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

In this paper, I analyse the reciprocal social influence on investment decisions within an international group of roughly 2,000 mutual fund managers who invested in companies in the DAX30. Using a robust estimation procedure, I provide empirical evidence that the average fund manager puts 0.69% more portfolio weight on a particular stock, if his peers on average assign a weight to the corresponding position which is 1% higher compared to other stocks in the portfolio. The dynamics of this influence on the choice of 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 stems from the social learning. While this form of influence varies much over time, the magnitude of influence resulting from the exchange of opinion is more or less constant.

4.1 Introduction

As of September 30^{th} 2011, mutual funds worldwide had $ 9,043 billion of 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, as similar investment decisions might drive prices into a specific direction. In this context, it is important to point out how analogous decisions arise. Mutual fund managers are institutional investors with similar investment strategies, such that it is likely that they independently make the same decisions. However, they might also influence each other such that subsequently investment decisions are aligned.

There is a large body of financial literature that provides empirical evidence in favour of the latter explanation, i.e. social influence among mutual fund managers (see e.g. Hirshleifer and Teoh (2008) for a recent survey). Social influence exclusively refers to the situation where fund managers directly influence each other. This is opposed to indirect influence that for instance arises via market price mechanisms. The empirical literature on social influence among mutual fund managers can be divided into two main strands depending on how fund managers learn about other fund managers' investment decisions. Observational influence, also known as social learning, is generally stated by the strand of literature that deals with herding behaviour (see e.g. Lakonishok et al. (1992), Wermers (1999), Walter and Weber (2006), Oehler and Wendt (2009) and Pomorski (2009)). The second important strand is concerned with fund managers' interpersonal communication and the resulting

[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/.

exchange of opinion, also known as word-of-mouth effect[3] (see e.g. Shiller and Pound (1989), Hong et al. (2005) and Pareek (2011)).
With this paper, I contribute to both strands of literature by empirically 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 of the way the influence takes place, I allow it to be heterogeneous among fund managers. This means I do not assume that a single fund manager is equally influenced by all other fund managers. As a major contribution, I relate both observational influence as well as the influence from the exchange of opinion to the prevailing market environment, i.e. to the state of the stock market (upturn or downturn).
In order to organise the empirical analysis, I use three hypotheses. With my first hypothesis, I state that social influence among fund managers generally represents a considerable effect. By the second hypothesis, I postulate that the magnitude of this influence varies over time according to the prevailing market environment and is lower (higher) during an economic upturn (downturn). 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. The theoretical foundations for the three hypotheses are outlined later in this paper (see chapter 4.3).
For the empirical strategy, I borrow from the literature on social interaction (see e.g. Manski (1993), Brock and Durlauf (2001), Moffitt (2001), Bramoullé et al. (2009), Blume et al. (2010) and Lee et al. (2010)). A fund manager's action (and therefore the dependent variable within the empirical analysis) is represented by the portfolio weight he assigns to a particular stock on a particular reporting date. Hence, I analyse how fund managers choose the distribution of their portfolio weights on a specific date and how they get influenced by contemporaneous portfolio allocations of other fund managers.

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

The choice of the dependent variable is motivated by the fact that the portfolio composition represents the relevant subset of the entirety of a fund manager's current opinions. The advantage of using 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 to or from the equity asset class. This is a crucial aspect for the verification of my second hypothesis that states a relationship between the magnitude of social influence and the prevailing market environment. Unlike quite all empirical studies before, fund managers' trades or stock picking activities are not considered as dependent variable within the empirical analysis. The reason is given by the fact that both would have to be inferred by portfolio changes. This is problematic, as portfolio holdings generally and therefore also in the dataset of this paper are only available on a quarterly or semi-annually basis, such that most round trip trades cannot be captured and the date on which the trade actually took place also remains uncertain. Elton et al. (2010) has shown that this fact strongly biases empirical results.

In order to be able to estimate the overall magnitude of social influence without the assumption of homogeneous influence, one has to know the topology of the underlying influential network. The topology provides the information by whom a single fund manager might or might not be influenced. I do not know the topology of the underlying network a priori, but unlike many authors before, I do neither presume a specific structure. Instead, I determine it endogenously. Therefore, I empirically analyse every possible single link between two fund managers.

After having determined the underlying influential network, the overall average magnitude of influence can be estimated. Thereafter, I separate observational influence and influence from the exchange of opinion by the working locations of the fund managers. Based on Hong et al. (2005), an intra-city link between two fund managers is defined as influence through the exchange of opinion, while all inter-city links are considered to be observational influence. This can be justified as follows. Fund managers working in the same city can regularly meet each other, e.g. for lunch, and thereby are able to maintain a social relationship, which facilitates an informal exchange of opinion. Fund managers working in different cities of course could also exchange their opinions via telephone or email, however, it is rather unlikely that major informal information travels via this channel. It is certainly more reasonable to assume that most of the fund managers working in different cities don't even know each other personally and therefore only observe each other. Observational influence in this context cannot arise by regarding other fund managers' quarterly or semi-annually reports, which although published contemporaneously refer to a preceding period. Hence, observational influence is rather based on the expectation how other fund managers act, given their portfolio decisions in previous periods. Nevertheless, observational influence also results from public interviews and statements of other fund managers as well as the general market mood, which is measured by diverse investors' opinions indices.

My dataset consists of portfolio holdings of roughly 2,000 equity mutual funds that had invested at least \$ 10 million in companies in 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 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 by 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 in 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. Note however that although I select fund managers according to a minimum investment in DAX30 stocks, I analyse the social influence on the investment decisions regarding all stocks in a fund manager's portfolio.

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 local preferences. The database of portfolio holdings has been enriched by all these control variables and therefore is unique. In total, 6 million portfolio weights (of different fund managers regarding different stocks on different dates) have been matched with stock specific data of about 17,000 companies whose stocks are held by at least one fund manager at at least one point of time.

Results show that an average fund manager puts 0.69% more portfolio weight on a particular stock, if his peers on average assign a weight to the corresponding position which is 1% higher compared to other stocks in the portfolio. The magnitude of this 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 stems from purely observing and imitating other fund managers. While the magnitude of this observational influence varies much over 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 4.2, I give a brief overview of the empirical literature on social influence among mutual fund managers. I use theoretical foundations about fund managers' behaviour in order to derive three testable hypotheses in chapter 4.3. In chapter 4.4, I present the empirical model and introduce a robust estimation procedure. Chapter 4.5 serves to present the dataset used for the empirical analysis in chapter 4.6. Chapter 4.7 sets out the checks for robustness which have been undertaken. Chapter 4.8 concludes.

4.2 Literature review

There are two main strands of the literature on social influence among mutual fund managers, which can be distinguished by the way a fund manager learns about other fund managers' behaviour. Observational influence is analysed by the strand of literature that deals with herding behaviour. A pioneer work in this field has been presented by Lakonishok et al. (1992). With their empirical measure, which has been applied in many studies since then,[4] they provide weak empirical evidence for herding behaviour among US pension fund managers. In a comprehensive study of a 20 years period, Wermers (1999) finds that mutual fund managers exhibit a slightly greater tendency to herd than pension fund managers. For the German market, Walter and Weber (2006) also detect herding behaviour among 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. Oehler and Wendt (2009) find that German fund managers show herding behaviour when they face market-wide cash inflows or cash outflows. 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 managers and provides evidence that influence on fund managers that performed poorly in the past is greater than on fund managers with moderate past performance.

The second important strand of empirical literature on fund managers' social influence deals with the influence by the exchange of opinion. First evidence in this domain 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

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

milestone is represented by the work of Hong et al. (2005) who provide empirical evidence that the investment decisions of fund managers 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, such that the authors conclude that fund managers exchange their opinions 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 of their working location. This assumption is justified by correlated trading behaviour that cannot be explained by style investing or local preferences.

4.3 Hypotheses

In order to organise the empirical analysis, I set up three hypotheses based on theoretical foundations about fund managers' behaviour. My first hypothesis is that social influence among fund managers represents a noteworthy effect. The theoretical literature about the behaviour of mutual fund managers offers a wide range of explanations in favour of this hypothesis.[5] In his famous book "Irrational exuberance", Shiller states that fund managers' actions are driven by human greed and fear (see Shiller (2000)). However, there also 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). Similarly, other fund managers might be perceived to have a better ability to process available pieces of information,

[5]See e.g. Bikhchandani and Sharma (2000) and Hirshleifer and Teoh (2003) for a survey of theoretical and empirical research on herd behaviour on financial markets or Hirshleifer and Teoh (2008) for a more recent survey about general social influence on financial markets.

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) and 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 analysis 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 both vary over time according to the prevailing market environment and are lower (higher) during an economic upturn (downturn). The theoretical foundation for this hypothesis is as follows. In a bull market fund managers 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 competitors who are not personally known to the fund manager during an economic downturn (upturn).

4.4 Methodology

4.4.1 Estimation of the magnitude of social influence

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) and Lee et al. (2010)):[6]

$$w_{ict} = \delta_t \sum_{j \neq i} \gamma_{ijt} w_{jct} + \mathbf{x}_{ict} \beta_{\mathbf{t}} + \epsilon_{ict}, \tag{4.1}$$

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 $\gamma_{ijt} \geq 0$.[7] The weighting coefficients are normalised, such that

$$\sum_{j \neq i} \gamma_{ijt} = \begin{cases} 1 & \text{if fund manager i is influenced by at least one other fund manager} \\ 0 & \text{otherwise} \end{cases} . \tag{4.2}$$

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

[6]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.

[7]More generally 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.

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 influence the fund managers have on each other.

Regarding the error term of the model, I allow ϵ_{ict} to be 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 on a given reporting date 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 across 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 4.1 can be rewritten in a matrix form

$$\mathbf{w}_t = \delta_t \mathbf{\Gamma_t} \mathbf{w}_t + \mathbf{X}_t \beta_\mathbf{t} + \epsilon_t. \tag{4.3}$$

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 4.3

$$\mathbf{w}_t = \left(\mathbf{I} - \delta_t \mathbf{\Gamma_t}\right)^{-1} \left(\mathbf{X}_t \beta_\mathbf{t} + \epsilon_t\right). \tag{4.4}$$

it follows that

$$\mathrm{Cov}(\mathbf{\Gamma_t}\mathbf{w}_t, \epsilon_t) = \mathrm{Cov}(\mathbf{\Gamma_t}\left(\mathbf{I} - \delta_t \mathbf{\Gamma_t}\right)^{-1} \left(\mathbf{X}_t \beta_\mathbf{t} + \epsilon_t\right), \epsilon_t) = \sigma^2_{\epsilon_t}\ tr(\mathbf{\Gamma_t}\left(\mathbf{I} - \delta_t \mathbf{\Gamma_t}\right)^{-1}). \tag{4.5}$$

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 upwardly biased.[8] 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 4.3 is estimated by a 2SLS estimator using the instruments $\mathbf{Z} = [\mathbf{\Gamma_t X}_t, \mathbf{X}_t]$. In the appendix, I show 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

$$\hat{\lambda}_t = (\mathbf{Q}'\mathbf{Z}(\mathbf{Z}'\mathbf{Z})^{-1}\mathbf{Z}'\mathbf{Q})^{-1}\mathbf{Q}'\mathbf{Z}(\mathbf{Z}'\mathbf{Z})^{-1}\mathbf{Z}'\mathbf{w}_t, \tag{4.6}$$

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 4.4. 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

$$\hat{\hat{\lambda}}_t = (\tilde{\mathbf{Z}}'\mathbf{Q})^{-1}\tilde{\mathbf{Z}}'\hat{\mathbf{w}}_t. \tag{4.7}$$

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

$$V(\hat{\hat{\lambda}}_{\mathbf{t}}) = (\tilde{\mathbf{Z}}'\mathbf{Q})^{-1}\tilde{\mathbf{Z}}'\hat{\Omega}\tilde{\mathbf{Z}}(\mathbf{Q}'\tilde{\mathbf{Z}})^{-1}, \tag{4.8}$$

with the block matrix $\hat{\Omega}$ that contains the estimates of the error variance and the within portfolio correlation obtained by the second step.

[8] Lee (2002) has shown that this bias vanishes, if the overall influence of an individual is very small. This applies if the matrix $\mathbf{\Gamma_t}$ is dense. My results however suggest that the influential network of fund managers is sparse, such that the influence of a single fund manager indeed cannot be ignored.

4.4.2 Determination of the underlying influential network

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 to make assumptions about its structure. Hong et al. (2005) for instance assume that γ_{ijt} is only different from 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 more strongly 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 different from 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 from the exchange of opinions as well as from observational learning. For this reason, I do not impose any assumptions on the structure of $\mathbf{\Gamma_t}$, but determine it endogenously. Therefore, I estimate Equation 4.3 for every possible combination[9] of two fund managers i and j by setting

$$\gamma_{ijt} = \begin{cases} 1 & \text{if } i = i^* \text{ and } j = j^* \\ 0 & \text{otherwise} \end{cases}, \tag{4.9}$$

where fund managers i^* and j^* are those fund managers who are under consideration for the estimation of a particular combination. The influence of fund manager j^* on fund manager i^* is then given by δ_t. As stated above, Equation 4.3 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 4.9 introduces an omitted variable problem, because the influence of fund managers $j \neq j^*$

[9] 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 on a particular reporting date, such that a social influence might be considered. Otherwise, γ_{ijt} is set to zero. This is a reasonable approach, because the distribution of a fund manager's portfolio weights cannot be influenced by other fund managers who hold completely different portfolios.

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 one would have to use 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[10] 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 $\gamma_{i^*j^*t}$.

4.4.3 Dealing with the problem of "zero weights"

One remaining important question is how to deal with "zero weights". Portfolio 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 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

[10] 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.

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 2,000 largest companies. This reduces the problem. But the risk of false inference is still high, if fund managers tend to 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 4.3. Hence, if a particular stock is not held by a particular fund manager on a specific date, then the theoretical observation of the resulting zero portfolio weight is dropped. 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 conditional on holding the stock and putting a specific weight on it. The influence for not holding a particular stock is not captured. This might restrict the generality of my conclusions. Nevertheless, it ensures robust results, because the magnitude of influence is rather underestimated. Note that on the right hand side of Equation 4.3, 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 on a specific reporting date. This can be illustrated by having a closer look at the structure of $\mathbf{\Gamma_t}$, which is given by

$$\mathbf{\Gamma_t} = \begin{bmatrix} \mathbf{0}_{C_{1t}\times C_{1t}} & \gamma_{12t}\mathbf{M}_{C_{1t}\times C_{2t}} & \cdots & \gamma_{1Nt}\mathbf{M}_{C_{1t}\times C_{Nt}} \\ \gamma_{21t}\mathbf{M}_{C_{2t}\times C_{1t}} & \mathbf{0}_{C_{2t}\times C_{2t}} & \cdots & \gamma_{2Nt}\mathbf{M}_{C_{2t}\times C_{Nt}} \\ \vdots & \vdots & \ddots & \vdots \\ \gamma_{N1t}\mathbf{M}_{C_{Nt}\times C_{1t}} & \gamma_{N2t}\mathbf{M}_{C_{Nt}\times C_{2t}} & \cdots & \mathbf{0}_{C_{Nt}\times C_{Nt}} \end{bmatrix}, \qquad (4.10)$$

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 4.3 is given by

$$\mathbf{w}_t = \begin{bmatrix} w_{11t} \\ w_{12t} \\ w_{21t} \end{bmatrix}. \tag{4.11}$$

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

$$\mathbf{\Gamma_t} = \left[\begin{array}{cc|c} 0 & 0 & \gamma_{12t} \\ 0 & 0 & 0 \\ \hline \gamma_{21t} & 0 & 0 \end{array}\right], \tag{4.12}$$

such that the product

$$\mathbf{\Gamma_t}\mathbf{w}_t = \begin{bmatrix} \gamma_{12t}w_{21t} \\ 0 \\ \gamma_{21t}w_{11t} \end{bmatrix} \tag{4.13}$$

contains zeros.

4.5 Data

4.5.1 Construction of the variables

The data regarding portfolio compositions of mutual funds has been obtained from the Thomson Reuters ownership database. I selected only funds that had invested at least \$ 10 million in companies in the DAX30 as of December 31^{st} 2010. For these funds all obtainable sets of portfolios compositions (not only stockholdings of DAX30 companies) 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 corresponding 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 1,943 funds with 5,809,739 portfolio weights.[11] On December 31^{st} 2010, the total money invested by these funds in companies in 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 important to find strong exogenous variables that explain their investment behaviour (matrix $\mathbf{X}_t$ in Equation 4.3). Otherwise, spurious correlation might be interpreted as intentional influence. In his survey about the investment behaviour of fund managers, Arnswald (2001) detects that investment decisions regarding a particular stock are primarily based on fundamental values, past stock returns and a general portfolio optimisation. In order to capture these components, I enriched the database of portfolio weights by market data obtained from Bloomberg. For 16,732 companies out of those that are held by at least one fund manager on at least one reporting date, stock prices and analysts' consensus price targets as well as the mean value of the consensus earnings forecasts referring to the three fiscal years following a particular reporting date have been obtained. Moreover, the corresponding P/E ratio has been retrieved. Comparability is ensured by converting all quotes into euro with the prevailing exchange rates. This market data has then been matched with the portfolio data in the following way. For every publication date of portfolio weights in the database, the three months' average and volatility of daily stock returns in the preceding quarter have been calculated for all 16,732 companies and assigned to the portfolio weights that fund managers chose for these companies. The same assignment has been done for price targets, averaged earnings forecasts and P/E ratios on a given reporting date. The two former have both been normalised through the division by the stock price, such that these variables represent forecasted returns.

Portfolio decisions depend on fund managers' utility functions as well as their restrictions regarding the investment universe. A manager of a growth fund for

[11] In order to put these numbers into a perspective, note that in a comparable context e.g. Hong et al. (2005) used data of 1,635 funds during a two-year period, which leads to less than a quarter of the number of observations used in this paper.

instance accepts a higher risk than a manager of a value fund does. Therefore, an investment opportunity with a moderate risk and an expected return of 3% might be attractive for the latter, while it most probably is not for the former. This is an important issue that has to be considered, if market data shall be employed as control variables. In order to account for the individual portfolio situation of a fund manager, I relate the market data of a given stock to the market data of all other stocks in his portfolio on a specific reporting date. Therefore, I took the difference between a stock related variable and its weighted average using portfolio weights of all other stocks that a particular fund manager holds on a given reporting date. 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 an exemplary portfolio with four stocks that are weighted with 50%, 25%, 12.5% and 12.5%, respectively. The past returns of these stocks are assumed to equal 3%, 1%, 2% and 5%, respectively. Now, the value of DIFF_RET for the first stock is calculated by $3\% - \frac{0.25 \cdot 1\% + 0.125 \cdot 2\% + 0.125 \cdot 5\%}{0.5} = 0.75\%$. This means, from the perspective of this exemplary fund manager, the first stock has a higher-than-average return. Therefore, it might appear to be attractive, which could explain a higher-than-average portfolio weight. The calculation of DIFF_RET for the remaining three stocks is analogous.

Turning back to the main determinants of investment decisions based on the survey evidence of Arnswald (2001), DIFF_PT, DIFF_EARN and DIFF_P/E account for stocks' fundamental values. Past stock returns are captured by DIFF_RET and portfolio optimisation is taken into account 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 be known.

Among all 1,943 fund managers in the database, there are 277 who 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 be 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 1,666 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. If there are several passive fund managers who replicate the same index or if an index is included in another index, the active fund manager's portfolio weights are likely to be significantly correlated with the portfolio weights of more than one passive fund manager. In this case, I used all relevant benchmark portfolio weights regarding a particular stock and took the weighted average according to the magnitude of the bivariate regression coefficients. 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 nearby. In order to account for this effect, I retrieved information about the location of the headquarters for the afore mentioned 16,732 companies from Thomson Reuters. 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.

4.5.2 Descriptive analysis

In order to illustrate how the group of the analysed 1,666 active fund managers is composed, table 4.1 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 4.2 shows the working locations of the managers of the analysed funds 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 4.3 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 on average a fund manager holds 156 stocks on a particular reporting date. Table 4.4 shows how the numbers of funds and available portfolio weights are distributed over the period from 2002 to 2010. The average number of analysed funds per half-year equals 1,164. This means that not all 1,666 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 4.5 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 stocks where he works near the headquarter the issuing 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 earnings ratio does not seem to be decisive for fund managers' portfolio se-

Table 4.1: 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 4.2: 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%			
	1,666	**100%**			

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

Table 4.3: 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 as 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 as the company whose stock he holds.

Table 4.4: 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	1,029
2004/I	167,069	1,007
2004/II	203,472	1,102
2005/I	211,041	1,084
2005/II	242,202	1,169
2006/I	248,259	1,201
2006/II	272,548	1,263
2007/I	274,041	1,261
2007/II	301,352	1,398
2008/I	332,090	1,401
2008/II	323,982	1,427
2009/I	342,310	1,461
2009/II	383,330	1,482
2010/I	311,922	1,082
2010/II	219,584	824
sum / mean	**4,399,889**	**1,164**

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

Table 4.5: 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 as 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 as the company whose stock he holds. The table contains the correlation coefficients. P-values are reported in parenthesis.

lections as the corresponding correlation coefficient is almost zero and not significant on a 10% level.

4.6 Results

4.6.1 Determination of the underlying influential network

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 fund manager fixed effects. The results are shown in table 4.6. 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. I estimate the coefficients of Equation 4.3 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.[12] For every half-year, I further remove all funds where less than 30 portfolios weights have been available. This ensures enough degrees of freedom for the empirical analysis. As described in chapter 4.4, 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. Remember 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

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

Table 4.6: OLS panel regression with fund manager fixed effects

	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 as 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 as the company whose stock he holds. The table contains the regression coefficients $\beta_\mathbf{t}$ that result from the estimation of equation 4.3 with $\delta_t = 0$ 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.

fund managers under consideration, then the columns of $\mathbf{Z}$ will 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

$$\mathbf{Z} = [\mathbf{\Gamma_t}[\mathbf{X}_t^{(1-6)}, \mathbf{c}], [\mathbf{X}_t^{(1-6)}, \mathbf{c}]], \tag{4.14}$$

with $\mathbf{c}$ being a column vector of ones. The matrix $\mathbf{X}_t^{(1-6)}$ contains the six variables (DIFF_RET, DIFF_VOLA, DIFF_EARN, BENCHMARK, CITY, COUNTRY) as explained above. Now, Equation 4.14 can be reformulated as

$$\mathbf{Z} = [\mathbf{\Gamma_t}\mathbf{X}_t^{(1-6)}, \mathbf{\Gamma_t}\mathbf{c}, \mathbf{X}_t^{(1-6)}, \mathbf{c}]. \tag{4.15}$$

The rows of $\mathbf{\Gamma_t}$ are normalised, such that the single row elements sum up to one. This yields $\mathbf{\Gamma_t}\mathbf{c} = \mathbf{c}$. 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 $\mathbf{Z} = [\mathbf{\Gamma_t}\mathbf{X}_t^{(1-3)}, \mathbf{X}_t]$, 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 publish their portfolio weights within the same month. Moreover, I require them to hold at that time at least 30 stocks in common, because the distribution of a fund manager's portfolio weights cannot be influenced by other fund managers who hold completely different portfolios. Furthermore, I do not examine the reciprocal influence of funds that belong to the same fund family, as this does not represent a form of external influence.

The overall average density of the resulting network equals 0.65%. On average, 59% of the links connect fund managers within the same world region (e.g. Europe, North America, etc.). 22% of the links represent relationships between fund managers working in the same country, while 8% of the links are due to intra-city connections.

4.6.2 Estimation of the magnitude of social influence

After having obtained the matrix $\mathbf{\Gamma_t}$, the two step procedure outlined in chapter 4.4 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 the set of instruments, where $\mathbf{X}_t^{(1-6)}$ contains the same column as $\mathbf{X}_t$ 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 4.7. 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 4.2, 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 (see appendix).

The average estimate of the coefficient δ_t equals 0.6878. This means that if a portfolio position is 1% higher weighted by the relevant fund managers of the underlying influential network, then a particular fund manager also puts 0.69% more weight on the relevant stock compared to other stocks in his portfolio. The magnitude of social influence might appear to be higher than results of other empirical studies suggest. Hong et al. (2005) for instance obtain a value of 0.13. Wermers (1999) finds that if 100 fund managers trade a particular stock in a quarter, then approximately 3 more funds would trade on the same side of the market in that stock than would be expected if stocks were choosing randomly. However, afore cited authors analyse fund managers' trades and stock picking behaviour and therefore examine changes of portfolio weights that occur during one quarter, while my study aims to shed light on the distribution of portfolio weights on a specific date. Moreover, Hong et al. (2005) only determine the magnitude of social influence that arises from the exchange of opinion, while I also consider observational influence.

Among the variables that are decisive for the portfolio selection, BENCH-

Table 4.7: Estimation results for the magnitude of social influence

	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)	1,116
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)	1,237
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)	1,262
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)	1,369
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)	1,411
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 as 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 as 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 δ_t and $\beta_{\mathbf{t}}$ of equation 4.3 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.

MARK 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, on 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 issuing 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, remember that the average portfolio weight equals 0.64%. The afore presented results show that after controlling for the key determinants of the portfolio selection, the effect of social influence among fund managers is statistically and economically significant. This corroborates my first hypothesis.

4.6.3 Fluctuations of social influence

Table 4.8 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 4.8 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

Table 4.8: 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%**

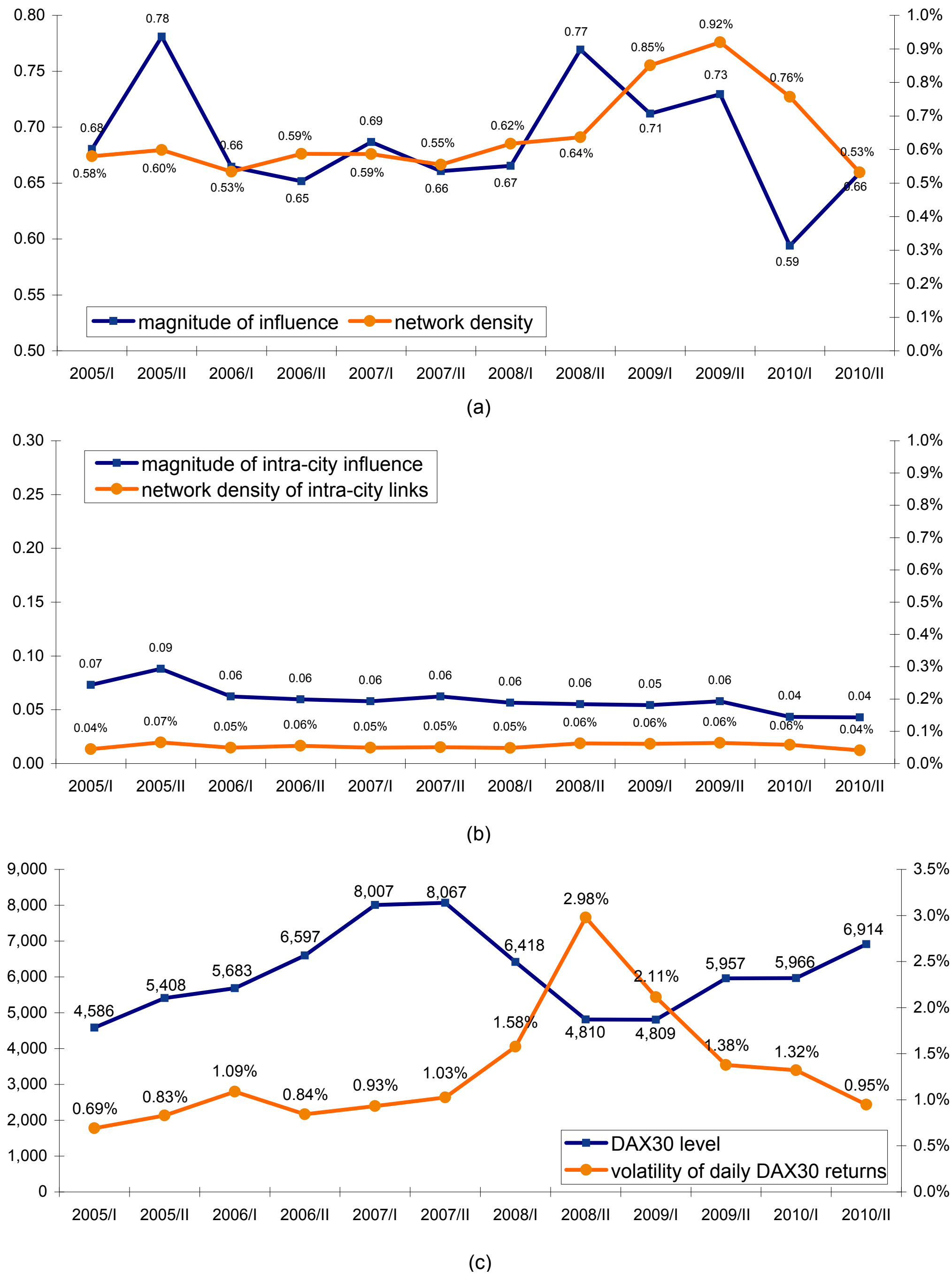
The first column displays the total network density. The second column shows the portion of network density that is generated by intra-city links. The third column also contains the portion of network density resulting from intra-city links, however, every link is weighted with the corresponding coefficient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

resulting weighted fraction of the total density is also displayed in table 4.8. The mean network density equals 0.65%. This means the underlying influential network is very sparse. On 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 the intra-city links and 8.62% of the average magnitude of social influence results from intra-city influence. The latter means that, on 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 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 4.1(a) shows the magnitude of influence as well as the network density. Figure 4.1(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 4.1(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 at 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 to below the level experienced before the crisis and returned 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 began to grow significantly in the first half-year of 2009 and returned 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 re-

Figure 4.1: DAX30 related fluctuation of social influence



(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.

muneration, such that they are more prone to align their 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 by whom they had also been (less strongly) influenced before. During the crisis, the number of fund managers by whom a particular fund manager was influenced increased notably. This led 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 over 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 in line 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.

4.7 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, i.e. a given presumed network which is not just determined within the empirical analysis. Therefore, I assumed that a fund manager can be influenced by any

Table 4.9: 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 δ_t 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.

other fund manager 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 weighting the influence of fund managers differently, I chose equal weights for every fund manager. The results can be seen in table 4.9 (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 upwardly biased through the usage of an endogenous network. Having a closer look at 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 4.9). 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 4.9 (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 of social influence compared the standard model, while specification IV yields a lower difference. This is in line 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.

4.8 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. On average, a fund manager puts 0.69% more portfolio weight on a particular stock, if the fund managers in his reference group assign a weight to the corresponding position which is 1% higher compared to other stocks in the portfolio. Looking at intra-city influence, I found 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 in line with the fact that the influence from the exchange of opinion, defined as intra-city influence, does not alter with the prevailing market environment. The empirical findings of this paper regarding the behaviour of fund managers can be taken into account while creating remuneration schemes in order to avoid negative outcomes that might result from a herding behaviour during a market downturn.

Appendix

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 4.3 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 4.4 in the following way

$$\mathbf{\Gamma_t w}_t = \mathbf{\Gamma_t} \left(\mathbf{I} - \delta_t \mathbf{\Gamma_t}\right)^{-1} \left(\mathbf{X}_t \beta_{\mathbf{t}} + \epsilon_t\right). \tag{4.16}$$

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

$$\mathbf{\Gamma_t w}_t = \mathbf{\Gamma_t} \left(\mathbf{I} + \delta_t \mathbf{\Gamma_t} + \delta_t^2 \mathbf{\Gamma_t}^2 + \ldots\right) \left(\mathbf{X}_t \beta_{\mathbf{t}} + \epsilon_t\right). \tag{4.17}$$

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 4.3.

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