)	1116
2008/I	0.6654***	0.1564***	−1.0590***	0.0067***	1.2108***	0.0028***	0.0011***	0.0050***	249,314
	(0.0087)	(0.0043)	(0.0169)	(0.0003)	(0.0545)	(0.0001)	(0.0000)	(0.0000)	1237
2008/II	0.7693***	0.2170***	−0.3005***	0.0028***	1.2342***	0.0027***	0.0011***	0.0050***	234,275
	(0.0100)	(0.0036)	(0.0090)	(0.0003)	(0.0659)	(0.0001)	(0.0000)	(0.0000)	1262
2009/I	0.7095***	0.0646***	−0.6326***	0.0045***	2.3453***	0.0028***	0.0011***	0.0048***	255,197
	(0.0092)	(0.0039)	(0.0118)	(0.0002)	(0.1217)	(0.0001)	(0.0000)	(0.0000)	1369
2009/II	0.7247***	0.1393***	−1.0176***	0.0093***	0.7959***	0.0022***	0.0009***	0.0045***	303,547
	(0.0082)	(0.0039)	(0.0174)	(0.0002)	(0.0471)	(0.0001)	(0.0000)	(0.0000)	1411
2010/I	0.5917***	0.0726***	−0.9350***	0.0101***	1.0187***	0.0023***	0.0009***	0.0043***	247,488
	(0.0099)	(0.0043)	(0.0180)	(0.0003)	(0.0579)	(0.0001)	(0.0000)	(0.0000)	957
2010/II	0.6571***	0.1344***	−1.2916***	0.0081***	1.3203***	0.0019***	0.0009***	0.0047***	172,590
	(0.0173)	(0.0058)	(0.0309)	(0.0003)	(0.0787)	(0.0001)	(0.0000)	(0.0000)	698
mean	**0.6878**	**0.1466**	**-1.1668**	**0.0091**	**1.2282**	**0.0024**	**0.0011**	**0.0050**	**193,647**

The dependent variable is given by the portfolio weight an active fund manager puts on a specific stock at a particular point. DIFF_RET, DIFF_VOLA, DIFF_EARN, denote the three months average daily stock return, the three months volatility of daily stock returns and the normalised three years average earnings, respectively, minus the corresponding portfolio specific weighted mean value. BENCHMARK represents the portfolio weight a specific stock receives in the average benchmark portfolio of passive fund managers that is relevant for a particular active fund manager. CITY and COUNTRY are dummy variables. CITY equals one if an active fund managers works in the same city like the company whose stock he holds. COUNTRY is equal to one if an active fund manager does not work in the same city but in the same country like the company whose stock he holds. N represents the number of observation and K the number of fund managers used in the empirical analysis. The table contains the regression coefficients that are obtained by the two step estimation as explained in the text. The significance of coefficients is indicated by stars (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$). The corresponding standard deviations are reported in parenthesis.

Table 8: Network dynamics

	$\frac{\text{num all links}}{\text{num all possible links}}$	$\frac{\text{num unweighted city links}}{\text{num all links}}$	$\frac{\text{num weighted city links}}{\text{num all links}}$
2005/I	0.58%	7.7%	10.75%
2005/II	0.60%	10.9%	11.28%
2006/I	0.53%	9.2%	9.38%
2006/II	0.59%	9.5%	9.15%
2007/I	0.59%	8.3%	8.42%
2007/II	0.55%	9.2%	9.45%
2008/I	0.62%	7.9%	8.49%
2008/II	0.64%	9.8%	7.16%
2009/I	0.85%	7.2%	7.64%
2009/II	0.92%	7.0%	7.94%
2010/I	0.76%	7.6%	7.30%
2010/II	0.53%	7.7%	6.50%
mean	**0.65%**	**8.49%**	**8.62%**

The first column displays the total network density. The second column shows the portion of network density that is generated by intra-city links. The third column also contains the portion of network density resulting from intra-city links, however, every link is weighted with the corresponding coefficient γ_{ijt}.

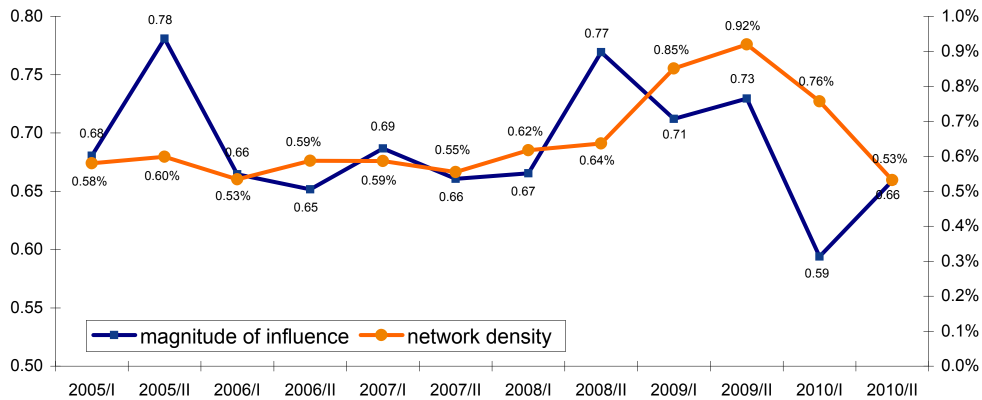
nificant. This corroborates my first hypothesis.

Table 8 shows the evolution of the network density over time. The network density is defined by the number of all network links given by $\mathbf{\Gamma_t}$ divided by the number of all possible network links. The number of all possible links is given by $K(K-1)$, where K is the number of fund managers that are analysed in a particular half-year. Following Hong et al. (2005), I define the influence between fund managers that work in the same city as influence from the exchange of opinion. Table 8 also provides the fraction of the total density that is due to links that connect fund managers in the same city. The relevance of the influence from the exchange of opinion can be expressed more precisely, if every intra-city link is weighted with the corresponding coefficient γ_{ijt}. The resulting weighted fraction of the total density is also displayed in table 8. The mean network density equals 0.65%. This means the underlying influential network is very sparse. In the average, a particular fund manager is influenced by 6.6 other fund managers. The mean portion of weighted and unweighted network links that connect fund managers within the same city are quite similar and equal 8.49% and 8.62%, respectively. Hence, 8.49% of the average network density is due intra-city links and 8.62% of the average magnitude of social influence results from intra-city influence. The latter means that, in the average, a fund manager increases the portfolio weight of a particular stock by 0.06%, if the fund managers, with whom he exchanges his opinion, increase the corresponding portfolio weight by 1%. It can be stated that the portion of intra-city influence slightly decreases slightly over time, which could be due to the effect of increasing globalisation.

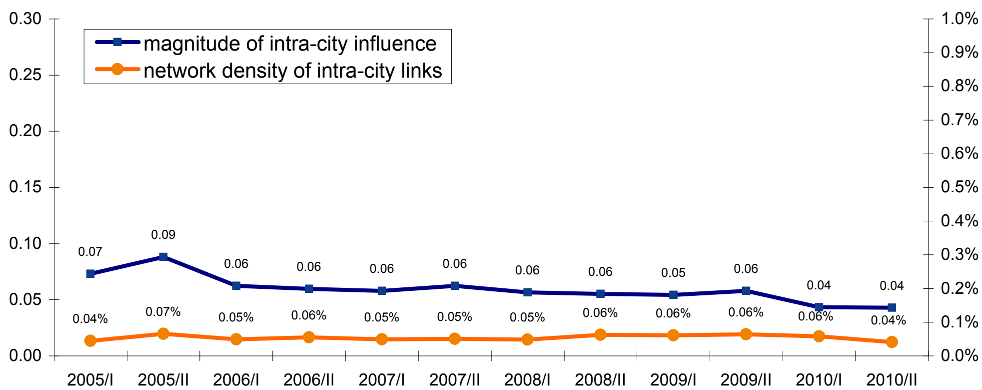
In order to test the second and third hypothesis, the magnitude of social influence and the density of the underlying influential network are related to the prevailing market environment represented by the dynamics of the DAX30. Figure 1(a) shows the magnitude of influence as well as the network density. Figure 1(b) displays the magnitude of influence, that is due to fund managers working in the same city as well as the network density resulting from links between those fund managers. In figure 1(c) the price level of the DAX30 and the volatility of daily returns for every half-year during the period of analysis are shown. One can see that the magnitude of influence has been on a stable level of about 0.67 since 2006. A sudden increase can be observed at the beginning of the recent economic crisis in the second half-year of 2008, where the level of the DAX30 was low and the volatility of stock returns was high. As the bottom line of the DAX30 level was reached and returns began to get positive again, the magnitude of influence decreased under the level before the crisis and turned back to this level in the second half-year of 2010. Surprisingly, there is a singular peak in the magnitude of influence in the second half-year of 2005 that does not correspond to a specific evolution of the DAX30. The density of the underlying influential network remained stable on the level of about 0.59% between 2005 and 2008. It significantly began to grow in the first half-year of 2009 and turned back to the pre-crisis level in the second half-year of 2010.

The temporal variations of the magnitude of social influence provide empirical evidence in favour of my second hypothesis. During the period until the beginning of the economic crisis in 2008 as well as in 2010, social influence among fund managers was considerably lower than during the crisis. This suggests that fund managers try to differentiate from their competitors during an economic upturn in order to get a superior remuneration. During an economic turndown, however, they fear the loss of reputation and consequently of remuneration, such that they are more prone to align their

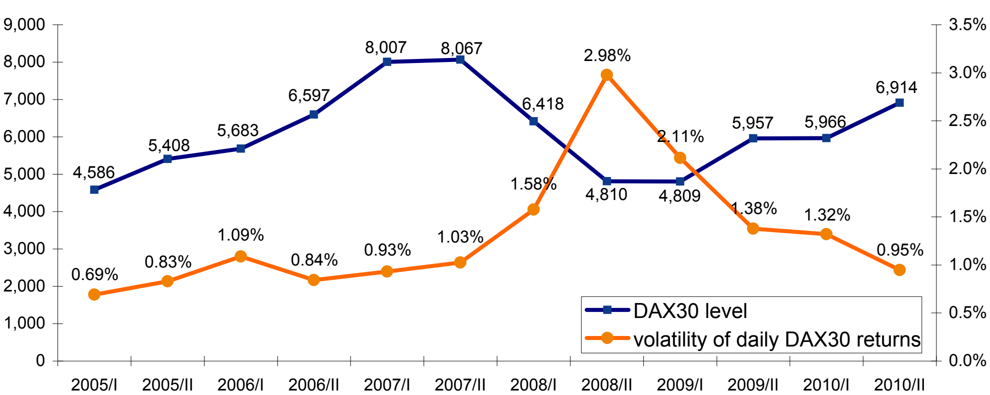
Table 8: Dynamics of the DAX30



(a)



(b)



(c)

(a) Average magnitude of influence and overall network density. (b) Magnitude of influence, that is due to fund managers working in the same city and network density of those fund managers. (c) Price level of the DAX30 and volatility of daily DAX30 returns

portfolio decisions with other fund managers. This theory is also supported by the evolution of the network density. At the beginning of the crisis, fund managers were only influenced by those fund managers, they had also been (but less strongly) influenced before. During the crisis, the number of fund managers by whom a particular fund manager is influenced increased notably. This lead to a market wide alignment of portfolio weights, which could be based on afore cited effects of reputation and remuneration.
Now, turning to the third hypothesis, I intend to shed light on the temporal fluctuation of the influence from the exchange of opinion, defined as social influence among fund managers that work in the same city. It can be stated that the magnitude of influence as well as the network density is more or less constant in time. This means, that the increase of influence and the enlargement of the influential network during the crisis are not due to an increase of influence from the exchange of opinion. This is inline with the argumentation, that interaction with social contacts does not vary with the prevailing market environment, such that variations are due to fluctuations of observational influence most probably for motives of reputation and remuneration.

5. Robustness checks

In order to rule out the possibility, that the results presented in the previous chapter are driven by factors that are not related to the presented explanations, I provide some robustness checks. A key factor that potentially could lead to biased results is that the underlying social network is determined endogenously. Thereby, only the influence from those fund managers with correlated portfolio weights is considered. Moreover, this influence is a priori weighted with the corresponding coefficients from the pair-wise regressions. As a first robustness check, I repeated the empirical analysis with an exogenous network. Therefore, I assumed that a fund manager can be influenced by any other fund managers with whom he holds at least 30 stocks in common. I kept the restriction regarding the minimum number of common stocks, because fund managers can only (intentionally) align their portfolios if they have a minimum intersection of stocks. In order to illustrate this fact, consider two fund managers that only share one common stock. The weight of this stock depends on the weights of all other stocks in the respective portfolios, such that a correlation of these single stock's weights could only be spurious. In order to overcome the potential bias that could result by

Table 9: Robustness checks: Temporal mean values of the magnitude of social influence δ_t for different specifications

	whole period	bear market	bull market	difference
(I) min. 30 com. st. (standard)	0.6859	0.7376	0.6687	0.0689
(II) min. 30 com. st., exog. netw.	0.9346	0.9743	0.9214	0.0529
(III) min. 15 com. st., endog. netw.	0.7867	0.8423	0.7681	0.0742
(IV) min. 100 com. st., endog. netw.	0.5157	0.5446	0.5060	0.0385

Specification I represents the standard model used for the empirical analysis of this paper. Specification II is based on an exogenous network as explained in the text. Specifications III and IV are used to vary the minimum number of stocks two fund managers have to hold in common, such that they could potentially influence each other. The corresponding minimum numbers are 15 and 100. In the first column, the overall temporal mean values of regression coefficients measuring the magnitude of social influence are displayed. The second and the third columns show the corresponding temporal mean values for the bearish market environment (2008/II, 2009/I, 2009/II) and the bullish market environment (remaining period of analysis). In the last column, the differences of average social influence between the two different market environments are presented.

weighting the influence of fund managers differently, I chose equal weights for every fund manager. The results can be seen in table 9 (specification II). The overall average coefficient of social influence equals 0.9346. This is by far higher than the magnitude of social influence obtained by the standard model in the previous chapter and indicates that my results are not upward biased through the usage of an endogenous network. Having a closer look to the dynamics of social influence, I compared the mean value of the coefficients obtained for the second half-year of 2008 and both half-years of 2009 (bearish market environment) with the temporal average of the coefficients obtained for the remaining period of analysis (bullish market environment). The difference equals 0.0529 and is only slighter lower than the difference found by applying the standard model amounting to 0.0689 (see specification I in table 9). Hence, even if one does not trust the absolute values of social influence, temporal variations attest a relative difference between the periods of bull and bear markets.
In order to provide further robustness checks, I varied the minimum number of stocks that two fund managers have to hold in common, such that they could potentially influence each other. First, I reduced this number to 15.

Thereafter, I augmented it to 100. The results are also shown in table 9 (specifications III and IV). The difference of social influence between the two market environments equals 0.0742, if 15 common stocks are requested and amounts to 0.0385, if the threshold is set to 100. Hence, specification III leads to a higher difference social influence compared the standard model, while specification IV yields a lower difference. This is inline with the explanations provided in the proceeding chapter. The number of minimum common stocks controls the number of fund managers by whom a particular fund manager is assumed to be potentially influenced. The more fund managers are considered to influence a particular fund manager, the higher is the measured magnitude of influence in case of a market wide portfolio alignment. Hence, the difference of social influence between the two states of the economy which resulted to be higher for a smaller threshold can be interpreted as evidence in favour of a market wide portfolio alignment during an economic downturn.

6. Conclusion

In this paper, I analysed the social influence on portfolio decisions that fund managers investing in DAX30 companies have on each other. I first determined the underlying influential network by examining every possible link between two fund managers. The constructed network resulted to be very sparse. Using a two step estimation procedure, I then estimated the magnitude of influence. In the average, a fund manager increases the portfolio weight of a particular stock by 0.69%, if the fund managers in his reference group increase the corresponding weight by 1%. Looking at intra-city influence, I concluded that 8.62% of the total influence is based on the exchange of opinion.

Relating the influence among fund managers to the dynamics of the DAX30, I concluded that fund managers adapt their behaviour to the prevailing market situation. In times of a bull market, fund managers rather try to differentiate themselves from their competitors. During a bear market, they are more prone to align their portfolio weights with the others. These behavioural patterns are most probably due to reputational reasons and effects of remuneration. This is inline with the fact, that the influence from the exchange of opinion, defined as intra-city influence, does not alter with the prevailing market environment.

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Appendix A.

In this appendix, it shall be shown, that the instruments $\mathbf{Z} = [\mathbf{\Gamma_t X}_t, \mathbf{X}_t]$ can be used to estimate equation 3 by a 2SLS estimator, if $\mathbf{X}_t$ is uncorrelated with the error term and if the spectral radius of $\delta_t \mathbf{\Gamma_t}$ is smaller than one. The endogenous regressor $\mathbf{\Gamma_t w}_t$ can be expressed by the reduced form equation 4 in the following way

$$\mathbf{\Gamma_t w}_t = \mathbf{\Gamma_t} \left(\mathbf{I} - \delta_t \mathbf{\Gamma_t}\right)^{-1} \left(\mathbf{X}_t \beta_\mathbf{t} + \epsilon_t\right). \tag{A.1}$$

If the spectral radius of $\delta_t \mathbf{\Gamma_t}$ is lower than one, the Neumann expansion can be used and leads to

$$\mathbf{\Gamma_t w}_t = \mathbf{\Gamma_t} \left(\mathbf{I} + \delta_t \mathbf{\Gamma_t} + \delta_t^2 \mathbf{\Gamma_t}^2 + \ldots\right) \left(\mathbf{X}_t \beta_\mathbf{t} + \epsilon_t\right). \tag{A.2}$$

If $\mathbf{X}_t$ is not correlated with ϵ_t, it thereof follows that $\mathbf{\Gamma_t X}_t$ is a valid instrument for $\mathbf{\Gamma_t w}_t$, because it is correlated with $\mathbf{\Gamma_t w}_t$, but does not have a direct impact on $\mathbf{w}_t$, as it does not appear in equation 3.