Soziale Interaktion auf Finanzmärkten

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Verzeichnis der enthaltenen Aufsätze

Die folgenden Aufsätze sind Bestandteil dieser kummulativen Dissertation:

1. Frederik König (2012)
   Does Social Interaction destabilise Financial Markets?

2. Frederik König (2012)
   Analyst Behaviour: the Geography of Social Interaction

3. Frederik König (2012)
   Fluctuations of Social Influence: Evidence from the Behaviour of Mutual Fund Managers during the Economic Crisis 2008/09

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1 Einleitung

Die vorliegende kumulative Dissertation behandelt das Thema der sozialen Interaktion auf Finanzmärkten. Unter dem sehr weit gefassten Begriff der sozialen Interaktion wird im Folgenden die aufeinander bezogene Wechselwirkung von Individuen verstanden. Dies beinhaltet die Übertragung von Informationen im Rahmen der direkten Kommunikation. Darüber hinaus schließt soziale Interaktion aber auch das Empfangen von Informationen bzw. Informationssignalen ein, die aus der Beobachtung des Handels anderer Individuen abgeleitet werden. Soziale Interaktion umfasst jedoch nicht indirekte Mechanismen wie zum Beispiel die Entwicklung der makroökonomischen Lage oder die Entstehung von Marktpreisen, von denen gleichermaßen eine Wechselwirkung ausgehen kann.

Im finanztheoretischen Kontext ist die Berücksichtung von sozialen Effekten relativ neu und steht in starkem Widerspruch zur klassischen Finanztheorie, der *Modern Finance*. Diese Lehre, die zu Beginn der zweiten Hälfte des letzten Jahrhunderts entstand, besteht im Wesentlichen aus den folgenden drei Säulen: der Kapitalstrukturtheorie (Modigliani and Miller, 1958), dem *Capital Asset Pricing Model* (Sharpe, 1964, Lintner, 1965), welches auf der Portfoliotheorie von Markowitz (1952) fußt, sowie der Optionspreistheorie (Black and Scholes, 1973). Über allem steht die Hypothese von effizienten Finanzmärkten (Fama, 1970). Diese beinhaltet die Annahme, dass unter allen oder zumindest innerhalb eines Großteils der Finanzmarktteilnehmer Einigkeit in Bezug auf den fairen Wert eines Wertpapiers besteht und der Marktpreis diesen fundamentalen Wert jederzeit widerspiegelt.

Die Effizienzmarkthypothese ermöglich zwar die Beschreibung von Finanzmärkten auf Basis einfacher mathematischer Modelle, jedoch fußt die starke Simplifizierung auf teils sehr unrealistischen Annahmen, allen voran die Homogenität der Marktteilnehmer. Wäre diese gegeben, so gäbe es beispielsweise keinen oder nur sehr geringen Wertpapierhandel, welches nicht in Einklang mit den täglich beobachteten Handelsvolumina stünde (Milgrom and Stokey, 1982). Zur Widerlegung der Existenz effizienter Finanzmärkte zeigte Shiller (1981) Anfang der achtziger Jahre, dass Aktienkurse nicht jederzeit den fundamentalen Wert widerspiegeln können, da sie deutlich volatiler als die zugrunde liegenden fundamentalen Informationen sind. Auf ähnliche Thematik abzielend enthüllte 1985 die empirische Untersuchung von de Bondt and Thaler (1985) eine deutliche Überreaktion von Marktteilnehmern auf negative fundamentale Informationen und läutete damit einen Paradigmenwechsel ein. Seitdem wurde eine Vielzahl von empirischen Studien veröffentlicht, die Anomalien im Sinne der klassischen Finanztheorie aufdeckten.[1] Diese zu erklären entstand eine neue, als *Behavioural Finance* bekannte Finanztheorie, die von der Annahme des *homo oeconomicus* abweicht und mathematische Modelle der klassischen Finanztheorie um psychologische und soziologische Verhaltensmuster der Marktteilnehmer ergänzt. Wesentliche Beiträge stammen von den Psychologen Daniel Kahneman und Amos Tversky, die bereits 1979 mit der Vorstellung einer neuen Erwartungstheorie, der *Prospect Theory*, ein Fundament der neuen Lehre schufen (Kahneman and Tversky, 1979).[2] Wenngleich die Berücksichtigung von kognitiven Verzerrungen und die damit einhergehende Annahme von heterogenen Investoren ein getreueres Bild der Realität zeichnen, so könnte es doch vorkommen, dass sich die Effekte bei einer großen Anzahl von Marktteilnehmern ausgleichen (Friedman, 1953). Besondere Bedeutung wird daher der Berücksichtigung von Aspekten der Soziologie zuteil. Diese beschreiben die gegenseitige Beeinflussung von Marktteilnehmern, die

[1] Für einen umfassenden Überblick siehe beispielsweise Barberis and Thaler (2003).

[2] Eine ausführliche Aufbereitung psychologischer Aspekte findet sich zum Beispiel in dem Buch von Shefrin (2000).

aus der sozialen Interaktion erwächst, und je nach Konstellation der Beziehungen dafür sorgt, dass das Gesetz der großen Zahlen nicht mehr greift und Marktpreise erheblich verzerrt werden können (Banerjee, 1992, Bikhchandani et al., 1992).
Die Gründe für eine wechselseitige Beeinflussung durch soziale Interaktion sind vielfältig und hängen davon ab, ob Marktteilnehmer sich nur gegenseitig beobachten oder ob sie auch direkt miteinander kommunizieren. Im Falle des reinen Beobachtens können allen voran irrationale, mit der Psychologie der Marktteilnehmer erklärbare Motive zum Tragen kommen. So kann zum Beispiel das Handeln anderer adaptiert werden, wenn diese in der Überzahl sind, da dies durch die Annahme, dass „sich die Masse nicht irrt", eine Art Sicherheitsgefühl erzeugt (Keynes, 1936). Gleichermaßen besteht die Angst vor einem starken Bedauern, wenn man sich für eine unpopuläre Handlungsalternative entscheidet und diese sich als falsch erweist (Bell, 1982). Generell werden Fehlentscheidungen als weniger schlimm angesehen, wenn sie von einer Vielzahl anderer Marktteilnehmer ebenfalls getroffen wurden (Scharfstein and Stein, 1990). Nicht zuletzt könnte auch ein Konformitätsstreben Antrieb für das Nachahmen anderer Marktteilnehmer sein (Bikhchandani et al., 1992). Gleichwohl gibt es aber auch durchaus rationale Beweggründe, die das Beobachten und Imitieren des Handelns anderer Marktteilnehmer rechtfertigen. Letztere könnten beispielsweise, zumindest subjektiv wahrgenommen, bessere Informationen zur Verfügung haben (Welch, 1992, Ellison and Fudenberg, 1993, 1995, Avery and Zemsky, 1998, Bala and Goyal, 1998, Bikhchandani et al., 1998). Gleichermaßen könnte es auch sein, dass andere Marktteilnehmer eine bessere Fähigkeit haben, öffentliche Informationen zu verarbeiten (Banerjee, 1992, Bikhchandani et al., 1992). Im Bereich der institutionellen Investoren haben zudem Fehlentscheidungen geringere Konsequenzen, wenn sie auch von Marktteilnehmern mit einer höheren Reputation getroffen wurden (Scharfstein and Stein, 1990, Dasgupta and Prat, 2008). Ferner sind in diesem Zusammenhang bei einem Vergütungssystem, welches auf die relative Leistung im Vergleich zur Konkurrenz ausgerichtet ist, geringere Gehaltseinbußen zu erwarten, wenn

man die eigenen Investitionseinscheidungen an denen anderer ausrichtet (Maug and Naik, 1996).
Der Einfluss durch die direkte Kommunikation zwischen Marktteilnehmern basiert ebenfalls zunächst auf irrationalen Komponenten. So mag zum Beispiel der Meinungsaustausch mit anderen Marktteilnehmern bereits bekannte Argumente bekräftigen und somit die wahrgenommene Unsicherheit reduzieren (DeMarzo et al., 2003). Aber auch ganz rational betrachtet kann der einzelne Marktteilnehmer durch den Austausch von Meinungen bzgl. Investitionsopportunitäten und Bewertungsansätzen profitieren. Dies gilt im Übrigen auch für institutionelle Investoren, für die, obwohl sie als Konkurrenten auftreten, ein Ideenaustausch lohnend sein kann (Eren and Ozsoylev, 2006, Stein, 2008, Gray, 2010).
Internationale Finanzmärkte sind in den zurückliegenden Jahren von starken Verwerfungen gekennzeichnet. Nach einer vorangegangenen weltweit ausgeprägten Boomphase sorgte 2007 das Platzen der Immobilienblase in den USA für den Beginn einer globalen Finanzkrise. Diese griff 2008 nach dem Zusammenbruch der Investmentbank Lehman Brothers auf die Realwirtschaft über und führte zu einer weltweiten Rezession. Zur Bekämpfung der negativen Auswirkungen setzten viele Staaten stabilisierende Maßnahmen ein und erhöhten dadurch die eigene Finanzverschuldung, was wiederum die aktuell noch andauernde Staatschuldenkrise hervorrief. Vor dem Hintergrund der zahlreichen Motive für eine gegenseitige Beeinflussung von Finanzmarktteilnehmern und den möglichen Auswirkungen auf die Preisbildungsprozesse, stellt sich die Frage, wie diese Effekte in den Kontext der skizzierten Geschehnisse auf internationalen Finanzmärkten einzuordnen sind.

1.1 Forschungsschwerpunkte der Dissertation

Ziel dieser Dissertation ist die empirische Analyse von Auswirkungen der sozialen Interaktion zwischen Akteuren auf Finanzmärkten. Der Fokus liegt dabei auf Aktienmärkten.

In meinem ersten Aufsatz mit dem Titel „Does Social Interaction destabilise Financial Markets?“ stelle ich ein Marktpreismodell vor, welches dem Einfluss durch soziale Interaktion Rechnung trägt. Mit Hilfe dieses Modells gehe ich der Fragestellung nach, ob soziale Interaktion zwischen Marktteilnehmern, unabhängig davon, ob es sich um Privatpersonen oder institutionelle Investoren handelt, eine stabilisierende oder eine destabilisierende Wirkung auf Finanzmärkte hat.

Während der erste Aufsatz eine Betrachtung der Makroebene darstellt, steige ich mit meinem zweiten Aufsatz mit dem Titel „Analyst Behaviour: the Geography of Social Interaction“ in die Analyse der Mikroebene einzelner Finanzmarktteilnehmer ein. Dazu untersuche ich das Verhalten von Aktienanalysten, die als wesentlicher Impulsgeber für Finanzmärkte gelten. Konkret untersuche ich, ob Analysten stärker von anderen Analysten beeinflusst werden, wenn diese im gleichen Land arbeiten oder wenn sogar ein regelmäßiger Informationsaustausch erfolgt. Beides setzte ich ins Verhältnis zum jeweiligen Marktumfeld. Hierfür vergleiche ich das Verhalten im Zeitraum vor und während der jüngsten Wirtschaftskrise.

In meinem dritten Aufsatz mit dem Titel „Fluctuations of Social Influence: Evidence from the Behaviour of Mutual Fund Managers during the Economic Crisis 2008/09“ beschäftige ich mich mit der sozialen Interaktion zwischen institutionellen Investoren, im Speziellen zwischen Fondsmanagern. Diese verwalten in etwa ein Drittel des frei handelbaren Aktienvermögens und haben folglich einen nennenswerten Einfluss auf Finanzmärkte. Mit Hilfe einer neuartigen Schätzmethode[3] bestimme ich die Größe des sozialen Einflusses und untersuche auch hier temporale Variationen im Verhältnis zum zu Grunde liegenden Marktumfeld. Des Weiteren differenziere ich die zwei Arten der sozialen Interaktion, das heißt reine Beobachtung zum einen und Kommunikation zum anderen und untersuche getrennt deren Bedeutung vor und während der Wirtschaftskrise 2008/09.

[3]Siehe Kelejian and Prucha (1998), Lee (2003) und Bramoullé et al. (2009).

1.2 Methodik

Alle empirischen Untersuchungen dieser Dissertation basieren auf dem linearen Modell der ökonometrischen Literatur über soziale Interaktion. In einer richtungweisenden Arbeit formulierte Manski (1993) dieses wie folgt:

$$a_i = \mathbf{x}_i\beta + \sum_j \gamma_{ij}\mathbf{x}_j\nu + \delta\sum_j \gamma_{ij}a_j + \epsilon_i. \tag{1.1}$$

Dabei steht a_i für die mathematisch stetige Aktion eines Individuums. Der Zeilenvektor $\mathbf{x}_i$ beinhaltet exogene Variablen, die ein Individuum ohne den Einfluss anderer zu einer bestimmten Handlung veranlassen. Der entsprechende lineare Zusammenhang wird durch den Koeffizienten β ausgedrückt. Daneben gibt es noch zwei Komponenten, die den sozialen Einfluss modellieren. Zum einen wird angenommen, dass ein Individuum auch durch die exogenen Variablen anderer Individuen beeinflusst wird. Dies wird durch den zweiten Term in Gleichung 1.1 ausgedrückt und als exogener sozialer Einfluss bezeichnet. Zum anderen wird davon ausgegangen, dass eine direkte Beeinflussung durch die gewählte Aktion anderer erfolgt. Dieser dritte Term in Gleichung 1.1 berücksichtigt den sogenannten endogenen sozialen Einfluss. Der lineare Zusammenhang beider Komponenten in Bezug auf die Handlung eines Individuums wird durch die Koeffizienten ν und δ dargestellt. Während β und ν Vektoren sind, so handelt es sich bei δ um ein Skalar. Die Berücksichtigung des endogenen sozialen Einflusses sollte mit den vorangegangenen Beschreibungen im Hinblick auf die Motive und Beweggründe einer gegenseitigen Beeinflussung plausibel erscheinen. Die Einbeziehung eines exogenen sozialen Einflusses hingegen bedarf einer gesonderten Erklärung. Der Ursprung liegt in der Literatur, die das Verhalten von Jugendlichen erforscht.[4] In diesem Zusammenhang ist es beispielsweise durchaus denkbar, dass ein Jugendlicher nicht nur durch das Bildungsniveau seiner Eltern, sondern auch durch das Bildungsniveau der Eltern seiner Freunde geprägt wird. Im finanztheoretischen Kontext hingegen,

[4] Ein aktuelles Beispiel repräsentiert die Arbeit von Bramoullé et al. (2009).

in welchem sich exogene Variablen eher auf vorhandene Informationen und bestehende Portfolien beziehen, erscheint die Berücksichtung eines exogenen sozialen Einflusses wenig sinnvoll. Folglich kommt diese Komponente in meinen empirischen Analysen nicht zum Tragen.

Die Koeffizienten γ_{ij} in Gleichung 1.1 geben an, wie stark der Einfluss des Individuums j auf i im Vergleich zu anderen Individuen gewichtet wird. Um sicherzustellen, dass ν und δ den gesamten Betrag des sozialen Einflusses messen, gilt folgende Normierung:

$$\sum_j \gamma_{ij} \stackrel{!}{=} 1. \tag{1.2}$$

In seinem Artikel geht Manski (1993) davon aus, dass sich alle Individuen in gleicher Art und Weise beeinflussen. Folglich setzt er $\gamma_{ij} = \frac{1}{N}$, wobei N die Anzahl der Individuen ist, von denen sozialer Einfluss ausgeht (Referenzgruppe). Da dies die implizite Annahme beinhaltet, dass sich ein Individuum auch selbst beeinflusst, nimmt Moffitt (2001) in einer Weiterentwicklung des Modells an, dass $\gamma_{ii} = 0$. Mit der Normierungsbedingung aus Gleichung 1.2 ergibt sich hieraus $\gamma_{ij} = \frac{1}{N-1}$. In Anlehnung an die Modelle der räumlichen Ökonometrie, *spatial econometrics*,[5] berücksichtigen Bramoullé et al. (2009) und Lee et al. (2010) eine völlig freie Netzwerkstruktur, in der nicht jedes Individuum den Einfluss anderer in gleicher Art und Weise gewichtet.

Während ich in meinem ersten Aufsatz aufgrund der Analyse auf der Makroebene die Annahme treffe, dass alle Marktteilnehmer den Einfluss anderer gleich gewichten, so gilt beim zweiten Aufsatz die Prämisse, dass eine gleichförmige Beeinflussung nur innerhalb von definierten Referenzgruppen erfolgt. Im dritten Aufsatz wird zunächst das zu Grunde liegende inhomogene Netzwerk des sozialen Einflusses ermittelt und anschließend die empirische Analyse hierauf aufgesetzt.

[5] Siehe hierzu unter anderem Kelejian and Prucha (1998), Lee (2002), Lee (2003), Lee (2007), Kapoor et al. (2007) und Kelejian and Prucha (2010). Einen umfassenden Literaturüberblick gibt Anselin (2010).

Das Modell aus Gleichung 1.1 kann wie folgt in die Vektorschreibweise überführt werden:[6]

$$\mathbf{a} = \mathbf{X}\beta + \delta\Gamma\mathbf{a} + \epsilon. \tag{1.3}$$

Löst man Gleichung 1.5 nach dem Vektor der Aktionen einzelner Individuen **a** auf, so ergibt sich:

$$\mathbf{a} = (\mathbf{I} - \delta\Gamma)^{-1}(\mathbf{X}\beta + \epsilon), \tag{1.4}$$

wobei **I** die Einheitsmatrix ist. Es zeigt sich, dass der Einfluss der exogenen Variablen mit $(\mathbf{I} - \delta\Gamma)^{-1}$ multipliziert wird. Dies repräsentiert den sogenannten sozialen Multiplikator (Glaeser and Scheinkman, 2001, Glaeser et al., 2003). Geht man davon aus, dass sozialer Einfluss gleichgerichtet ist, das heißt, dass eine Erhöhung (Verringerung) des Wertes der Handlung anderer Individuen auch zu einer Erhöhung (Verringerung) des Wertes der Aktion eines einzelnen Individuums führt, so gilt $\delta \geq 0$. Mit dieser Voraussetzung ist der soziale Multiplikator positiv und der Wert der durchschnittlichen Aktion immer größer als er es ohne den Einfluss soziale Interaktion wäre. Diese Annahme ist sinnvoll, wenn es beispielsweise darum geht Herdenverhalten bei Kauf- und Verkaufsentscheidungen zu modellieren. In diesem Falle würde ein erhöhter sozialer Einfluss dazu führen, dass bestimmte Wertpapiere stärker ge- oder verkauft werden, als dies bei reiner Betrachtung der exogenen Variablen der Fall wäre. Wenn es allerdings darum geht, den Einfluss sozialer Interaktion im Rahmen des Preisbildungsprozesses zu berücksichtigen, so erscheint das Vorhandensein eines sozialen Multiplikators wenig angemessen, da dies bedeuten würde, dass Wertpapiere durch soziale Beeinflussung permanent überbewertet werden. Jedoch kann in Bezug auf Krisenzeiten durchaus angenommen werden, dass sozialer Einfluss auch zu einer Unterbewertung von Wertpapieren führt. Da der erste Aufsatz soziale Interaktion im Rahmen eines Marktpreismodells berücksichtigt, wird das Standardmodell in der folgender Art und Weise modifiziert:

[6] Hier erfolgt aus genannten Gründen keine Berücksichtigung des exogenen sozialen Einflusses.

$$\mathbf{a} = \mathbf{X}\beta + \delta\left(\Gamma\mathbf{a} - \mathbf{X}\beta\right) + \epsilon, \tag{1.5}$$

wodurch das Entstehen eines sozialen Multiplikators verhindert wird.[7] Im zweiten Aufsatz stellt sich diese Thematik nicht, da die Analyse ohne Einbeziehung von exogenen Variablen durchgeführt wird. Im dritten Aufsatz repräsentiert die Handlung eines Individuums das Portfoliogewicht, welches ein institutioneller Investor einem bestimmten Wertpapier zuordnet. Hier wiederum ist die Berücksichtigung eines sozialen Multiplikators adäquat, da ein Fondsmanager im Falle der sozialen Beeinflussung geneigt ist, das Portfoliogewicht zu erhöhen, wenn andere Fondsmanager ihre Portfolien ebenfalls mit einem bestimmten Wertpapier aufstocken.

1.3 Daten

Zur Analyse der speziellen Fragestellungen in den einzelnen Aufsätzen der Dissertation sind sehr unterschiedliche Daten erforderlich. Nachfolgend soll beschrieben werden, wie die einzelnen Datensätze zusammengestellt wurden und aus welchen Quellen die Daten stammen.

In meinem ersten Aufsatz untersuche ich, ob der Einfluss durch soziale Interaktion eine stabilisierende oder destabilisierende Wirkung auf Finanzmärkte hervorruft. Dazu analysiere ich die täglichen Kursverläufe der Aktien, die per Dezember 2010 im DAX30 Index vertreten waren und betrachte jeweils die Differenz zwischen Marktpreis und fundamentalem Wert. Letzterer lässt sich aus der Analystenkonsensusschätzung für Kursziele herleiten. Diese entstammen der Analystendatenbank I/B/E/S, die von dem Datenbankanbieter Thomson Reuters betrieben wird. Um einen konsistenten Datensatz zu erhalten, in dem beispielsweise Aktiensplits in gleicher Art und Weise berücksichtigt sind, entstammen die Kursdaten ebenfalls der I/B/E/S Datenbank. Der gewählte Un-

[7] Für die entsprechende mathematische Herleitung wird auf den Anhang A.2 des ersten Aufsatzes verwiesen.

tersuchungszeitraum vom 1. Januar 2004 bis zum 31. Dezember 2010 berücksichtigt sowohl die Boomphase vor der jüngsten Finanz- und Wirtschaftskrise, als auch die Krise an sich.
Zur Erforschung des sozialen Einflusses zwischen Aktienanalysten im zweiten Aufsatz verwende ich die Kurszielschätzungen der einzelnen Analysten. Das Kursziel reflektiert den Wert, den ein Analyst einer Aktie beimisst und repräsentiert somit auch die Meinung und Erwartung eines Analysten. Für die empirische Untersuchung werden Schätzungen bezüglich der Aktien, die per Mai 2010 im DAX30 Index beinhaltet waren verwendet. Diese entstammen wiederum der I/B/E/S Datenbank. Darüber hinaus habe ich den Datensatz noch um Kurszielschätzungen ergänzt, die auf der Internetseite www.aktiencheck.de veröffentlich werden. Während die I/B/E/S Datenbank primär auf große Investmentbanken fokussiert ist, so konnte durch die Daten von www.aktiencheck.de auch eine Berücksichtung kleinerer Researchboutiquen und Investmentnewsletter erreicht werden, die gleichermaßen auf den Meinungsbildungsprozess von Investoren einwirken. Zum Abruf der Daten von der Internetseite habe ich ein Tool entwickelt, das den Abruf und die automatische Auswertung von insgesamt rund 27.000 Analystenberichten ermöglichte. Hieraus konnten knapp 17.000 Kurszielschätzungen gewonnen werden. Der gewählte Beobachtungszeitraum vom 1. Januar 2005 bis zum 31. Mai 2010 ermöglicht auch hier eine Verhaltensanalyse in Bezug auf die unterschiedlichen vorherrschenden Marktgegebenheiten. Zur Erforschung des Einflusses, der aus der Kommunikation und dem damit zusammenhängenden Meinungsaustausch erwächst, habe ich zudem eine Umfrage unter den Analysten in meiner Datenbank durchgeführt. Die Intention war es herauszufinden, welche Analysten miteinander kommunizieren. Um nicht die Rücklaufquote zu gefährden, die letztlich bei zufriedenstellenden knapp 30% lag, wurden Analysten allerdings nicht direkt nach Namen gefragt, sondern über diverse Kriterien versucht, das zugrunde liegende Kommunikationsnetzwerk zu rekonstruieren. Je nach Beobachtungszeitpunkt ist dies mit einer Wahrscheinlichkeit von 60%-80% für jene knapp 200 Analysten möglich, die an der Umfrage teilgenommen haben.

Der dritte Aufsatz behandelt das Investitionsverhalten von Fondsmanagern, welches sich in den Portfoliogewichten äußert, die sie bestimmten Aktien zuordnen. Daten über diese Gewichtungen werden von dem Datenbankanbieter Thomson Reuters gesammelt und in einer sogenannten Eigentümerdatenbank (*Ownership Database*) abgelegt. Zum Abruf dieser Daten ist entweder ein Unternehmen auszuwählen, so dass alle (bekannten) Eigentümer ausgegeben werden können oder aber es erfolgt die Selektion eines bestimmten Fonds, für welchen dann alle im Portfolio befindlichen Aktien mit den dazugehörigen Gewichten angezeigt werden. Da ein für die empirische Analyse erforderlicher Abruf aller Daten nicht möglich war, habe ich auch hier ein Tool entwickelt, über welches ich automatisiert die Daten für alle rund 2.000 Fonds erhalten habe, die mindestens 10 Mio. US$ in jene Aktien investiert hatten, die per Dezember 2010 im DAX30 Index enthalten waren. Um wiederum einen Zusammenhang zum jeweiligen Marktumfeld herstellen zu können, reicht der gewählte Betrachtungszeitraum vom 1. Januar 2002 bis zum 31. Dezember 2010. Die daraus resultierende Datenbank umfasst für alle Fonds zu den unterschiedlichen Zeitpunkten insgesamt rund 6 Mio. Portfoliogewichte. Zur Identifikation des sozialen Einflusses habe ich diese vorhandene Datenbasis um diverse exogene Variablen, die die einzelnen Aktien betreffen, ergänzt. Diese umfassen den Durchschnitt historischer Renditen, die historische Volatilität sowie Analystenkonsensusschätzungen in Bezug auf das Kursziel, den erwarteten Gewinn und das Kursgewinnverhältnis. Darüber hinaus wurden auch die Gewichtung einer Aktie in nationalen und internationalen Aktienindices sowie die Stadt und das Land des Firmensitzes berücksichtigt. Die zuerst genannten fundamentalen Daten entstammen dem professionellen Informationsdienst Bloomberg. Indexgewichte konnten über passive Fonds in der Eigentümerdatenbank von Thomson Reuters bestimmt werden. Geografische Information bezüglich der Aktiengesellschaften sind in der Standarddatenbank von Thomson Reuters enthalten. Um möglichst aussagekräftige und repräsentative Ergebnisse zu erhalten untersuche ich den Einfluss durch soziale Interaktion im dritten Aufsatz nicht nur in Bezug auf DAX30-Werte, sondern hinsichtlich jeweils al-

ler im Portfolio eines Fondsmanagers enthaltenen Aktien. Vor diesem Hintergrund war ein Abruf der exogenen Variablen für alle Aktien, die zumindest zu einem Zeitpunkt in dem Portfolio von mindestens einem Fondsmanager enthalten waren, erforderlich. Zum Abruf dieser Datenmengen aus Bloomberg kam ebenfalls wieder ein selbstentwickeltes Tool zu Einsatz. Insgesamt wurden so die Fundamentaldaten von knapp 17.000 Unternehmen gesammelt.
Die Beschreibungen zeigen, dass zumindest im zweiten und dritten Aufsatz sehr individuelle und im Vergleich zu bestehenden Studien neuartige Datensätze verwendet werden. Bisherige Untersuchungen des Verhaltens von Analysten basieren überwiegend[8] nur auf Daten aus der, hauptsächlich auf große Investmentbanken ausgerichteten I/B/E/S Datenbank bzw. im Falle von Graham (1999) ausschließlich auf Empfehlungen von Investmentnewslettern. Eine ganzheitliche Betrachtung ist meines Wissens nach bislang noch nicht erfolgt. Bei Analysen des Verhaltens von institutionellen Investoren wurde zwar bislang auf vergleichbare Quellen wie die Eigentümerdatenbank von Thomson Reuters abgestellt,[9] allerdings wurde nach meinem Kenntnisstand bisher in keiner Studie eine Berücksichtigung exogener Kontrollvariablen vorgenommen. Darüber hinaus wurden Untersuchungen bezüglich deutscher Fondsmanager bislang nur auf Basis kleiner manuell zusammengestellter Datenbanken durchgeführt.[10]

1.4 Ausführliche Beschreibung der Aufsätze dieser Dissertation

Nach dem vorangegangenen Überblick soll nun eine detaillierte Beschreibung der einzelnen Aufsätze folgen. Dabei liegt der Schwerpunkt auf der Einordnung der Fragestellungen in die bestehende Literatur, der Erläuterung der empirischen Methodik sowie der Präsentation der Ergebnisse.

[8]Siehe beispielsweise Hong et al. (2000), Cooper et al. (2001), Zitzewitz (2001), Bernhardt et al. (2006), Krishnan et al. (2006), Kim and Zapatero (2009), Naujoks et al. (2009) und Jegadeesh and Kim (2010).

[9]Siehe unter anderem Lakonishok et al. (1992), Hong et al. (2005) und Pareek (2011).

[10]Siehe Walter and Weber (2006) und Oehler and Wendt (2009).

1.4.1 Does Social Interaction destabilise Financial Markets?

Problemstellung. Mit diesem Aufsatz soll herausgestellt werden, welche Wirkung von einer gegenseitigen Beeinflussung durch soziale Interaktion zwischen Marktteilnehmern in Bezug auf die Stabilität von Finanzmärkten ausgeht.

Motivation und Einordnung. Vor dem Hintergrund der zuvor dargelegten Motive für eine soziale Interaktion zwischen Marktteilnehmern belegen bereits diverse empirische Studien das Vorhandensein einer gegenseitigen Beeinflussung. Im Bereich der institutionellen Investoren sind hier exemplarisch die Arbeiten von Shiller and Pound (1989), Lakonishok et al. (1992), Arnswald (2001), Hong et al. (2005), Pareek (2011) und Kremer and Nautz (2012) zu nennen. Hinsichtlich des Verhaltens von Privatinvestoren kommen Hong et al. (2004), Ivkovic and Weisbenner (2007), Massa and Simonov (2005a) und Massa and Simonov (2005b) zu vergleichbaren Ergebnissen. Die resultierende Wirkung auf die Bildung von Marktpreisen wurde unter anderem von Lakonishok et al. (1992), Jones et al. (1999), Nofsinger and Sias (1999), Wermers (1999), Sias (2004), Walter and Weber (2006), San (2007), Puckett and Yan (2008), Hsieh (2012) und Kremer and Nautz (2012) untersucht. Die Ergebnisse sind teils sehr unterschiedlich und hängen davon ab, wie das Vorhandensein einer gegenseitigen Beeinflussung, zumeist getrennt nach institutionellen und privaten Investoren, bestimmt wird. Allen Studien ist allerdings gemeinsam, dass die Wirkung auf Finanzmärkte anhand der Entwicklung des Marktpreises abgeleitet wird, der sich ergibt, nachdem eine gegenseitige Beeinflussung stattgefunden hat. Eine Renditeumkehr wird dabei als Indiz für eine destabilisierende Wirkung interpretiert.

Gang der Untersuchung. Da Marktpreisentwicklungen von vielen verschiedenen Faktoren getrieben werden können, benutze ich, anders als vorangegangene Studien, ein Marktpreismodell aus der *Behavioural Finance*, um den Effekt der

sozialen Interaktion genauer identifizieren zu können. Dazu verwende ich das Modell von Brock and Hommes (1997) und Brock and Hommes (1998), welches ich um die lineare Komponente des sozialen Einflusses ergänze. Unabhängig davon, ob es sich um Privatpersonen oder institutionelle Investoren handelt wird angenommen, dass es zwei Typen von Investoren gibt: Fundamentalisten und Chartisten. Während Erstere nur auf den fundamentalen Wert einer Aktie abstellen und davon ausgehen, dass Börsenkurse diese Marke immer wieder erreichen werden, so extrapolieren Chartisten Preisbewegungen aus der Vergangenheit und projizieren diese auf die Zukunft. Folglich haben Fundamentalisten eine stabilisierende Wirkung, während Gegenteiliges von Chartisten ausgeht. Ein einzelner Investor kann seinen Typ ändern, je nachdem wie erfolgreich sich eine bestimmte Strategie in der Vergangenheit erwiesen hat. Zusätzlich nehme ich an, dass sich Investoren gegenseitig beeinflussen. Wenn Chartisten stärker von Fundamentalisten beeinflusst werden als umgekehrt, so kann daraus geschlossen werden, dass soziale Interaktion eine stabilisierende Wirkung hat. Ist der soziale Einfluss hingegen in die andere Richtung stärker, so deutet dies auf einen destabilisierenden Effekt hin.
Die zu schätzende Modellgleichung gestaltet sich als Funktion der einzelnen Parameter wie folgt:

$$x_t = F\left(\underset{(+)}{\Phi_F}, \underset{(+)}{\Phi_C}, \underset{(-)}{n_{Ft}}, \underset{(+)}{\Delta\delta}\right) + \epsilon_t. \tag{1.6}$$

Dabei ist x_t die Differenz zwischen Kurs und fundamentalem Wert einer Aktie zum Zeitpunkt t. Zur Erwartungsbildung bezüglich zukünftiger Preisentwicklungen gewichten Fundamentalisten die Abweichung aus der Vorperiode x_{t-1} mit $\Phi_F < 1$, während Chartisten eine Extrapolation mit dem Faktor $\Phi_C > 1$ vornehmen. Der Anteil von Fundamentalisten im Markt n_{Ft} (sowie der Chartisten $1 - n_{Ft}$) variiert je nach Profitabilität einer bestimmten Strategie in der Vorperiode. Die Höhe des sozialen Einflusses, der auf Fundamentalisten respektive Chartisten wirkt, wird durch δ_F und δ_C gemessen. Die Differenz aus beidem ergibt $\Delta\delta = \delta_F - \delta_C$.

Die Vorzeichen unter den Variablen geben an, ob ein höherer Wert stabilisierend oder destabilisierend wirkt. Bei Variablen mit positiven Vorzeichen führen höhere Werte zu größeren Abweichungen vom fundamentalen Wert. Die Wirkung ist folglich destabilisierend. Gegenteiliges gilt für Variablen mit negativem Vorzeichen.
Aufgrund der Nichtlinearität des Modells erfolgt die Schätzung im Rahmen der empirischen Analyse mittels eines nichtlinearen Kleinste-Quadrate-Schätzers.

Ergebnisse. Die empirischen Ergebnisse zeigen, dass soziale Interaktion tendenziell eher eine destabilisierende Wirkung hat. Zumindest kann man zu dem Schluss kommen, dass von sozialer Interaktion kein stabilisierender Effekt ausgeht. Die Ergebnisse deuten des Weiteren darauf hin, dass die Einbeziehung des sozialen Einflusses in ein Marktpreismodell dazu beiträgt, Preisbewegungen besser zu erklären. Folglich bildet der Aufsatz auch einen wissenschaftlichen Beitrag zur Literatur der Modellierung und Schätzung von Preisen auf Finanzmärkten.[11]

1.4.2 Analyst Behaviour: the Geography of Social Interaction

Problemstellung. Ziel dieses Aufsatzes ist es zu untersuchen, welche Rolle die geografische Nähe und der Meinungsaustausch zwischen Aktienanalysten in Bezug auf eine gegenseitige Beeinflussung spielen.

Motivation und Einordnung. Aktienanalysten haben als Informationsintermediäre großen Einfluss auf Kursentwicklungen. Aufgrund der Vielzahl von Investitionsopportunitäten sind Marktteilnehmer auf die Schätzungen und Vorhersagen von Analysten angewiesen und nutzen diese als Basis für ihre Investiti-

[11] Siehe beispielsweise Shiller (1984), Vigfusson (1997), Gilli and Winker (2003), Westerhoff and Reitz (2003), Alfarano et al. (2005), Boswijk et al. (2007), Amilon (2008), ap Gwilym (2008), Franke (2008), Franke (2009) und Lux (2012).

onsentscheidungen. Vor diesem Hintergrund ist es interessant herauszustellen, in wie weit Prognosen durch den Einfluss sozialer Interaktion zwischen Analysten verzerrt sind. Bereits diverse empirische Studien zeigen, dass eine gegenseitige Beeinflussung stattfindet (siehe Graham (1999), Hong et al. (2000), Welch (2000), Cooper et al. (2001), Zitzewitz (2001), Bernhardt et al. (2006), Krishnan et al. (2006), Kim and Zapatero (2009), Naujoks et al. (2009) und Jegadeesh and Kim (2010)). In den meisten Fällen wird dabei aber nur die Konsensusschätzung als Quelle einer sozialen Beeinflussung berücksichtigt.[12] Dies entspricht einer Gleichgewichtung des Einflusses aller Analysten.

Gang der Untersuchung. Im Gegensatz zu vielen der vorangegangenen Untersuchungen analysiere ich die Heterogenität einer gegenseitigen Beeinflussung. Das heißt, ich nehme nicht an, dass sich alle Analysten in gleicher Art und Weise beeinflussen, sondern untersuche, in wie weit Analysten stärker von jenen Analysten beeinflusst werden, die geografisch näher sind oder mit denen ein regelmäßiger Meinungsaustausch erfolgt. Darüber hinaus setze ich diese heterogene Beeinflussung noch ins Verhältnis zum jeweiligen Marktumfeld. Für die Analyse verwende ich eine vergleichweise einfache empirische Methode, indem ich die Korrelation von Analystenschätzungen innerhalb und außerhalb einer bestimmten Referenzgruppe vergleiche. Hierzu schätze ich folgende Regressionsgleichung:

$$P_{ict} = \alpha \overline{P_{ct}^{(g1)}} + \beta \overline{P_{ct}^{(g2)}} + \epsilon_{ict}. \tag{1.7}$$

Dabei ist P_{ict} das Kursziel bezüglich einer bestimmten Aktie c, welches ein einzelner Analyst zum Zeitpunkt t veröffentlicht hat. $\overline{P_{ct}^{(g1)}}$ ist der Mittelwert der Kursziele einer Referenzgruppe, die sich, je nach durchgeführter Untersuchung, aus Analysten, die in der gleichen Stadt oder dem gleichen Land arbeiten, oder aber aus Analysten, die regelmäßig ihre Meinungen austauschen zusammensetzt. $\overline{P_{ct}^{(g2)}}$ repräsentiert den Mittelwert der Kursziele der verbleibenden Analysten. Aus der Schätzgleichung 1.7 folgt, dass nicht die absolute Höhe

[12]Einzige Ausnahmen sind Graham (1999), Welch (2000) und Cooper et al. (2001).

des sozialen Einflusses, sondern nur die relative Beeinflussung, die von einer bestimmten Referenzgruppe ausgeht, geschätzt wird. Dieser relative Einfluss ergibt sich aus der Differenz zwischen den Koeffizienten α und β. Vorteil der beschriebenen Herangehensweise ist das fehlende Erfordernis exogener Kontrollvariablen.

Wie bereits zuvor geschildert entstammen die Informationen über einen regelmäßigen Meinungsaustausch zwischen Analysten einer Umfrage. Zur Wahrung einer ordentlichen Rücklaufquote konnten jedoch nicht direkt die Namen der Analysten abgefragt werden, mit denen ein Meinungsaustausch erfolgt. Deswegen habe ich stattdessen nach der Zahl der Analysten gefragt, mit denen sich ein bestimmter Analyst regelmäßig bzgl. bestimmter Aktien austauscht und die entweder in der gleichen Stadt, im gleichen Land oder im Ausland arbeiten. Je nach Konstellation der unterschiedlichen Antworten ergibt sich dann eine bestimmte Wahrscheinlichkeit (im vorliegenden Fall ca. 70%), das richtige zugrundeliegende Kommunikationsnetzwerk rekonstruieren zu können. Dies kann mit Hilfe eines Beispiels wie folgt beschrieben werden: Angenommen es gäbe vier Analysten (A, B, C, D) in Düsseldorf, die Prognosen bzgl. der Siemensaktie veröffentlichen und einer dieser Analysten (A) hätte in der Umfrage geantwortet, dass er seine Meinung mit zwei anderen Analysten austauscht, die in der gleichen Stadt arbeiten und das gleiche Unternehmen analysieren (also zwei aus B, C, D), dann könnte aus Sicht des betrachteten Analysten (A) mit einer 100%-tigen Wahrscheinlichkeit mindestens einer der übrigen drei Analysten (B, C, D) der richtigen Referenzgruppe zugeordnet werden. Die Wahrscheinlichkeit zwei Analysten korrekterweise der Referenzgruppe zuzuordnen, von welcher ein sozialer Einfluss auf erstgenannten Analyst (A) ausgeht, würde 33% betragen. Sollte nun noch einer der letztgenannten drei Analysten (B, C, D) angegeben haben, dass er mit keinem anderen Analyst seine Meinung austauscht, so könnte das Kommunikationsnetzwerk bezüglich dieser vier Analysten mit einer Wahrscheinlichkeit von 100% korrekt rekonstruiert werden.

Ergebnisse. Hinsichtlich der geografischen Nähe belegen die empirischen Ergebnisse, dass in Deutschland tätige Analysten stärker von anderen Analysten beeinflusst werden, die ebenfalls in Deutschland ihren Arbeitsplatz haben. Dies gilt unabhängig von vorherrschenden Marktgegebenheiten. Was den Meinungsaustausch anbelangt, so führt dieser nur in einer Boomphase zu einer stärken Beeinflussung. In Krisenzeiten hingegen erfolgt eine stärkere Ausrichtung an der Konsensusschätzung, das heißt die gegenseitige Beeinflussung ist homogener, was zum Beispiel mit der Angst vor einem Reputations- oder gar Arbeitsplatzverlust begründet werden kann.

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

Problemstellung. Intention dieses Aufsatzes ist es, die Größe des gegenseitigen Einflusses zwischen Fondsmanagern zu bestimmen. Es soll untersucht werden, ob diese von den Gegebenheiten des jeweils vorherrschenden Marktumfelds abhängt und welche Bedeutung dabei den zwei Arten der sozialen Interaktion, das heißt Beobachtung und Kommunikation, zuteil wird.

Motivation und Einordnung. Fondsmanager haben aufgrund der Größe des von Ihnen verwalteten Aktienvermögens einen wesentlichen Einfluss auf die Entwicklungen an Finanzmärkten. Zahlreiche Untersuchungen des sozialen Verhaltens dieser institutionellen Investoren wurden daher bereits durchgeführt. Analysen wurden dabei allerdings stets getrennt nach der Art der sozialen Interaktion und des daraus resultierenden Einflusses vorgenommen. Im Bereich des reinen Beobachtens ist hier die richtungweisende Arbeit von Lakonishok et al. (1992) zu nennen, die ein empirisches Maß entwickelten, welches anschließend in vielen empirischen Studien Berücksichtigung gefunden hat.[13] Das Maß

[13]Siehe Frey et al. (2006) für einen Überblick der Studien, welche die Methodik von Lakonishok et al. (1992) verwendet haben.

basiert auf der Annahme, dass sich alle Investoren in gleicher Art und Weise beeinflussen. Hinsichtlich der Kommunikation und des Meinungsaustausches sind die Studien von Shiller and Pound (1989), Arnswald (2001), Hong et al. (2005) und Pareek (2011) anzuführen.

Gang der Untersuchung. Im Gegensatz zu vorherigen Arbeiten, schätze ich in diesem Aufsatz die Gesamtgröße des sozialen Einflusses. Erst im Anschluss daran differenziere ich die beiden Arten der sozialen Interaktion, Beobachtung und Kommunikation. Um keine Annahmen bzgl. der zugrundeliegenden Netzwerkstruktur treffen zu müssen, bestimme ich diese zunächst durch eine paarweise Betrachtung von Fondsmanagern. Anschließend schätze ich halbjahresweise die Höhe des sozialen Einflusses, um Aufschluss über temporale Variationen zu erhalten. Die dazugehörige Schätzgleichung sieht wie folgt aus:

$$w_{ict} = \delta_t \sum_{j \neq i} \gamma_{ijt} w_{jct} + \mathbf{x}_{ict} \beta_{\mathbf{t}} + \epsilon_{ict}. \tag{1.8}$$

Das Portfoliogewicht, welches ein einzelner Fondsmanager einer bestimmten Aktie c zum Zeitpunkt t zuordnet, ist durch w_{ict} gegeben. Der Zeilenvektor $\mathbf{x}_{ict}$ enthält exogene Kontrollvariablen. Die Gesamtgröße des sozialen Einflusses wird durch δ_t gemessen. Dabei erfolgt eine Gewichtung des Einflusses anderer Fondsmanager anhand der Koeffizienten γ_{ijt}.

Die Koeffizienten in Gleichung 1.8 lassen sich nicht unverzerrt mittels eines Kleinste-Quadrate-Schätzers bestimmen. Das liegt daran, dass der Fehlerterm ϵ_{ict} mit $\sum_{j \neq i} \gamma_{ijt} w_{jct}$ korreliert. Dies lässt sich wie folgt erklären: Regressiert man die Portfoliogewichte eines Fondsmanagers auf die eines anderen, so enthält der resultierende Regressionskoeffizient δ_t auch den Einfluss, der in die umgekehrte Richtung wirkt.[14] Diesen Umstand berücksichtigend verwende ich ein Verfahren aus der räumlichen Ökonometrie (Kelejian and Prucha, 1998, Lee, 2003, Bramoullé et al., 2009), welches aus zwei Schritten besteht, in de-

[14] Lee (2002) hat gezeigt, dass dies vernachlässigbar ist, wenn der Einfluss eines Einzelnen sehr gering ist. Das trifft im vorliegenden Fall allerdings nicht zu.

nen jeweils eine Instrumentenvariablenschätzung vorgenommen wird.
Die Differenzierung nach der Art der sozialen Interaktion nehme ich anhand von geografischen Gegebenheiten vor. Fondsmanager, die in der gleichen Stadt arbeiten, können sich regelmäßig treffen und sich insbesondere informell über Portfoliothemen austauschen. Dies geht nicht bei Fondsmanagern, die auf unterschiedlichen Kontinenten arbeiten. Folglich trenne ich sozialen Einfluss in Beeinflussung auf dem Wege der Kommunikation, wenn es sich um Fondsmanager handelt, die in der gleichen Stadt arbeiten und in Beeinflussung nach vorheriger Beobachtung in den übrigen Fällen.

Ergebnisse. Die empirischen Ergebnisse deuten darauf hin, dass sich Fondsmanager bei der Zusammenstellung ihrer Portfolien gegenseitig beeinflussen. Dieser Einfluss ist besonders zu Krisenzeiten stark. Ähnlich wie bei der Betrachtung des Verhaltens von Analysten deutet dies auf die Angst vor einem Reputations- oder Arbeitsplatzverlust hin. Auch befürchtete Gehaltseinbußen können Treiber des beschriebenen Verhaltens sein. Diese Argumentation wird dadurch bekräftigt, dass in Krisenzeiten lediglich die Beeinflussung auf dem Wege des reinen Beobachtens stark zunimmt, während sich der Einfluss durch Kommunikation und Meinungsaustausch unabhängig vom jeweiligen Marktumfeld als relativ konstant erweist.

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2 Does Social Interaction destabilise Financial Markets?

With this paper, I propose a simple asset pricing model that accounts for the influence from social interaction. Investors are assumed to make up their mind about an asset's price based on a forecasting strategy and its past profitability as well as on the contemporaneous expectations of other market participants. Empirically analysing stocks in the DAX30 index, I provide evidence that social interaction rather destabilises financial markets. At least, it does not have a stabilising effect.

2.1 Introduction

In 2008, the DAX30 index fell by more than 40%. The market capitalisation of the underlying companies declined by 380 bln €. In the subsequent year, however, the DAX30 index caught up roughly 25% although the economy still was in a severe crisis. Stock price fluctuations with exaggerations like these make it hard to believe that market prices only reflect fundamental valuations as postulated by the efficient market hypothesis (Fama, 1970).

Therefore, the literature of behavioural finance proposed a variety of asset pricing models considering bounded rationally acting investors.[1] All these models have in common that they deviate from the rather unrealistic statement that all investors have homogeneous beliefs about the asset price. Rejecting the assumption of homogeneous beliefs allows describing those asset price variations that are not related to an underlying process of fundamental information.

The interaction among investors with heterogeneous beliefs generally transmits via the market pricing mechanism. However, it is also reasonable to consider a direct influence through observation or communication. There is already large empirical evidence that confirms the existence and influence of such social interaction in financial markets. A general herding tendency of institutional investors has first been found by Lakonishok et al. (1992). Their seminal empirical herding measure has thereafter been applied in many studies providing similar evidence.[2] Regarding the communication among institutional investors, positive evidence of influential effects has been provided by Shiller and Pound (1989), Arnswald (2001), Hong et al. (2005) and Pareek (2011). In the domain of retail investors, analogous behaviour has been revealed by Hong et al. (2004), Ivkovic and Weisbenner (2007), Massa and Simonov (2005a) and Massa and Simonov (2005b).

With this paper, I intend to answer the question whether social interaction among investors causes large deviations from the fundamental benchmark and thereby destabilises financial markets. There are situations where social interaction does not have any effect, irrespective of its intensity. If for instance, investors a priori all have homogeneous beliefs about an asset's price, then social influence would not affect their behaviour at all. Moreover, even if be-

[1] Examples include Beja and Goldman (1980), Kyle (1985), Day and Huang (1990), Long et al. (1990), Chiarella (1992), Föllmer and Schweizer (1993), Lux (1995), Brock and Hommes (1998), Kurz (1998), Iori (2002), Chiarella et al. (2003), de Grauwe and Grimaldi (2004), Horst (2005), Föllmer et al. (2005), Dieci et al. (2006), Cipriani and Guarino (2008) and Huang et al. (2010). Extensive surveys are provided by Hommes (2006) and LeBaron (2006).

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

liefs are heterogeneous, social interaction can still be without effect, if the influence is symmetric. This can be explained as follows. Symmetric social influence refers to the situation where every investor influences every other investor with equal intensity. This makes investors' beliefs more homogeneous and reduces the variance of opinions. However, the average opinion remains unchanged. In a sufficiently liquid market, where the asset price more or less reflects the average opinion about an asset's value, social influence thus has no effect. Given these facts, I propose an asset pricing model where investors have heterogeneous beliefs and the influence from social interaction among these investors is allowed to be asymmetric. Particularly, I make use of the well-known adaptive beliefs model of Brock and Hommes (1997) and Brock and Hommes (1998) and enrich it by the inclusion of social influence. In order to empirically analyse the impact of social interaction, I presume the existence of two investor types, fundamentalists and chartists, who a priori either have a stabilising or a destabilising effect on financial markets.[3] I then contrast the original model of Brock and Hommes (1998) with my extended version that accounts for asymmetric social influence. If the null hypothesis of symmetric social influence can be rejected, then it can be concluded that social interaction has an impact. The sign of the estimated difference between social influence on fundamentalists and chartists indicates whether this impact rather is stabilising or destabilising.

With this paper, I contribute to the literature that empirically analyses price impacts of social interaction, particularly herding behaviour among investors. On the basis of quarterly stock holdings, Lakonishok et al. (1992), Jones et al. (1999), Wermers (1999) and Sias (2004) provide empirical evidence that the herding behaviour of institutional investors is information driven and thus

[3]Note that e.g. Huang et al. (2010) proposes a framework where chartists might have both a destabilising as well as a stabilising effect. The definitions of fundamentalists and chartists in this paper, however, are chosen in a way such that fundamentalists always drive stock prices towards the fundamental benchmark, whereas chartists always drive the stock price away from it.

rather stabilises the market. This is in line with the results of Nofsinger and Sias (1999), who raise the same conclusion on the basis of institutional investors' annually stock holdings. On a semi-annually basis, Walter and Weber (2006) show that for the German market institutional herding at least does not have a destabilising effect. However, differentiating between herding on buy and sell decisions, San (2007) on a quarterly basis finds a destabilising tendency for institutional sell herding. Analysing shorter time intervals, Puckett and Yan (2008) similarly show that institutional herding on stock sales, which is inferred on weekly portfolio changes, indeed may destabilise markets and thereby causes short-term fluctuations. Considering intra-day trades, Hsieh (2012) concludes for the Taiwan stock market that herding behaviour of institutional investors rather stabilises while the same behaviour of retail investors rather destabilises the market. All afore cited papers have in common that the effect on stock prices is inferred from subsequent stock returns. A stock return reversal is interpreted as a destabilising effect. Contrarily, my approach offers the possibility to directly infer the effect of social interaction from the estimates of the model parameters. Moreover, I do not classify investors into institutional and retail investors as I state that there might be investors of both categories, who either stabilise or destabilise market prices. Therefore, I follow the literature about heterogeneous agents on financial markets and assume the existence of two representative investor types: fundamentalists, who believe that stock prices revert to a fundamental benchmark and chartists, who extrapolate trends that move the stock price away from its fundamental value.

My paper is further related to the upcoming literature that is engaged in the empirical investigation of non linear asset pricing models. An early contribution has been provided by Shiller (1984), who by linear regression estimates a stock pricing model with two heterogeneous investor types, namely smart money investors with rational expectations and ordinary investors. Vigfusson (1997) uses a Markov regime-switching technique to estimate the exchange rate model of Frankel and Froot (1988) with two representative investor types, namely fundamentalists and chartists. Westerhoff and Reitz (2003) and ap Gwilym (2008) use non linear estimation techniques to estimate exchange rate models with the same representative investor types. Using the method of simulated moments, Franke (2009) estimates the exchange rate model of Manzan and Westerhoff (2005) for both stock indices and exchanges rates. Considering social interaction, Gilli and Winker (2003) and Alfarano et al. (2005) estimate Kirman's herding model (Kirman, 1993) again with afore mentioned two representative investor types. Although, Alfarano et al. (2005) account for an asymmetric autonomous switching tendency for an individual investor to change his type, both Gilli and Winker (2003) and Alfarano et al. (2005) consider symmetric influence from social interaction. Franke (2008) and Lux (2012) also take the influence from social interaction into account. Therefore, they estimate the relation between stock price returns and an underlying opinion index. My paper is most strongly related to Boswijk et al. (2007) and Amilon (2008), who estimate the model of Brock and Hommes (1998), however, in its original form, i.e. without the inclusion of social interaction.

In this paper, I analyse the price evolution of the stocks that were included in the DAX30 index as of Dec 31^{st} 2010. For 16 out of 30 stocks, the null hypothesis of the suitability of the original model can be rejected. This suggests the presence of asymmetric influence from social interaction. The parameter estimates indicate that fundamentalists are more prone to be socially influenced by other market participants than chartists. This means fundamentalists skew their beliefs more strongly to those of the chartist than past performance of the strategy would suggest. Therefore, I conclude that if social interaction has an influence on stock prices, then this influence represents a destabilising impact.

The remainder of the paper is structured as follows. In chapter 2.2, I review the literature about asset pricing models that consider the influence from social interaction. I present my asset pricing model, derive conditions for the existence of equilibria and explain the strategy for empirical identification of the model parameters in chapter 2.3. In chapter 2.4, I empirically estimate the model and contrast it with the original model of Brock and Hommes (1998). Chapter 2.5 concludes.

2.2 Literature review

The literature of behavioural finance brought out a variety of theoretical asset pricing models that take the influence from social interaction into account. There are two general types of models which have evolved. On the one hand, authors of so called heterogeneous agent models assume a small amount of groups that are formed by investors with representative investment behaviour. On the other hand, the computationally more challenging agent based models account for every investor's individual behaviour. While the latter type offers the possibility to model asset price fluctuation based on the very micro level, the advantage of the former type is the mathematical tractability such that in most cases closed form solutions can be derived. Hommes (2006) and LeBaron (2006) provide a comprehensive survey of the two concepts. Surveys of asset pricing models that take the influence from social interaction into account have been provided by Hirshleifer and Teoh (2008) and Lux (2009).

An early example of heterogeneous agent models considering social influence is represented by Lux (1995), who proposes a framework that is based on the "ant"-model of Kirman (1993). He assumes that there are two types of investors in the market, namely fundamentalists and chartists. Chartists are either optimistic and expect price increases or they are pessimistic and expect the asset price to decrease. The probability that a chartist changes his belief from optimistic to pessimistic or vice versa on the one hand depends on an idiosyncratic component and on the other hand is related to the portion of chartists in the market that have a particular either optimistic or pessimistic expectation. By the second factor a direct influence from social interaction is introduced. Simulation results of Lux (1995) show that the model is capable to reproduce stylised facts which can be observed in financial markets. In Lux (1998), the model is extended by a learning mechanism to switch between the fundamental and chartist strategy. The work of Alfarano et al. (2008) is closely related to the two afore cited papers. Contrarily, Alfarano et al. (2008) assume that social influence does not only depend on the relative portion of market participants following a particular strategy, but on the explicit group sizes and therefore also on the absolute number of market participants.

Providing an alternative model, Chiarella et al. (2003) assume that investors follow either a fundamentalist strategy or are herding agents. The latter infer their beliefs from past excess demand in the market and therefore are affected by a direct social influence from other market participants.

Horst (2005), Wu (2007) and Horst and Rothe (2008) state that investors choose between a fundamentalist and chartist strategy depending on which strategy they expect that the majority of the whole market will adopt ("market mood"). Horst (2005) moreover takes the influence from the observable choice of the nearest neighbours into account. Working with fundamentalists and noise trades, Pakkanen (2009) proposes an asset pricing model where investors either trade the asset or revise their belief, i.e. change their type. When an investor trades the asset, the decision whether to buy or sell it depends on his own prior belief and the general market mood, which represents a compound measure of all individual investors' beliefs.

Most closely related to this paper, Chang (2007) uses the model of Brock and Hommes (1998) and introduces the influence from social interaction into the mechanism of investor's switching between a fundamental and a chartist strategy. The social influence is modelled by the framework of Brock and Durlauf (2001b) and Brock and Durlauf (2001a). Different to Chang (2007), I account for an asymmetric social influence while switching from one strategy to another. Moreover, I assume that social influence induces an investor to bias his beliefs towards the beliefs of other investors without completely rejecting the own and adopting an alternative strategy.

In the domain of agent based models, one of the first contributions in the context of social interaction has been provided by Baker and Iyer (1992). They assume that investors randomly receive exogenous buy or sell signals and transmit them via a communication network. If an investor by inter-investor transmission receives an equal number of buy and sell signals, these signals cancel out each other, such that the particular investor does not trade at all. Simulation results show that the topology of this network has a considerable effect on asset price volatility and trading volume.

Cont and Bouchaud (2000) propose a framework where investors within the same neighbourhood always make the same trading decisions. All neighbourhoods are isolated. The size of these clusters is obtained by a random graph.

Iori (2002) also states that investors are influenced by the trades of neighbouring investors. However, an individual investor's choice does not necessarily coincide with those of his neighbours. Instead, an individual decision is made based on the weighted average decision of neighbouring investors within a lattice network as well as on an idiosyncratic component.

Proposing an explicit function for the process of investors' information elaboration, Schütz et al. (2009) construct a theoretical framework where investors build up exogenous sell or buy signals based on the difference between their own fundamental valuation of the asset and the current market price. An investor's decision whether to buy or to sell an asset then depends on the own signal and the weighted average of neighbouring investors' demands.

While afore cited authors, only assumed that an individual investor is influenced by other investors' actions, i.e. trading decisions, Ozsoylev (2006) and Ozsoylev and Walden (2011) state that social networks permit the transmission of information such that better connected investors have more precise information. Social influence in this case is not based on other investors' outcomes, but on their original information signals.

In the same vein, Panchenko et al. (2010) state that well connected investors are better off. Particularly, like in this paper, they consider the heterogeneous agent model of Brock and Hommes (1998). However, in their framework, investors can only observe the past profitability of a strategy, if there are investors in the neighbourhood who adopted this strategy in the past. This means for instance, an investor is unable to get to know the profitability of the chartist strategy if he is only surrounded by fundamentalists. The difference to my approach is that I assume that real markets offer a minimum of transparency that makes it possible to observe the past profitability of all strategies. Social influence in my framework thus only affects the elaboration of the information that is available to every market participant.

Also based on the assumption of information transmission within a social network, Colla and Mele (2010) propose a framework where trades are positively correlated if investors are located nearby because of the exchange of information and trades are negatively correlated if investors are further away acting as counterparties in the market clearing mechanism.

The approach of Kaizoji (2000) originally stems from the domain of agent based models. For the sake of an empirical analysis however, the underlying social network is simplified such that analytical tractability as in heterogeneous agent models is obtained. Investors are supposed to be either willing to buy or willing to sell the asset. An investor bases his decision on the general market environment and furthermore is directly influenced by the contemporaneous asset demand of other investors in the market.

With my approach, I set up on a heterogeneous agent model that trough the inclusion of social influence becomes an agent based model offering the possibility to account for every individual investor's behaviour. However, in order to ensure analytical tractability, which is needed for the empirical analysis, I simplify the structure of the underlying social network and thereby again obtain a heterogeneous agent model.

2.3 Asset pricing in the presence of social interaction

In the following, I present the model of Brock and Hommes (1998) and enrich it by an influential component based on social interaction among investors.

2.3.1 Market price mechanism

Considering a market with one risky and one riskless asset, investors are confronted to the decision how to allocate their present wealth in order to maximise next period's wealth, which is given by

$$W_{i,t+1} = (1+r)W_{i,t} + (p_{t+1} + y_{t+1} - (1+r)p_t)z_{it}, \tag{2.1}$$

where p_t and p_{t+1} are this period's and next period's market price of the risky asset that pays an uncertain dividend y_{t+1}. The return of the risk free asset with perfectly elastic supply is given by r. An investor's individual demand for the risky asset equals z_{it}. Investors are assumed to be myopic mean-variance optimisers, such that z_{it} results from

$$\max_{z_{it}} \mathrm{E}_{it}[W_{i,t+1}] - \frac{a_{it}}{2}\mathrm{Var}_{it}[W_{i,t+1}], \tag{2.2}$$

where E_{it} and Var_{it} are an investor's conditional expectation and variance at time t and a_{it} stands for an investor's constant average risk aversion. In order to keep the model analytically tractable, Brock and Hommes (1998) introduced the following assumptions:

$$\mathrm{Var}_{it}[W_{i,t+1}] := \sigma^2 \tag{2.3}$$

$$a_{it} := a. \tag{2.4}$$

This means that the conditional variance about next period's wealth and the coefficient of risk aversion are presumed to be constant among investors as well as in time. The resulting demand of an individual investor is hence given by

$$z_{it} = \frac{\mathrm{E}_{it}[p_{t+1} + y_{t+1} - (1+r)p_t]}{a\sigma^2}. \tag{2.5}$$

The model is closed by the following market clearing equation

$$\sum_i z_{it} = L_t, \tag{2.6}$$

where L_t is the contemporaneous net supply of the risky asset. Plugging equation 2.5 into equation 2.6 and solving for p_t yields

$$p_t = \frac{1}{1+r}\left(\sum_i \frac{1}{N}\mathrm{E}_{it}[p_{t+1} + y_{t+1}] - \frac{a\sigma^2 L_t}{N}\right), \tag{2.7}$$

with N being the total number of investors in the market. It is possible to derive the fundamental equilibrium, which arises when all investors have homogeneous beliefs, i.e. have the same conditional expectation about the risky asset:

$$p_t^* = \frac{1}{1+r}\left(\mathrm{E}_t[p_{t+1}^* + y_{t+1}] - \frac{a\sigma^2 L_t}{N}\right). \tag{2.8}$$

The fundamental price is indicated by a star. Subtracting equation 2.8 from equation 2.7 offers the possibility to express the price equation as deviations from the fundamental price:

$$x_t = \frac{1}{1+r}\sum_i \frac{1}{N}\mathrm{E}_{it}[x_{t+1}], \tag{2.9}$$

with $x_t = p_t - p_t^*$. Please note that equation 2.9 contains the implicit assumption that dividends follow a stochastic process with constant temporal mean. For notational convenience, an investor's beliefs about next period's deviation from the fundamental value are henceforth denoted by f_{it}, i.e.

$$f_{it} = \mathrm{E}_{it}[x_{t+1}]. \tag{2.10}$$

2.3.2 Heterogeneous beliefs and social interaction

An investor is assumed to make up his beliefs about future deviations of the market price from the fundamental benchmark based on two sources. On the one hand, he considers his own a priori expectation. On the other hand and additionally to the original model of Brock and Hommes (1998), I assume that he also takes into account the beliefs of other market participants. In order to consider the influence from this social interaction, I make use of the linear model from the social interaction literature (e.g. Manski (1993), Moffitt (2001), Bramoullé et al. (2009), Blume et al. (2010) and Lee et al. (2010)):[4]

$$f_{it} = \theta_{it} + \delta_i \left(\sum_{j \neq i} \gamma_{ij} f_{jt} - \theta_{it} \right), \tag{2.11}$$

where θ_{it} represents the expectation of the future deviation from the fundamental benchmark that an investor makes up on his own. The coefficient δ_i measures the magnitude of social influence. Every other investor's influence is weighted with $\gamma_{ij} \geq 0$. Ensuring that δ_i captures the total magnitude of influence, the following constraint shall be imposed:

$$\sum_{j \neq i} \gamma_{ij} \stackrel{!}{=} 1. \tag{2.12}$$

In the social interaction literature, stronger social influence generally leads to higher (absolute) outcomes (Glaeser and Scheinkman, 2001, Glaeser et al., 2003). Such a social multiplier is however not reasonable in this context, as social influence can be assumed to drive asset prices towards to or away from the fundamental benchmark. Hence, social interaction could induce investors to believe that next period's asset price will move further away from the fundamental benchmark (in either direction) or could make investors to suppose that the difference between the asset price and the fundamental benchmark will be reduced. In order to take this into account, I considered the difference between the weighted average of other investor's beliefs and an investor's own a priori expectation in equation 2.11. In the appendix A.2, it is shown, that thereby no social multiplier can arise.
The values of the coefficient of social interaction δ_i can be interpreted as follows. If $0 < \delta_i < 1$, then an investor skews his initial expectation towards the expectation of other investors. The resulting expectation then represents a

[4]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 relatively unlikely that an investor's beliefs are influenced by the background of another investors.

weighted average of the own initial and other investors' beliefs. This situation shall be henceforth referred as moderate social influence. For $\delta_i = 0$, an investor is not influenced by other investors at all, whereas for $\delta_i = 1$, an investor completely rejects his own a priori expectation and adapts the weighted beliefs of other investors. It is also possible that an investor is such strongly influenced that he skews his own expectation even beyond those of other investors. In this case, henceforth denoted extreme social influence, δ_i can take values greater than one. Values below zero are not considered for δ_i as this would represent a negative influence from social interaction. Indeed, arbitrageurs might act as contrarians and therefore have opposite beliefs. This however represents a form of influence which translates through the market price mechanism and hence cannot be understood as a direct influence from social interaction.
The integration of social influence into the original model of Brock and Hommes (1998) could lead to infeasible solutions for the asset price depending on the values of δ_i. The following propositions state, under which conditions the existence of exactly one equilibrium price is ensured.

Proposition 1: If all investors are only moderately influenced by other investors ($\delta_i < 1$), then exactly one feasible market equilibrium arises from equation 2.9.

The proof is given in the appendix A.4. Proposition 1 shows that for an arbitrary structure of the underlying social network, there exists always an equilibrium, if social influence is moderate. Having a closer look at the particular network structure where every investor equally weights other investors' beliefs, proposition 2 and 3 state under which conditions the presence of extreme social influence still leads to feasible model solutions. The structure of equal weights is very convenient as it ensures analytical tractability, which is needed for the empirical analysis later in this paper.

Proposition 2: Suppose that there are N investors who all equally weight other investors' beliefs ($\gamma_{ij} = \frac{1}{N-1}$) and that at least two investors are only mod-

erately influenced by other investors ($\delta_i < 1$). If for all investors that are extremely influenced ($\delta_i > 1$), the magnitude of influence does not reach or exceed an upper bound given by $\delta_i < \frac{N-1}{\sum_{j\neq i}\min\{\delta_j,1\}}$, then exactly one feasible market equilibrium arises from equation 2.9.

Appendix A.5 provides the proof of this proposition. In order to restrict the number of degrees of freedom in the empirical analysis, only two representative investor types and a large number of investors are considered. The following proposition derives the equilibrium condition for this constellation still assuming a network structure with equal weights.

Proposition 3: Assume that there are two representative investor types in a market with a large number of investors ($N \to \infty$). Investors of one type shall be influenced by investors of both types with a particular type-specific magnitude (δ_1 and δ_2). Suppose further that all investors equally weight other investors' beliefs ($\gamma_{ij} = \frac{1}{N-1}$). Equation 2.9 yields exactly one feasible market equilibrium, if the following inequality is fulfilled: $n\delta_1 + (1-n)\delta_2 \neq 1$, where n is the portion of investors of a particular type.

See appendix A.6 for the proof of proposition 3.

2.3.3 Fundamentalists vs. chartists and adaptive beliefs

Brock and Hommes (1998) assume that an investor infers his a priori expectation from past observations, i.e.

$$\theta_{it} = \Phi_i + \sum_k \Phi_{ik} x_{t-k}. \tag{2.13}$$

Φ_i represents an investor's constant bias compared to the fundamental benchmark. The coefficients Φ_{ik} are individual weights of past observations and define whether an investors rather has a stabilising or a destabilising effect on the market price. If $\Phi_{ik} < 1$, then investor i expects that the deviation

of the asset price from its fundamental value will decrease during the next period. Therefore, he is willing to buy (sell) the asset, if its market price is below (above) the fundamental benchmark and thereby stabilises the market. Contrarily, investor i believes that the market price further divagates from the fundamental equilibrium, if $\Phi_{ik} > 1$. He thereby destabilises the market.
In order to keep the model analytically tractable and to make an empirical analysis possible, I hereafter assume that there are only two types of investors in the market, namely fundamentalists and chartists. Mathematically, the fundamental strategy shall be defined by

$$\Phi_i = 0 \tag{2.14}$$

$$\Phi_{ik} = \begin{cases} \Phi_F < 1 & \text{if } k = 1 \\ 0 & \text{if } k \neq 1 \end{cases} \tag{2.15}$$

$$\delta_i = \delta_F \tag{2.16}$$

$$\gamma_{ij} = \frac{1}{N-1}, \tag{2.17}$$

with N being the total number of investors in the market. Analogously the chartist strategy shall be given by

$$\Phi_i = 0 \tag{2.18}$$

$$\Phi_{ik} = \begin{cases} \Phi_C > 1 & \text{if } k = 1 \\ 0 & \text{if } k \neq 1 \end{cases} \tag{2.19}$$

$$\delta_i = \delta_C \tag{2.20}$$

$$\gamma_{ij} = \frac{1}{N-1}. \tag{2.21}$$

With these definitions and assuming a large number of investors ($N \to \infty$), investors' beliefs turn out to be

$$f_{Ft} = (1 - \delta_F)\Phi_F x_{t-1} + \delta_F \left(n_{Ft} f_{Ft} + n_{Ct} f_{Ct}\right) \tag{2.22}$$

and

$$f_{Ct} = (1 - \delta_C)\Phi_C x_{t-1} + \delta_C \left(n_{Ft} f_{Ft} + n_{Ct} f_{Ct}\right), \tag{2.23}$$

where n_{Ft} and n_{Ct} are the portions of investors in the market who either follow the fundamental or the chartist strategy. As only two investor types are assumed, the portion of chartists can be expressed by $n_{Ct} = 1 - n_{Ft}$. Equations 2.24 and 2.25 can be written as

$$f_{Ft} = \frac{(1-\delta_F)(1-\delta_C(1-n_{Ft}))\Phi_F x_{t-1} + \delta_F(1-\delta_C)(1-n_{Ft})\Phi_C x_{t-1}}{1-\delta_F n_{Ft} - \delta_C(1-n_{Ft})} \tag{2.24}$$

and

$$f_{Ct} = \frac{(1-\delta_C)(1-\delta_F n_{Ft})\Phi_C x_{t-1} + \delta_C(1-\delta_F) n_{Ft}\Phi_F x_{t-1}}{1-\delta_F n_{Ft} - \delta_C(1-n_{Ft})}. \tag{2.25}$$

Plugging equations 2.24 and 2.25 into equation 2.9 yields

$$\begin{aligned} x_t = {} & \frac{1}{1+r}\left(n_{Ft}\frac{(1-\delta_F)(1-\delta_C(1-n_{Ft}))\Phi_F x_{t-1} + \delta_F(1-\delta_C)(1-n_{Ft})\Phi_C x_{t-1}}{1-\delta_F n_{Ft} - \delta_C(1-n_{Ft})}\right. \\ & \left.+(1-n_{Ft})\frac{(1-\delta_C)(1-\delta_F n_{Ft})\Phi_C x_{t-1} + \delta_C(1-\delta_F)n_{Ft}\Phi_F x_{t-1}}{1-\delta_F n_{Ft} - \delta_C(1-n_{Ft})}\right) \\ = {} & \frac{1}{1+r}\frac{(1-\delta_F)n_{Ft}\Phi_F x_{t-1} + (1-\delta_C)(1-n_{Ft})\Phi_C x_{t-1}}{1-\delta_F n_{Ft} - \delta_C(1-n_{Ft})}. \end{aligned} \tag{2.26}$$

Investors are assumed to choose a strategy based on its past profitability ("adaptive beliefs"). In this context, however, they do not consider effects of social interaction in the past. Hence, I presume that they do not take into account that they would have been influenced by other investors while choosing a particular strategy. The profitability π_{t-1} of a strategy in the last period is obtained by the multiplication of the return R_{t-1} which would have been realised in the last period $t-1$, with the corresponding hypothetical quantity z_{t-2} being bought or sold at $t-2$, if this particular strategy had been chosen at $t-2$, i.e.

$$\pi_{t-1} = R_{t-1} z_{t-2}. \tag{2.27}$$

The profitability of the fundamental strategy is given by

$$\begin{aligned} \pi_{F,t-1} &= (x_{t-1} - (1+r)x_{t-2})\frac{E_{F,t-2}[x_{t-1}] - (1+r)x_{t-2}}{a\sigma^2} \\ &= (x_{t-1} - (1+r)x_{t-2})\frac{\Phi_F x_{t-3} - (1+r)x_{t-2}}{a\sigma^2}. \end{aligned} \tag{2.28}$$

Analogously the profitability of the chartist strategy turns out to be

$$\pi_{C,t-1} = (x_{t-1} - (1+r)x_{t-2})\frac{\Phi_C x_{t-3} - (1+r)x_{t-2}}{a\sigma^2}. \tag{2.29}$$

An investor's utility as a function of the realised profitability shall be given by

$$U_{it} = \pi_{t-1} + \epsilon_{it}, \tag{2.30}$$

where ϵ_{it} is an individual investor's identically independently distributed error when perceiving the profitability of a particular strategy. This noise term is assumed to be drawn from a double exponential distribution (Gumbel distribution).[5] As the number of investors goes to infinity, the portion of investors in the market that follow the fundamental strategy turns out to be

$$\begin{aligned} n_{Ft} &= \frac{e^{\beta\pi_{F,t-1}}}{e^{\beta\pi_{F,t-1}} + e^{\beta\pi_{C,t-1}}} \\ &= \frac{1}{1+e^{-\beta(\pi_{F,t-1}-\pi_{C,t-1})}}, \end{aligned} \tag{2.31}$$

where β is the intensity of choice measuring investors' tendency to choose the strategy which has better performed in the past. For $\beta = 0$, investors do not take into account past profitability at all. As β goes towards infinity, investors always choose the strategy with the highest past profitability. Please note that the switching mechanism is symmetric. Hence, the probability for choosing a particular strategy only depends on the strategy's past profitability and not on the strategy itself.

Plugging equations 2.28 and 2.29 into equation 2.31 yields

$$n_{Ft} = \frac{1}{1+e^{-\beta((x_{t-1}-(1+r)x_{t-2})\frac{(\Phi_F-\Phi_C)x_{t-3}-(1+r)x_{t-2}}{a\sigma^2})}}. \tag{2.32}$$

[5]Brock and Hommes (1998) chose a double exponential distribution (logit model) instead of e.g. a normal distribution (probit model) in order to be able to provide a closed form solution for the adaptive beliefs system. The mean value and the standard deviation of the double exponential distribution equal $\frac{\gamma}{\beta}$ and $\frac{\pi}{\beta\sqrt{6}}$, respectively, where γ is the Euler-Mascheroni constant and β the intensity of choice being explained later in the text.

2.3.4 Empirical identification

The purpose of this paper is to empirically investigate, whether the influence of social interaction has a stabilising or a destabilising effect on financial markets. The estimation equations of the non linear adaptive beliefs model presented above are given by

$$x_t = \frac{1}{1+r}\frac{(1-\delta_F)n_{Ft}\Phi_F x_{t-1} + (1-\delta_C)(1-n_{Ft})\Phi_C x_{t-1}}{1-\delta_F n_{Ft} - \delta_C(1-n_{Ft})} + \epsilon_t \tag{2.33}$$

$$n_{Ft} = \frac{1}{1+e^{-\beta^*(x_{t-1}-(1+r)x_{t-2})(\Phi_F-\Phi_C)x_{t-3}-(1+r)x_{t-2}}}, \tag{2.34}$$

with $\beta^* = \frac{\beta}{a\sigma^2}$. Reformulating equation 2.33 yields

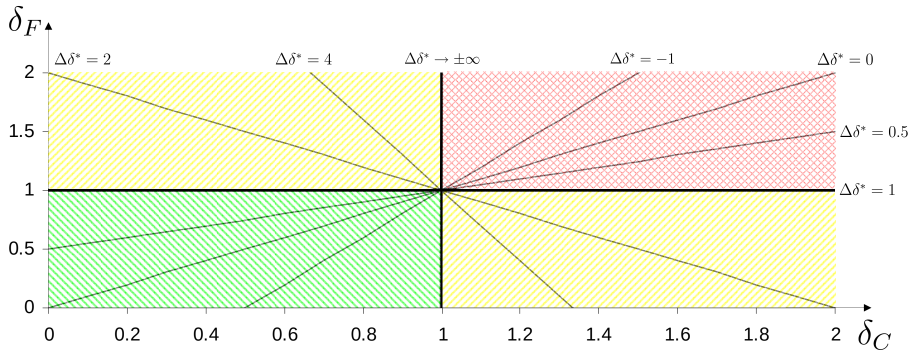
$$x_t = \frac{1}{1+r}\frac{n_{Ft}\Phi_F x_{t-1} + (1-n_{Ft})\Phi_C x_{t-1} - \frac{\Delta\delta}{1-\delta_C}n_{Ft}\Phi_F x_{t-1}}{1-\frac{\Delta\delta}{1-\delta_C}n_{Ft}} + \epsilon_t, \tag{2.35}$$

with $\Delta\delta = \delta_F - \delta_C$. Thereof, it follows that only the value of $\Delta\delta^* = \frac{\Delta\delta}{1-\delta_C}$ can be estimated, such that the absolute values of the coefficients of social interaction δ_F and δ_C are not directly identifiable. However, this doesn't matter, because only the difference between δ_F and δ_C is of interest, as solely asymmetric social influence, i.e. $\Delta\delta \neq 0$ irrespective of the absolute values of δ_F and δ_C, can have an impact on asset prices. Indeed, for $\Delta\delta = 0$ equation 2.35 reduces to the original model of Brock and Hommes (1998) without the inclusion of social influence.

If the estimate of $\Delta\delta^*$ turns out to be significantly different from zero, it can be concluded that social interaction has an impact on the asset price. Stated differently, if $\Delta\delta^* \neq 0$, the model fit is better, if social influence is taken into account, because there are deviations from the fundamental benchmark which are caused by the influence of social interaction.

Regarding the implications of different values for $\Delta\delta^*$, figure 2.1 shows that for $\Delta\delta^* > 1$ either $\delta_F > 1$ and $\delta_C < 1$ or $\delta_F < 1$ and $\delta_C > 1$. Hence, if $\Delta\delta^*$ is greater than one, then either fundamentalists or chartists are extremely influenced by social interaction. If $\Delta\delta^* < 1$, then it follows that $\delta_F < 1$ and

Figure 2.1: Relationship between δ_F and δ_C



The figure displays the relationship between δ_F and δ_C for different values of $\Delta\delta^* = \frac{\Delta\delta}{1-\delta_C}$.

$\delta_C < 1$, because the case where $\delta_F > 1$ and $\delta_C > 1$ shall be excluded, as it would imply that all investors are extremely influenced by social interaction. This doesn't make sense, because in such a situation, fundamentalists would just become chartists and vice versa. Hence, if $\Delta\delta^*$ is smaller than one, all investors are only moderately influenced by social interaction.

In order to disentangle, whether social interaction has a stabilising or destabilising effect on financial markets, one has to look at the sign of the estimated coefficient $\Delta\delta^*$. Figure 2.1 confirms that as long as $\Delta\delta^*$ is smaller than one, the sign of $\Delta\delta$ corresponds to the sign of $\Delta\delta^*$. For $\Delta\delta^*$ being greater than one, the sign of $\Delta\delta$ remains unclear.

Fundamentalists have a stabilising impact on the market price, as they (through market price mechanism) always push it back to its fundamental benchmark. The higher the fraction of fundamentalists in the market n_{Ft} and the closer the extrapolation coefficient Φ_F to zero, the smaller is the market price deviation from the fundamental benchmark. Contrarily, chartists have a destabilising effect on the market price, since they (through market price mechanism) drive it away from its fundamental benchmark. The higher the fraction of chartists in the market $n_{Ct} = 1 - n_{Ft}$ and the higher the (absolute) value of the extrapolation coefficient Φ_C, the greater is the deviation of the market price from the fundamental benchmark. The fraction of fundamentalists and chartists

evolve by the strategies' past profitabilities. The extrapolation coefficients are fixed. However, they get biased through the influence of social interaction. If fundamentalists get more strongly influenced by chartists and hence skew their opinion further towards the opinion of chartists than vice versa, i.e. $\delta_F > \delta_C$, then Φ_F gets more upward biased than Φ_C gets downward biased. Hence, $\Delta\delta > 0$ indicates that social interaction has a destabilising effect. If however chartists get more strongly influenced by fundamentalists and therefore skew their opinion further towards the opinion of fundamentalists than vice versa, i.e. $\delta_C > \delta_F$, then Φ_C gets more downward biased than Φ_F gets upward biased, wherefore $\Delta\delta < 0$ indicates that social interaction has a stabilising effect.
Summarising the theoretical chapter, the estimation equation 2.35 can be written in a simplified functional from in order to provide an overview of the variables that drive the (in-)stability of a financial market:

$$x_t = F\left(\underset{(-)}{n_{Ft}}, \underset{(+)}{\Phi_F}, \underset{(+)}{\Phi_C}, \underset{(+)}{\Delta\delta}\right) + \epsilon_t \tag{2.36}$$

A positive sign indicates that a higher value of the relevant variable has a destabilising impact enlarging the deviation of the market price from its fundamental benchmark on the left hand side of equation 2.36 and vice versa for a negative sign.

2.4 Empirical results

In order to determine the impact of social interaction, I estimate the model presented in the previous chapter by non linear least squares regression for all stocks that were included in the DAX30 as of Dec 31^{st} 2010. For the preceding seven years time period, i.e. from Jan 1^{st} 2004 to Dec 31^{st} 2010, I retrieved daily closing prices from Thomson Reuters. The choice of the time window is very convenient, as it captures the economic upturn until 2006 as well as the financial and economic crisis starting in 2007. In order to have a fundamental benchmark, I furthermore collected analysts' consensus price targets from the

Table 2.1: Estimation results

	$\Delta\delta^*$	β^*	Φ_F	Φ_C	R^2_{adj}
ADIDAS AG	0.6501***	35.7675***	0.9246***	1.0387***	0.9967
	(0.020919)	(142.444405)	(0.000042)	(0.000024)	
ALLIANZ SE	0.3044	5.3527**	0.9607***	1.0383***	0.9977
	(0.099270)	(4.945269)	(0.000019)	(0.000020)	
BASF SE	0.5899***	10.4456***	0.9094***	1.0461***	0.9965
	(0.013401)	(12.166114)	(0.000123)	(0.000041)	
BAY. MOTOREN WERKE AG (c.s.)	0.2086	4.7428**	0.8892***	1.0845***	0.9949
	(0.044880)	(3.734100)	(0.000352)	(0.000294)	
BAYER AG	0.1175	47.9942**	0.9443***	1.0411***	0.9960
	(0.136659)	(449.717985)	(0.000039)	(0.000033)	
BEIERSDORF AG	0.7784***	109.9968	0.9367***	1.0313***	0.9950
	(0.056343)	(5,040.095470)	(0.000050)	(0.000027)	
COMMERZBANK AG	0.4967**	0.3305	0.6845***	1.1596***	0.9980
	(0.043702)	(0.243851)	(0.045003)	(0.017597)	
DAIMLER AG	-0.2164	43.3092*	0.9636***	1.0299***	0.9974
	(0.482772)	(627.623548)	(0.000019)	(0.000020)	
DEUTSCHE BANK AG	0.2543	1.8519***	0.9350***	1.0495***	0.9979
	(0.038774)	(0.432202)	(0.000086)	(0.000075)	
DEUTSCHE BOERSE AG	0.7329***	1.1790***	0.9240***	1.0287***	0.9978
	(0.008016)	(0.154737)	(0.000083)	(0.000024)	
DEUTSCHE POST AG	0.7952***	527.5659	0.9425***	1.0300***	0.9956
	(0.072417)	(125,357.996408)	(0.000040)	(0.000024)	
DEUTSCHE TELEKOM AG	-0.0862	317.0287***	0.9618***	1.0386***	0.9984
	(0.098133)	(12,538.620584)	(0.000026)	(0.000029)	
E.ON AG	0.5056***	32.8602***	0.9500***	1.0312***	0.9978
	(0.033217)	(136.342429)	(0.000039)	(0.000023)	
FRESEN.MED.CARE KGAA (c.s.)	0.0697	6.0591*	0.8986***	1.0858***	0.9888
	(0.148020)	(10.476852)	(0.000752)	(0.000529)	
FRESENIUS SE (p.s.)	0.1779	11.0349***	0.9432***	1.0440***	0.9975
	(0.053081)	(14.114374)	(0.000048)	(0.000048)	
HEIDELBERGCEMENT AG	0.6028***	0.5679**	0.8850***	1.0481***	0.9970
	(0.024636)	(0.081493)	(0.000430)	(0.000276)	
HENKEL AG &CO KGAA (p.s.)	0.4634**	42.2867***	0.9257***	1.0432***	0.9958
	(0.035872)	(253.485100)	(0.000069)	(0.000042)	
INFINEON TECHNOLOGIES AG	0.4763***	41.2219***	0.9003***	1.0529***	0.9969
	(0.021067)	(198.262469)	(0.000162)	(0.000120)	
K+S AG	0.6789	100.0079	0.9722***	1.0217***	0.9978
	(0.181356)	(9,472.241923)	(0.000014)	(0.000014)	
LINDE AG	0.4901**	13.5113**	0.9409***	1.0349***	0.9968
	(0.041666)	(27.600937)	(0.000040)	(0.000025)	

	$\Delta\delta^*$	β^*	Φ_F	Φ_C	R^2_{adj}
LUFTHANSA AG	0.4188**	58.6607**	0.9354***	1.0451***	0.9964
	(0.044752)	(638.065119)	(0.000123)	(0.000085)	
MAN SE (c.s.)	0.6584***	7.2738**	0.9535***	1.0287***	0.9979
	(0.031407)	(8.080573)	(0.000027)	(0.000015)	
MERCK KGAA	0.4801***	1.1107**	0.9076***	1.0509***	0.9973
	(0.025386)	(0.237078)	(0.000290)	(0.000152)	
METRO AG (c.s.)	0.3575	41.5839**	0.9508***	1.0395***	0.9969
	(0.088946)	(316.530440)	(0.000028)	(0.000023)	
MUENCH. RUECKVERS. AG	0.5550***	3.3960***	0.9074***	1.0446***	0.9943
	(0.028974)	(1.571806)	(0.000108)	(0.000067)	
RWE AG (c.s.)	0.5002***	13.4324***	0.9456***	1.0374***	0.9975
	(0.032854)	(23.153506)	(0.000029)	(0.000020)	
SAP AG	-0.5612	185.2925*	0.9535***	1.0487***	0.9951
	(0.893932)	(10,647.624583)	(0.000033)	(0.000039)	
SIEMENS AG	0.3759	5.7225**	0.9463***	1.0356***	0.9966
	(0.066923)	(5.873838)	(0.000041)	(0.000033)	
THYSSENKRUPP AG	-2.4694	332.5254	0.9598***	1.0290***	0.9970
	(20.374941)	(89,305.542038)	(0.000021)	(0.000017)	
VOLKSWAGEN AG (p.s.)	0.1959	17.4221	0.9854***	1.0155***	0.9988
	(0.513363)	(221.431663)	(0.000009)	(0.000009)	

The table provides the estimated coefficients of the non linear least squares regression for the stocks that were included in the DAX30 as of Dec 31^{st} 2010. Common stocks are marked with "c.p.", preferred stocks are indicated by "p.s.". The difference between the magnitude of social influence of fundamentalists δ_F and chartists δ_C results from $\Delta\delta^* = \frac{\delta_F - \delta_C}{1-\delta_C}$. The intensity of choice, measuring investors' tendency to choose the strategy which has better performed in the past, divided by investors' constant rate of risk aversion and the expected price volatility is given by $\beta^* = \frac{\beta}{a\sigma^2}$. The coefficients Φ_F and Φ_C are the factors that fundamentalists and chartists use to form their expectations based on the past deviation of the asset price from its fundamental benchmark. 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/B/E/S database also provided by Thomson Reuters. The difference between the stock price and analysts' opinions about a stock's fair value represents the deviation from the fundamental benchmark, denoted by x_t in the model. For several reasons, analysts' predictions are biased.[6] In order to account for this fact, I demeaned the stocks' time series of deviations. Moreover, I considered weekly averages in order to suppress very short-term fluctuations. The weekly

[6] See for instance Graham (1999), Hong et al. (2000), Welch (2000), Cooper et al. (2001), Hong and Kubik (2003), Bernhardt et al. (2006), Chen and Jiang (2006), Clarke and Subramanian (2006), Naujoks et al. (2009), Jegadeesh and Kim (2010).

risk-free rate r is obtained from the yield curve of German government bonds as published on the homepage of the Deutsche Bundesbank.[7]

The results for all 30 stocks are given in table 2.1. It can be seen that without imposing any restriction on Φ_F and Φ_C, the estimate of Φ_F is smaller than one and the estimate of Φ_C is greater than one for all 30 stocks, such that the definitions of fundamentalists and chartists are met. Also remarkably, all estimates of $\Delta\delta^*$ are smaller than one. This implies that no investor is extremely influenced by social interaction. Moreover, the model always yields a feasible market equilibrium price as stated by the propositions in chapter 2.3.2. For 16 out of 30 stocks, the estimate of $\Delta\delta^*$ is significantly different from zero. Hence, for more than half of the stocks, the influence from social interaction explains a part of the stock price fluctuations around its fundamental benchmark. Interestingly, in all of these cases, the estimates of $\Delta\delta^*$ are greater than zero, which indicates that δ_F is greater than δ_C. Hence, fundamentalists skew their beliefs more strongly into the direction of chartists than chartists do into the opposite direction. Therefore, it can be concluded that social interaction rather has a destabilising impact on financial markets. Overall, one can state that social influence at least does not have a stabilising effect.

2.5 Conclusion

In this paper, I introduced an asset pricing model that takes the influence from social interaction into account. The framework is based on the adaptive beliefs system of Brock and Hommes (1997) and Brock and Hommes (1998). Empirically analysing all stocks in the DAX30 index as of Dec 31^{st} 2010, I found that social influence has an impact on prices of more than half of the stocks. Results show that social interaction enlarges the deviations from fundamental benchmarks and thereby destabilises stock prices. Hence, one can at least state that social interaction does not have a stabilising effect.

[7] See www.bundesbank.de

Appendix

A.1 Vectorial representation of equation 2.11

For notational convenience in the chapters of the appendix, equation 2.11 is henceforth written in the vectorial form:

$$\mathbf{f}_t = \theta_t + \mathbf{D}\left(\mathbf{\Gamma}\mathbf{f}_t - \theta_t\right), \tag{2.37}$$

where $\mathbf{f}_t = (f_{1t}, f_{2t}, \ldots, f_{it}, \ldots, f_{Nt})^T$ and $\boldsymbol{\theta}_t = (\theta_{1t}, \theta_{2t}, \ldots, \theta_{it}, \ldots, \theta_{Nt})^T$. The matrices $\mathbf{D}$ and $\mathbf{\Gamma}$ are given by

$$\mathbf{D} = \begin{bmatrix} \delta_1 & 0 & \ldots & 0 & \ldots & 0 \\ 0 & \delta_2 & \ldots & 0 & \ldots & 0 \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ 0 & 0 & \ldots & \delta_i & \ldots & 0 \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ 0 & 0 & \ldots & 0 & \ldots & \delta_N \end{bmatrix} \tag{2.38}$$

and

$$\mathbf{\Gamma} = \begin{bmatrix} 0 & \gamma_{12} & \ldots & \gamma_{1j} & \ldots & \gamma_{1N} \\ \gamma_{21} & 0 & \ldots & \gamma_{2j} & \ldots & \gamma_{2N} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \gamma_{i1} & \gamma_{i2} & \ldots & 0 & \ldots & \gamma_{iN} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \gamma_{N1} & \gamma_{N2} & \ldots & \gamma_{Nj} & \ldots & 0 \end{bmatrix}. \tag{2.39}$$

Solving equation 2.37 for $\mathbf{f}_t$ ones obtains

$$\mathbf{f}_t = \mathbf{M}^{-1}(\mathbf{I} - \mathbf{D})\theta_t, \tag{2.40}$$

where $\mathbf{I}$ is the identity matrix and $\mathbf{M}$ is given by

$$\mathbf{M} = \mathbf{I} - \mathbf{D\Gamma} = \begin{bmatrix} 1 & -\delta_1\gamma_{12} & \dots & -\delta_1\gamma_{1j} & \dots & -\delta_1\gamma_{1N} \\ -\delta_2\gamma_{21} & 1 & \dots & -\delta_2\gamma_{2j} & \dots & -\delta_2\gamma_{2N} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ -\delta_i\gamma_{i1} & -\delta_i\gamma_{i2} & \dots & 1 & \dots & -\delta_i\gamma_{iN} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ -\delta_N\gamma_{N1} & -\delta_N\gamma_{N2} & \dots & -\delta_N\gamma_{Nj} & \dots & 1 \end{bmatrix}. \quad (2.41)$$

A.2 Avoidance of a social multiplier

In order to show that equation 2.11 does not produce a social multiplier, the vectorial form as being outlined in appendix A.1 is used:

$$\mathbf{f}_t = \mathbf{M}^{-1}(\mathbf{I} - \mathbf{D})\theta_t. \quad (2.42)$$

Also transforming constraint 2.12 into the vectorial form, where ι represents a column vector of ones, and rearranging yields

$$\begin{aligned} \mathbf{\Gamma}\iota &= \iota \\ \Leftrightarrow \mathbf{D\Gamma}\iota &= \mathbf{D}\iota \\ \Leftrightarrow (\mathbf{I} - \mathbf{D\Gamma})\,\iota &= (\mathbf{I} - \mathbf{D})\,\iota \\ \Leftrightarrow (\mathbf{I} - \mathbf{D\Gamma})^{-1}(\mathbf{I} - \mathbf{D})\,\iota &= \iota \\ \Leftrightarrow \mathbf{M}^{-1}(\mathbf{I} - \mathbf{D})\,\iota &= \iota. \end{aligned} \quad (2.43)$$

Hence, the elements of $\mathbf{f}_t$ always represent a weighted average of the values of θ_t. Irrespective of the values of the matrix $\mathbf{D}$, i.e. the magnitude of social influence, the average value of $\mathbf{f}_t$ cannot be higher than the greatest value of θ_t and cannot be smaller that the lowest value of θ_t.

If one did not consider the subtraction of an investor's own a priori expectation θ_{it} in equation 2.11, then the vectorial form would be given by

$$\mathbf{f}_t = \mathbf{M}^{-1}\theta_t. \quad (2.44)$$

Rearranging constraint 2.12 in the vectorial form yields

$$
\begin{aligned}
(\mathbf{I}-\mathbf{D}\boldsymbol{\Gamma})^{-1}(\mathbf{I}-\mathbf{D})\,\iota &= \iota \\
\Leftrightarrow \left((\mathbf{I}-\mathbf{D}\boldsymbol{\Gamma})^{-1}-(\mathbf{I}-\mathbf{D}\boldsymbol{\Gamma})^{-1}\mathbf{D}\right)\iota &= \iota \\
\Leftrightarrow (\mathbf{I}-\mathbf{D}\boldsymbol{\Gamma})^{-1}\,\iota &= \iota+(\mathbf{I}-\mathbf{D}\boldsymbol{\Gamma})^{-1}\mathbf{D}\iota \\
\Leftrightarrow \mathbf{M}^{-1}\iota &= \iota+\left(\mathbf{D}^{-1}-\boldsymbol{\Gamma}\right)^{-1}\iota \\
\Leftrightarrow \mathbf{M}^{-1}\iota &= \iota+\mathbf{G}^{-1}\iota, \qquad (2.45)
\end{aligned}
$$

with

$$
\mathbf{G}=\mathbf{D}^{-1}-\boldsymbol{\Gamma}=\begin{bmatrix}
\frac{1}{\delta_1} & -\gamma_{12} & \cdots & -\gamma_{1j} & \cdots & -\gamma_{1N} \\
-\gamma_{21} & \frac{1}{\delta_2} & \cdots & -\gamma_{2j} & \cdots & -\gamma_{2N} \\
\vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\
-\gamma_{i1} & -\gamma_{i2} & \cdots & \frac{1}{\delta_i} & \cdots & -\gamma_{iN} \\
\vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\
-\gamma_{N1} & -\gamma_{N2} & \cdots & -\gamma_{Nj} & \cdots & \frac{1}{\delta_N}
\end{bmatrix}. \qquad (2.46)
$$

If for instance $0 \leq \delta_i < 1$, then $\mathbf{G}$ is diagonally dominant and has negative off-diagonal entries, wherefore all elements of $\mathbf{G}^{-1}$ are non negative (see e.g. Berman and Plemmons (1979)). In this case a social multiplier arises and causes the (absolute) mean value of the elements of $\mathbf{f}_t$ always being greater than a weighted average of the values of θ_t.

A.3 Equilibrium condition

All propositions in chapter 2.3.2 refer to conditions that if fulfilled lead to exactly one equilibrium market price given by equation 2.9. Such an equilibrium is obtained, if equation 2.11 has exactly one feasible solution for the vector of investors' beliefs $\mathbf{f}_t = (f_{1t}, f_{2t}, \ldots, f_{it}, \ldots, f_{Nt})^T$. Using the vectorial form as being outlined in appendix A.1 and solving for $\mathbf{f}_t$, equation 2.11 becomes

$$
\mathbf{f}_t = \mathbf{M}^{-1}(\mathbf{I}-\mathbf{D})\theta_t. \qquad (2.47)
$$

Equation 2.47 yields exactly one solution for $\mathbf{f}_t$, if the following condition is met:

$$\mathrm{Det}(\mathbf{M}) \neq 0. \tag{2.48}$$

Hence, if the determinant of $\mathbf{M}$ is unequal to zero, equation 2.9 leads to exactly one equilibrium market price.

A.4 Proof of proposition 1

In order to give the proof of proposition 1, it has to be shown that the determinant of $\mathbf{M}$ is always unequal to zero (see appendix A.3), if all δ_i are smaller than one. If $\delta_i < 1$, then $\mathbf{M}$ has a dominant diagonal, because constraint 2.12 ensures that for each row

$$1 > \sum_{j \neq i} |-\delta_i \gamma_{ij}| \tag{2.49}$$

is fulfilled. Therefore, the determinant of $\mathbf{M}$ is unequal to zero (Taussky, 1949). $\square$

A.5 Proof of proposition 2

If one allows δ_i to be greater than one for some investors, then the matrix $\mathbf{M}$ no longer has a dominant diagonal as stated in the proof of proposition 1. If however additionally a network structure with equal weights ($\gamma_{ij} = \frac{1}{N-1}$) is presumed, then $\mathbf{M}$ can be reformulated, such that still a dominant diagonal is obtained. Multiplying the rows of a matrix with a factor unequal to zero only scales the determinant by this factor, but never induces the determinant to become equal or unequal to zero. Therefore, the rows of the matrix $\mathbf{M}$ where $\delta_i > 1$ are multiplied by $\frac{1}{\delta_i}$. In order to demonstrate this, assume a market with four investors where $\delta_1 > 1$, $\delta_2 < 1$, $\delta_3 > 1$ and $\delta_4 < 1$. After multiplication, the matrix $\mathbf{M}$ is given by

$$\mathbf{M} = \begin{bmatrix} \frac{1}{\delta_1} & -\frac{1}{N-1} & -\frac{1}{N-1} & -\frac{1}{N-1} \\ -\delta_2\frac{1}{N-1} & 1 & -\delta_2\frac{1}{N-1} & -\delta_2\frac{1}{N-1} \\ -\frac{1}{N-1} & -\frac{1}{N-1} & \frac{1}{\delta_3} & -\frac{1}{N-1} \\ -\delta_4\frac{1}{N-1} & -\delta_4\frac{1}{N-1} & -\delta_4\frac{1}{N-1} & 1 \end{bmatrix}. \tag{2.50}$$

Looking at the rows 1 and 3, where $\delta_i > 1$, it can be seen that the conditions for a dominant diagonal are not fulfilled, because

$$\frac{1}{\delta_i} < \sum_{j\neq i} \left| -\frac{1}{N-1} \right| = 1 \text{ for } \delta_i > 1. \tag{2.51}$$

However, regarding the columns of the resulting matrix, there are two kinds of conditions that if fulfilled ensure a dominant diagonal. For those investors where $\delta_i < 1$ the diagonal element still is one as those rows remained unchanged by the multiplication. The conditions for the columns where the diagonal element is one is given by

$$1 > \sum_{j\neq i} \left| -\min\{\delta_j, 1\} \frac{1}{N-1} \right|. \tag{2.52}$$

This is always fulfilled, if there are at least two investors who are only moderately influenced ($\delta_i < 1$). The condition for investors where $\delta_i > 1$ is given by

$$\begin{aligned} \frac{1}{\delta_i} &> \sum_{j\neq i} \left| -\min\{\delta_j, 1\} \frac{1}{N-1} \right| \\ \delta_i &< \frac{1}{\sum_{j\neq i} \left| -\min\{\delta_j, 1\} \frac{1}{N-1} \right|} \end{aligned} \tag{2.53}$$

If this is met for all investors with $\delta_i > 1$, then a dominant diagonal is ensured and hence the determinant of $\mathbf{M}$ is unequal to zero, which is a sufficient condition for exactly one equilibrium market price given by equation 2.9 (see appendix A.3). $\square$

A.6 Proof of proposition 3

If there are only two investor types with specific values for the magnitude of social influence (δ_1 and δ_2) and the network structure still consists of equal weights ($\gamma_{ij} = \frac{1}{N-1}$), then the equilibrium conditions of proposition 2 can be stated more precisely. Particularly, the matrix $\mathbf{M}$ is then given by

$$\mathbf{M} = \left[\begin{array}{cccccc} 1 & \dots & -\delta_1\gamma_{1j} & -\delta_1\gamma_{1(j+1)} & \dots & -\delta_1\gamma_{1N} \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ -\delta_1\gamma_{K1} & \dots & 1 & -\delta_1\gamma_{K(j+1)} & \dots & -\delta_1\gamma_{KN} \\ \hline -\delta_2\gamma_{(K+1)1} & \dots & -\delta_2\gamma_{(K+1)j} & 1 & \dots & -\delta_2\gamma_{(K+1)N} \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ -\delta_2\gamma_{N1} & \dots & -\delta_2\gamma_{Nj} & -\delta_2\gamma_{N(j+1)} & \dots & 1 \end{array}\right], \tag{2.54}$$

where K is number of first type investors. The determinant of $\mathbf{M}$ turns out to be

$$\begin{aligned} \mathrm{Det}(\mathbf{M}) = (-1)^{(N-1)} \left(\frac{\delta_1}{N-1} + 1\right)^{(K-1)} \left(\frac{\delta_2}{N-1} + 1\right)^{(N-K-1)} \\ \left(-1 + \frac{K\delta_1}{N-1} + \frac{(N-K)\delta_2}{N-1} - \frac{\delta_1 + \delta_2 - \delta_1\delta_2}{N-1}\right). \end{aligned} \tag{2.55}$$

As $\delta_i \geq 0$, the determinant of $\mathbf{M}$ is always unequal to zero, if the last term of equation 2.55 is unequal to zero:

$$-1 + \frac{K\delta_1}{N-1} + \frac{(N-K)\delta_2}{N-1} - \frac{\delta_1 + \delta_2 - \delta_1\delta_2}{N-1} \neq 0. \tag{2.56}$$

As N tends towards infinity, inequality 2.56 becomes

$$n\delta_1 + (n-1)\delta_2 \neq 1, \tag{2.57}$$

with $n = \frac{K}{N}$. Hence, if inequality 2.57 is fulfilled, the sufficient condition for exactly one equilibrium market price given by equation 2.9 is met (see appendix A.3). □

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3 Analyst Behaviour: the Geography of Social Interaction

In this paper, I provide empirical evidence that an analyst working in Germany is more likely to publish a high (low) price target regarding a DAX30 stock when other Germany based analysts are also optimistic (pessimistic) about the same stock. This effect of geographical proximity is not biased by the fact that DAX30 companies are headquartered in Germany. Shedding light on how influence takes place, I show that influence through communication and the exchange of opinion within small groups of analysts plays a vital role. This mainly applies during a bullish market environment. When markets are bearish, analysts' incentives induce them not to deviate too much from the overall average, such that then observational learning has a greater impact.

3.1 Introduction

On June 30^{th} 2011, there have been roughly 42,000 actively traded stocks world wide.[1] Although financial markets are rather efficient regarding the availability of information nowadays, this quantity of investment opportunities makes it

[1]This number has been published by the World Federation of Exchanges members on www.world-exchanges.org and refers to the stocks that are traded on the 54 major stock exchanges in the world. Double counting has tried to be eliminated by only considering domestic stocks from the perspective of each stock exchange.

impossible for market participants to access and elaborate every piece of information. In this context, financial market analysts play a central role. Each of them focuses on a few investment opportunities, uses his sector expertise and tracking experience to provide forecasts of financial figures and thereof derives investment recommendations. The resulting impact analysts have on investment behaviour and market outcomes has led to a stream of literature that is concerned with how analysts derive their forecasts and recommendations and to what extend they are influenced by other analysts.

Empirical works of Hong et al. (2000) and Krishnan et al. (2006) show that equity sell-side analysts[2] herd while providing earnings forecasts. Zitzewitz (2001), Bernhardt et al. (2006) and Naujoks et al. (2009) find an anti-herding behaviour in the same context. Kim and Zapatero (2009) and Jegadeesh and Kim (2010) among others use analysts' investment recommendation to provide empirical evidence for herding behaviour.

All authors cited above assume that individual analysts are homogeneously influenced by all other analysts. Only few authors have considered heterogeneous influence among analysts so far. Graham (1999) finds that analysts are more strongly influenced by a lead analyst who is defined by his reputation. Cooper et al. (2001) consider several lead analysts who are determined by past performance and market recognition. Welch (2000) postulates that an analyst's investment recommendation is influenced by the consensus recommendation and the two most recently published recommendations of other analysts.

With this paper, I contribute to the literature on heterogeneous influence by providing a detailed analysis of the geographical structure of social interaction and relating it to the prevailing market environment. This represents a further step into the direction of understanding how analysts deviate from their own estimates and how analysts' forecasts thus have to be interpreted in or-

[2]Hereafter, the term analyst always refers to an equity analyst. Due to empirical data availability, the term analyst furthermore always refers to a sell-side analyst. See for instance Groysberg et al. (2007) for a detailed comparative analysis between buy-side and sell-side analysts.

der to get valuable investment recommendations. My first hypothesis is that analysts are more strongly influenced by analysts that are geographically proximate. The theoretical foundation for this hypothesis is derived from recent evidence in the psychological literature. Reis et al. (2011) found that individuals are more strongly attracted by individuals with whom they are more familiar. Translating this into the financial context, this means that forecasts and recommendations of analysts working in the same country could appear more reliable, as these analysts might be perceived to be more familiar due to the same language or a similar background. Analysts who work in the same city have a higher probability to know each other personally, which might amplify this effect. The hypothesis of familiarity is also motivated by the evidence that has already been provided in the context of portfolio selection (see e.g. Grinblatt and Keloharju (2001) and Huberman (2001)).

In the analyst literature, authors so far have always postulated that influence among analysts only takes place via "observation" (i.e. observational learning). It has mainly been argued that this is due to the fact that analysts work for different firms and thus are competitors. However, there are various theoretical settings that show that communication among competing participants on financial markets can be beneficial (Eren and Ozsoylev, 2006, Stein, 2008, Gray, 2010). The reason for this lies in the fact that through the exchange of opinion, also known as word-of-mouth[3], information and potential research advantage is not only given away. An analyst can also collect new pieces of information and learns about other analysts' views which helps to validate the own results.[4] Based on these theoretical considerations, my second hypothesis is that analysts are more strongly influenced by analysts with whom they

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

[4]One could also think of the situation where information is only given away, however, with the intention to influence other analysts such that they skew their valuation results into a desired direction, which makes the own already published result more credible for investors.

exchange their opinions. This hypothesis is related to the first one, because the likelihood that two analysts know each other and exchange their opinions is higher, if they are geographically proximate. Evidence in favour of this hypothesis has already been provided in the context of institutional investors (see e.g. Shiller and Pound (1989) and Hong et al. (2005)) as well as retail investors (see e.g. Ivkovic and Weisbenner (2007)).
With my third hypothesis, I state that effects of geographical proximity or the exchange of opinion are more strongly pronounced during an economic upturn compared to an economic downturn. I base this hypothesis on the incentive structure of analysts who are judged by their relative performance (Hong et al., 2000, Hong and Kubik, 2003, Chen and Jiang, 2006). This means that in times of a bull market they try to stand up from the crowd in order to distinguish themselves from their competitors (Zwiebel, 1995). Therefore, they seek to obtain research advantages from few other analysts who are familiar due to geographical proximity or with whom they exchange their opinions. However, during an economic downturn which generally induces a high uncertainty, they try not to deviate too much from the overall average in order to limit the potential loss (Scharfstein and Stein, 1990, Clarke and Subramanian, 2006).
My database consists of price targets regarding the stocks of DAX30 companies that have been published by sell-side analysts in the period from 2005 to mid 2010. A price target refers to the value of a stock an analyst considers to be fair and therefore expects to be reached by the market price within a predefined horizon that usually equals one year. Hence, price targets represent investment recommendations and thus might have a direct impact on market participants. In an empirical setting, the advantage of the price target compared to the verbal investment recommendation (buy, hold, sell) lies in the fact that it is a continuous variable that quantifies how optimistic or pessimistic an analyst is about a stock. The choice of DAX30 stocks is motivated by the high analyst coverage. Moreover, it allows the analysis of a homogenous group of international analysts who have an indirect impact on one of the major European indices. Such a focus has not been considered in the ana-

lyst literature so far. The database is unique to the extent that it represents a merger of the commonly used commercial database I/B/E/S provided by Thomson Reuters and the data of analyst reports that are publicly available on the webpage www.aktiencheck.de. While I/B/E/S is rather focussed on analyst reports of great brokerage houses and investment banks, the reports on www.aktiencheck.de include investment newsletters of research houses and daily newspapers that also have influence on market participants. The period of the database allows a very up-to-date analysis of analysts' behaviour before and during the recent financial and economic crisis that has not been conducted in the analyst literature yet. In order to examine the influence that results from the exchange of opinion, one has to identify the individual analysts who actually exchange their opinions with each other. In the context of institutional investors, Hong et al. (2005) assume that the exchange of opinion only or at least primarily takes place on the city level. In the context of retail investors, Massa and Simonov (2005) state that there are further important characteristics that indicate the exchange of opinion, namely the profession and the former university attendance. In order to go beyond relying on assumptions, I conducted a representative survey among DAX30 analysts to find out with whom analysts actually exchange their opinions.

Within the empirical analysis, I find that when German analysts on average increase their price targets by 1 EUR (1%), an individual German analyst increases his price target by 0.32 EUR (0.15%) *more* than he does when analysts working outside Germany on average increase their price targets by 1 EUR (1%). This corroborates the hypothesis of geographical proximity for German analysts. I show that this result is not related to the fact that DAX30 companies are headquartered in Germany, which one might think to be an informational advantage. Regarding the exchange of opinion, I discover that before the economic crisis an individual analyst's price target is more similar to the price targets of analysts with whom he exchanges his opinion compared to other analysts. Hence, my second hypothesis is affirmed at least for the period before the economic crisis. It is not approved for the period during the

economic crisis which in turn however is consistent with my third hypothesis that analysts strongly align their price targets with the consensus and are less influenced by the exchange of opinion within small groups of analysts in times of a great uncertainty which is generally given during a crisis.
The remainder of this paper is structured as follows. In chapter 3.2, I present the dataset as well as the survey results. Chapter 3.3 serves to outline how this data is used for the empirical analysis. The results are provided in chapter 3.4. An alternative explanation for these empirical results is offered in chapter 3.5. Chapter 3.6 concludes.

3.2 Data

3.2.1 Price Target Data

The empirical analysis of this paper is based on the price targets regarding the stocks of the thirty German companies included in the index DAX30 as of May 31^{st} 2010. In order to avoid confusions in the following, the term company shall always refer to the organisation having issued a stock, whereas firm denotes the organisation an analyst is employed by. The period of analysis comprises the almost five and a half year time window from January 1^{st} 2005 to May 31^{st} 2010 and thus includes the stock market peak preceding the financial crisis in 2007/08 as well as the crisis itself. The price targets are primarily extracted from I/B/E/S, the common database of analysts' estimates provided by Thomson Reuters. This yielded 10,972 values for the period of analysis. Further price targets were collected from analyst reports being published on www.aktiencheck.de[5]. For the same period of time 27,175 reports have been evaluated and 16,821 price targets extracted. Both databases have then been merged as follows. The I/B/E/S database has been used as a basis. Price targets from analysts employed by firms that are not included in I/B/E/S

[5]aktiencheck.de AG is an independent research firm that collects analysts reports and publishes them together with own reports on its webpage.

have directly been added. For those firms that appeared in both databases, the publication dates regarding a specific company have been compared. In the case they were equal, only the I/B/E/S data has been taken.[6] Otherwise, the price target from the analyst report on www.aktiencheck.de has been added. In order to avoid double entries due to differing publication dates, a time window of plus minus five days has been applied. Thereby, a buffer of ten days was generated cancelling out unreal price target updates. Moreover, firms' names instead of analysts' names have been used for this comparison in order to avoid double entries that result from the fact that two analysts of a research team who published one common price target appear with one analyst's name in the first database and with the other analyst's name in the second. Note that data of I/B/E/S is adjusted by stock splits. As the analyst reports published on www.aktiencheck.de represent the original reports as being published at the time, the extracted price targets also had to be adjusted by stock splits to be consistent with the I/B/E/S data. The merger of both databases yielded 25,534 price targets. Dropping all firms that published less than 30 price targets during the whole period of analysis reduced the number of firms by one half and led to a database of 24,893 price targets. The final database resulted by eliminating all entries where only the firm but not the corresponding analyst was known and consists of 17,898 price targets. This database is unique regarding to the following fact: While I/B/E/S primarily contains estimates of investment banks, reports on www.aktiencheck.de also comprise estimates from independent research firms and investment letters. The merger of both databases hence represents a broader spectrum of analysts' price targets. Table 3.1 gives an overview of firms included in the new database. Moreover, the original database and the corresponding number of price target publications are indicated.

In order to analyse the geographic structure of influence, an analyst's work-

[6] Ljungqvist et al. (2009) reported systematic errors in the historical I/B/E/S recommendation database. The comparison of price targets that appear in both databases, however, did not reveal remarkable deviations.

Table 3.1: Overview of the firms included in the new price target database

Firm	I/B/E/S	aktiencheck
ABN AMRO	-	7
AC Research	-	38
Actien-Börse	-	82
Ahorro Corporación Financiera S.V., S.A.	17	-
Banc of America Securities-Merrill Lynch Research	3	302
Banco Sabadell	42	-
Bankhaus Lampe	104	198
Bankhaus Metzler	335	-
Barclays Capital	34	3
Bear Stearns	15	2
Berenberg Bank	46	-
BHF-BANK	359	28
Cheuvreux	595	222
Citigroup	-	625
Collins Stewart	32	2
Commerzbank Corporates & Markets	268	196
Credit Suisse	219	169
Daiwa Securities SMBC Europe Limited	26	-
Der Aktionär	-	189
Der Aktionärsbrief	-	58
Deutsche Bank	269	139
Dexia Securities	5	37
DZ BANK	236	-
equinet AG	163	238
EURO am Sonntag	-	172
Evolution Securities	31	-
Exane BNP Paribas	-	84
FOCUS-MONEY	-	59
Fox Pitt & Kelton	14	-
Frankfurter Börsenbrief	-	84
Fuchsbriefe	-	37
Goldman Sachs	-	281
Helvea	43	20
HSBC	-	106
HypoVereinsbank	-	802
IIR Group	16	16
Independent Research	-	1,507
ING	1	78
J.P. Morgan Securities	-	324
Jefferies & Co	52	7
Jyske Bank	44	22
Keefe Bruyette & Woods	36	9
Kepler Capital Markets	201	64
Landesbank Baden-Württemberg	257	30
Lehman Brothers	53	25
LRP Landesbank Rheinland-Pfalz	217	898
M.M. Warburg & CO	448	143
Macquarie	59	4
Merck Finck & Co.	-	156
Morgan Stanley	-	206
National-Bank AG	-	159
Natixis Securities	143	-
Nomura Equity Research	171	19
Nord LB	112	583
Oddo Securities	117	-
Piper Jaffray	32	7
Prior Börse	-	48
Raymond James	39	14
Sal. Oppenheim	665	108
Sanford C. Bernstein & Co	157	34
Santander	37	-
SEB	-	1,171
SES Research	10	83
Société Générale	235	374
SRH AlsterResearch	20	21
Stockstreet.de	-	30
UBS	-	261
UniCredit Markets & Investment Banking	374	516
WestLB	280	169
	6,632	11,266
	17,898	

The table displays the firms' names and the number of published price targets originating from the two different sources.

ing location has to be known. Although the city is indicated on the analyst reports on www.aktiencheck.de, the data could not be used as it usually only referred to the headquarter of the particular firm and not to the actual place of work of an analyst. Hence, for each analyst in the database the city and the corresponding country have been searched by hand on the internet. Table 3.2 shows the distribution of firms, analysts and published price targets by country and city. Hereafter, an analyst's nationality is used interchangeably with the country where he works. This means for instance that a "German" analyst refers to an analyst who works in Germany although there might be German analysts who work abroad. Most of the firms are Germany based, however, closely followed by UK. London is the city where most of the analysts work and is followed by Frankfurt where less than a half of London based analysts work. German analysts published about 70% of all price targets. The portion of UK based analysts who all work in London equals approximately 20%. Analysts working in Frankfurt published about one third of all price targets.

3.2.2 Survey Evidence

In order to determine the influence resulting from the exchange of opinion among analysts, it has to be known which analysts exchange their opinions with each other. Aiming to get this information, a survey of DAX30 analysts has been conducted. In the period from June 15^{th} to July 8^{th} 2010, all analysts in the price target database have been contacted by email and asked to fill in a questionnaire. Out of 858 analysts in the database 718 could be reached[7] and 195 replied. This corresponds to a response rate of 27.2%, which ensures the representativeness of the survey. The questionnaire consisting of eleven questions is shown in table 3.3.

Concerning analysts' interaction and reciprocal influence from the exchange

[7] The remaining analysts could not be contacted, as they either left their firm or because no or not a valid email address could be found.

Table 3.2: Distribution of firms, analysts and price targets of DAX30 analysts by country and city

country	city	number of firms	number of analysts	number of targets
Belgium	Brussels	2	5	61
China	Hong Kong	1	1	1
Denmark	Silkeborg	1	5	66
Germany	Berlin	1	1	37
	Detmold	1	1	84
	Düsseldorf	6	34	815
	Essen	1	5	159
	Frankfurt	16	153	6,174
	Hamburg	4	25	739
	Hanover	1	17	695
	Cologne	2	4	303
	Kulmbach	1	1	189
	Mainz	2	12	1,152
	Munich	5	32	1,989
	Stuttgart	1	24	250
	Westerburg	1	3	38
France	Paris	13	80	882
India	Bangalore	1	1	3
	Bombay	1	12	32
the Netherlands	Amsterdam	3	5	44
Austria	Vienna	1	1	9
Sweden	Stockholm	1	1	1
Switzerland	Geneva	1	2	27
	Zurich	5	11	120
Spain	Madrid	4	18	94
South Korea	Seoul	1	1	22
UK	London	33	388	3,781
USA	New York	5	13	120
	San Francisco	2	2	11
		117	**858**	**17,898**

The table displays the number of different firms, analysts and price targets on the country and the city level. Please note that firms that are based at different locations are double counted. The same applies for analysts who changed their working location during the period of analysis.

Table 3.3: Questionnaire of the survey

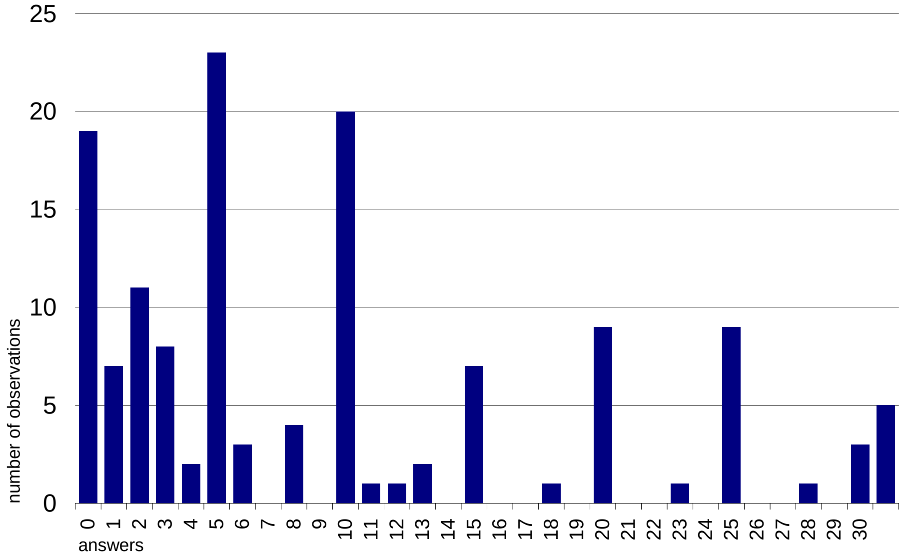
#1	How long have you been working at your firm?
#2	In which city do you work?
#3	Where have you been employed before?
#4	Which university did you attend?
#5	With about how many analysts who cover at least one of the DAX30 companies covered by you, did you already have personal contact?
#6	In which way do you most likely have contact with other analysts (e.g. telephone, meetings, events, lunch dates)?
#7	With how many analysts of question #5 do you exchange your opinion regarding **forecasts**?
#8	How many analysts of question #7 work in the same **country** as you?
#9	How many analysts of question #7 work in the same **city** as you?
#10	How many analysts of question #7 work in the same **firm** as you?
#11	How many analysts of question #7 attended the same **university** as you?

of opinions, the most important questions are #5 and #7 asking for the number of analysts, an analyst had already social contact with and an analyst regularly exchanges forecast results with, respectively. The figures 3.1 and 3.3 show the answers of these two questions. From the data, it can be seen that social contacts are quite numerous. Only 14.0% answered not personally knowing at least one other analyst who covers a common company. Additional comments of the respondents confirm that there is a community of analysts covering a stock wherein the members know each other and most often already had a personal contact. Question #6 asking for the most regular way of contact with other analysts provides the answer to this phenomenon. Analysts meet frequently on events like investors' days or analysts conferences and hence communicate with each other often. The results of question #6 are shown in figure 3.2.

Despite this regular contact, forecast results are not the main topic of conversation. Following question #7, only 34.6%[8] of the analysts exchange their

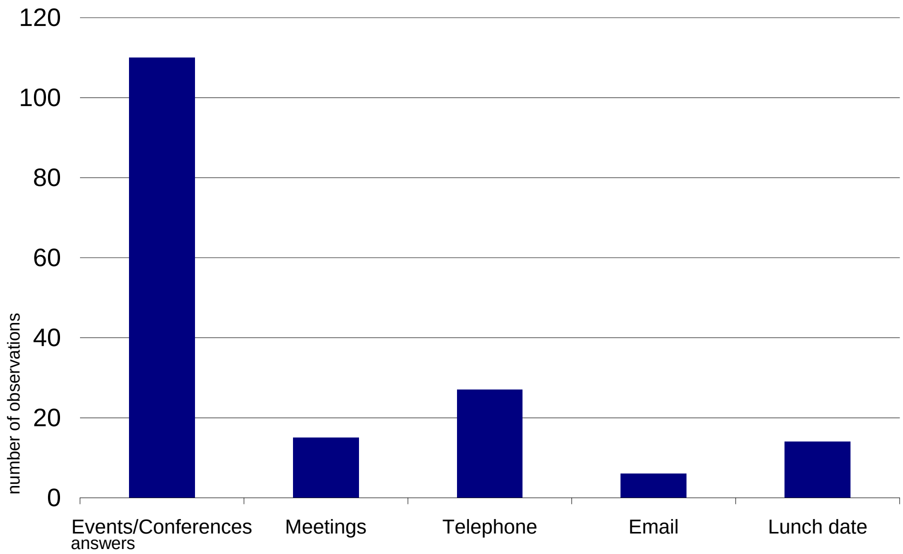
[8]The results of the question #7 to #9 and #11 are adjusted by the number of intra-firm exchanges as being asked by question #10. This is done for two reasons. Analysts in the same firm act as one unity and only publish one result. Furthermore, the exchange of opinion in a research team takes place by definition and does not provide any insight.

Figure 3.1: Histogram of the answers to survey question #5



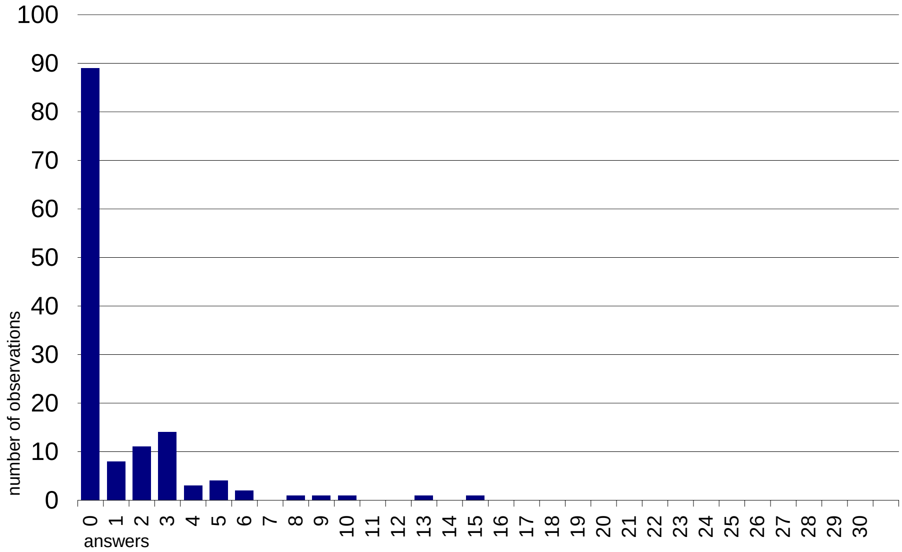
"With about how many analysts who cover at least one of the DAX30 companies covered by you, did you already have personal contact?"

Figure 3.2: Histogram of the answers to survey question #6



"In which way do you most likely have contact with other analysts (e.g. telephone, meetings, events, lunch dates)?"

Figure 3.3: Histogram of the answers to survey question #7



"With how many analysts of question #5 do you exchange your opinion regarding **forecasts**?"

opinions regarding forecasts with at least one other analyst. Note that this question is very delicate. Analysts in this context defined as sell-side analysts[9] are competitors. Hence, no one is interested in giving away his research advantage or to reveal his findings. Formally, firms' policy even obliges analysts not to do so. However, the fact that more than a third admitted to exchange their results shows that there is an informal component that weights stronger than policies or than obvious principles. As stated in the introduction, such behaviour can be beneficial, because an analyst who exchanges his opinion does not only loose a research advantage. Rather, he learns about other an-

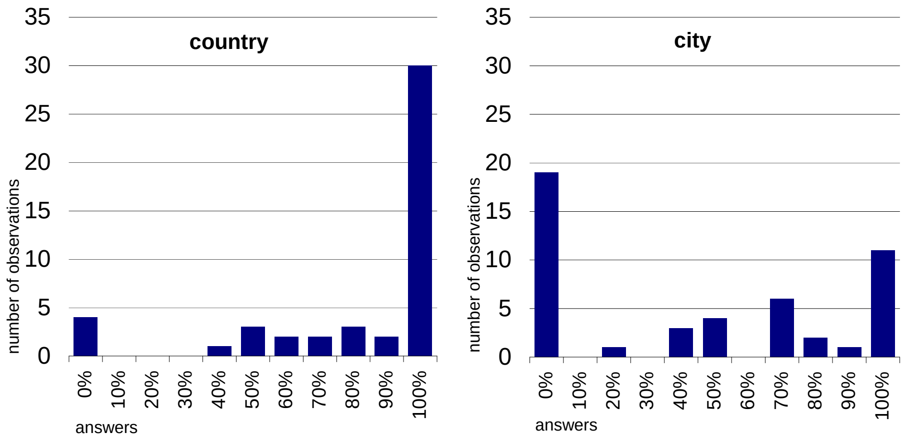
[9]Some respondents annotated that from the formulation of the questions it is not perceptible whether the word analyst refers to sell-side or buy-side analysts. Buy-side analysts are sell-side analysts' clients. Hence, the discussion of forecast results between these two types of analysts is natural and not worth of analysis. The fact that 95% of the answers to question #7 are below or equal to five proves that the questions have been understood as being indented, if one assumes that number of sell-side analysts' clients is usually greater than five. As a precaution, the two answers above 15 have been taken off.

alysts' views which helps him to validate the own results. This is especially relevant for the determination of price targets where also assumptions and valuation methods can be discussed without loosing a specific research advantage regarding an earnings forecast for instance. Indeed, some respondents who denied the exchange of forecast results, as question #7 was formulated, annotated that they nonetheless exchange assumptions and details about valuation techniques. This suggests the actual number of analysts' reciprocal influence from the exchange of opinions to be higher. Another fact that supports this tendency is that because of the question's delicate nature maybe not all answers reflect the actual situation.

The basic intention of the survey was to determine with whom an analyst exchanges his opinion. In order to get an acceptable feed-back ratio, no analyst has been asked for the names of analysts with whom he exchanges his opinion. Instead, I tried to reduce the universe of analysts that might be potential counterparts for the exchange of opinion. This can among others be done by using analysts' working locations. If for instance an analyst does not exchange his opinion with analysts working abroad, then all foreign analysts can be excluded as potential counterparts for the exchange of opinion. Survey questions #8 and #9 have been used in order to relate the exchange of opinion among analysts to their working locations. Figure 3.4 displays the portion of analysts from the same country or city, respectively, with whom a respondent exchanges his opinion. On average, 82% of the analysts who exchange their opinions regarding forecast results work in the same country (median: 100%). This result corroborates the statement in the introduction that geographical proximity (first hypothesis) and analysts' reciprocal exchange of opinion (second hypothesis) are strongly related. This finding is not biased by the fact that all analysts work in the same country as only 56% of the respondents work in the country where most of the respondents work (Germany).[10] Regarding the city level, on average only 44% of the analysts that exchange forecast results

[10]The second and third most respondents come from the UK (22%) and France (10%).

Figure 3.4: Histogram of the normalised answers to survey questions #8 and #9



"How many analysts of question #7 work in the same **country/city** as you?" The answers have been divided by the number of analysts with whom a respondent exchanges his opinion regarding forecasts (see survey question #7). The left chart shows for instance that 30 analysts only exchange their opinion with other domestic analysts. Analysts who answered not to exchange their opinions with any other analyst have been excluded.

work in the same city (median: 50%). This number is consistent with the answers of question #6 where only 10% of the respondents answered to use lunch dates as a regular way of having contact with other analysts. However, in the two cities where with 26% and 22% most of the respondents work (Frankfurt and London), this number lies at 65% and 78% respectively.

With Question #11 asking for the number of actual counterparts for the exchange of opinion who formerly attended the same university like the respondent, it was intended to get another criterion to reduce the universe of potential counterparts for the exchange of opinion. I considered this characteristic because it has been used in other empirical studies in the context of the exchange of opinion (see e.g. Massa and Simonov (2005) and Cohen et al. (2009)). However, it turned out not to be adequate, because on average only 1% of the respondents that exchange forecast results attended the same university (median: 0%).

3.3 Methodology

3.3.1 Analysis of heterogeneous influence by using different reference groups

Within the empirical analysis of this paper, I do not determine the absolute magnitude of influence or whether analysts influence each other at all. This has already done in several prior studies (see e.g. Graham (1999), Hong et al. (2000), Welch (2000), Cooper et al. (2001), Zitzewitz (2001), Bernhardt et al. (2006), Krishnan et al. (2006), Kim and Zapatero (2009), Naujoks et al. (2009) and Jegadeesh and Kim (2010)). Instead, I aim to analyse the structure of influence, i.e. an anlyst's individual weighting of other analysts' forecasts. Therefore, I divide the analysts of the database into two reference groups. The composition of these groups varies with the hypotheses to be contrasted. In order to test the first hypothesis, for instance, one group consists of all analysts who work in the same country while the other group is composed of analysts who work in other countries. The resulting basic regression is given by

$$P_{ict} = \alpha \overline{P_{ct}^{(g1)}} + \beta \overline{P_{ct}^{(g2)}} + \epsilon_{ict}, \tag{3.1}$$

where P_{ict} denotes the price target that is published by analyst i regarding stock c at time t. $\overline{P_{ct}^{(g1)}}$ and $\overline{P_{ct}^{(g2)}}$ represent the average price targets of the two different reference groups. The error term is given by ϵ_{ict}. As not all analysts publish their price target on the same day, t has to be understood as a time window. In case the influence among analysts was homogeneous, then the coefficients α and β should not differ significantly.
The variables P_{ict}, $\overline{P_{ct}^{(g1)}}$ and $\overline{P_{ct}^{(g2)}}$ represent time series of price targets. These series could turn out to be non-stationary like in the case of stock prices. In this situation, it has to be verified whether ϵ_{ict} is stationary, such that the

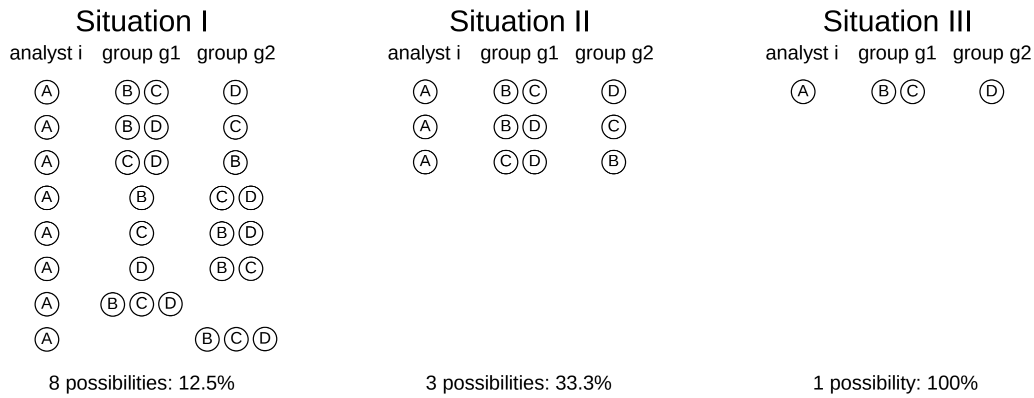
time series in equation 3.1 co-integrate (Engle and Granger, 1987). Otherwise, empirical outcomes have a high risk to be spurious.

3.3.2 Composition of the reference groups

The construction of the two reference groups in order to contrast the effect of geographical proximity is straight forward, because the working locations of all analysts are known. The determination of the effect of the exchange of opinion is somehow more challenging. The first group $g1$ has to be formed by analysts who exchange their opinions with analyst i, while the second group $g2$ has to contain only analysts who don't. As stated above, I do not certainly know which analyst has to be assigned to which group. A solution consists in randomly assigning the analysts to the two groups. Obviously, without further information, the probability of placing an analyst in the correct group equals 50%. This means that if one considers a particular analyst A on the left hand side of equation 3.1 and assumes that there are three other analysts B, C, D who cover the same company (i.e. on the right hand side of equation 3.1), then the probability for a correct overall assignment equals $0.5^3 = 12.5\%$. However, exploiting the survey evidence, this probability can be remarkably increased. If for instance, analyst A answered to exchange his opinion with two analysts who cover the same company, then taking randomly two out of the three remaining analysts B, C, D, from the perspective of analyst A, yields a probability of 100% to place at least one of the other analysts correctly and a probability of 33% to assign all analysts to the correct groups. The latter probability also increases to 100%, if one of these three analysts B, C, D answered not to exchange his opinion with any other analyst. Figure 3.5 displays the different constellations of this example.

Using real data from the survey, it is of course not possible to place all analysts correctly. However, aiming to contrast the influence that results from the exchange of opinion, it is not necessary reconstruct analysts' underlying communication network with a probability of 100%. Hereafter, I use the following

Figure 3.5: Examplary use of the survey data for a random group assignment



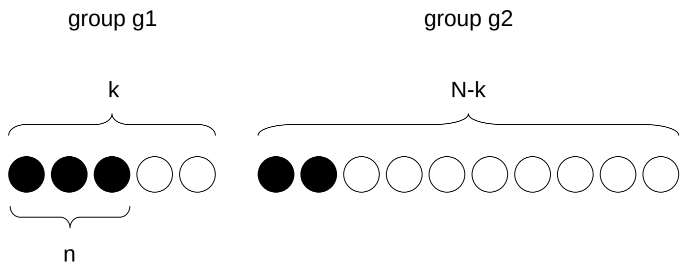
Illustrating the example in the text regarding a random group assignment for the exchange of opinion, the figure shows the possibilities that arise, if one considers a particular analyst A on the left hand side of equation 3.1 and randomly assigns three other analysts B, C, D to the two groups on the right hand side of equation 3.1. All four analysts shall cover the same company. In the first situation, one does not have any further information. In the second situation, one knows that analyst A exchanges his opinion with two other analysts that cover the same company. In the third situation, one additionally knows that analyst D does not exchange his opinion with any other analyst.

null hypothesis h_0 (not to be confused with the hypotheses one to three of this paper): A counterpart for the exchange of opinion has a higher influence compared to other analysts and the influence stemming from different counterparts for the exchange of opinions is equal. Now, if one randomly assigns the analysts to groups $g1$ and $g2$ while considering the information from the survey, then under h_0 the difference $\alpha - \beta$ in equation 3.1 should turn out to be positive, if there are enough analysts who are assigned to the right groups. From the perspective of a particular analyst, the condition for placing enough analysts correctly under h_0 can be expressed as follows:

$$\frac{n}{k} > \frac{k-n}{N-k} \Leftrightarrow n > \frac{k^2}{N}, \tag{3.2}$$

where N denotes the number of analysts who cover the same company and thus could be potential counterparts for the exchange of opinion from the perspective of a particular analyst. The number of analysts with whom a particular analyst actually exchanges his opinion is given by k. While N is determined by the database of price targets, the number k results from the answers of the survey (see survey question #7).[11] The number of analysts

Figure 3.6: Notation for analysts' group assignment



The figure displays an example of a random group assignment for the exchange of opinion. Filled circles represent analysts that are actual counterparts for the exchange of opinion from the perspective of a particular analyst. All other analysts are symbolised by empty circles. Hence, filled circles in the first group and empty circles in the second group stand for randomly correctly assigned analysts.

that are randomly correctly assigned to group $g1$ is represented by n. Figure 3.6 serves to clarify the notation.

Aiming to exploit further survey results (see survey questions #8 and #9), from the perspective of a particular analyst, the k analysts of group $g1$ can be separated into k_1 analysts who work in the same city, k_2 analysts who do not work in the same city but in the same country and k_3 analysts who do not work in the same country. N_1, N_2 and N_3 stand for the corresponding numbers of potential counterparts for the exchange of opinions. The resulting

[11] Using the answers from the survey, it is assumed that if two analysts exchange their opinions then they do so regarding all companies they have in common.

informational gain can be explained as follows. If for instance an analyst answered not to exchange his opinion with foreign analysts, then from his perspective all foreign analysts can be excluded for a random assignment to group $g1$. For each analyst i, the probability that condition 3.2 is fulfilled, i.e. that there are enough analysts who are randomly correctly placed in groups $g1$ and $g2$, such that under h_0 one obtains $\alpha > \beta$ in equation 3.1, is given by

$$P_i(\alpha > \beta | h_0) = P(n > \frac{k^2}{N}) = \frac{\sum_{m=\lfloor \frac{k^2}{N} \rfloor + 1}^{k} \prod_{j=1}^{3} \binom{k_j}{m_j} \binom{N_j - k_j}{k_j - m_j}}{\prod_{j=1}^{3} \binom{N_j}{k_j}} \tag{3.3}$$

$$s.t. \quad k = \sum_{j=1}^{3} k_j$$

$$N = \sum_{j=1}^{3} N_j$$

$$m = \sum_{j=1}^{3} m_j, \; m_j \leq k_j.$$

In the following, the Bernoulli variable I_i takes the value one with a probability of $P_i(\alpha > \beta | h_0)$, if for a particular analyst i inequality 3.2 is fulfilled and is zero otherwise with a probability of $1 - P_i(\alpha > \beta | h_0)$. The overall probability that the sign of $\alpha - \beta$ can be correctly estimated under h_0 is given by

$$P(\alpha > \beta | h_0) = \left(\sum_{i=1} w_i I_i > r \right), \tag{3.4}$$

where r is the percentage of observations in equation 3.1 for which inequality 3.2 has to be fulfilled in order to estimate the right sign of the difference $\alpha - \beta$. For the calculation of $P(\alpha > \beta | h_0)$, r is set equal to 50%, ensuring that inequality 3.2 is fulfilled for the majority of analysts. As not every analyst published the same number of price targets, the weighting coefficient w_i has been introduced.

In order to get an idea about the probability $P_i(\alpha > \beta | h_0)$ that inequality 3.2 is fulfilled for a particular analyst, table 3.4 provides the average values of N_1, N_2 and N_3 as well as of k_1, k_2 and k_3 for the cities where at least one

Table 3.4: Overview of the analysts who regularly exchange their opinions on DAX30 companies with other analysts

country	city	same city N_1	same country ex same city N_2	other countries N_3	exchange city level k_1	exchange country level ex city level k_2	exchange other countries k_3
Germany	Düsseldorf	3.5	36.5	42.0	2.0	0.0	2.8
	Frankfurt	14.7	14.3	50.0	2.3	0.8	3.7
	Hamburg	0.3	34.0	39.0	0.0	2.5	0.3
	Mainz	0.0	23.0	37.0	0.0	7.0	1.0
	Munich	1.3	29.3	33.3	0.3	1.3	0.6
	Stuttgart	0.0	26.5	32.0	0.0	2.2	0.3
France	Paris	3.0	0.0	44.7	0.7	0.0	1.3
Switzerland	Zurich	3.0	0.0	37.0	2.0	0.0	3.0
UK	London	14.0	0.0	43.7	1.3	0.0	1.7
overall		**7.8**	**17.9**	**43.3**	**1.3**	**1.1**	**2.1**

The first three columns of the table provide the average numbers of analysts in the same city N_1, the rest of same country N_2 and abroad N_3 who are theoretically available for the exchange of opinion because they cover the same company at the same time. The second three columns show the average numbers of actual counterparts for the exchange of opinions in the same city k_1, the rest of same country k_2 and abroad k_3 as obtained by the answers of the survey.

analyst participated in the survey. Remember that the numbers of all potential counterparts for the exchange of opinion, defined by the coverage of the same company, come from the price target database, whereas the numbers of actual counterparts for the exchange of opinion are obtained by the survey. Summing up the numbers in the second three columns of table 3.4 yields the size of group $g1$, i.e. the total number of analysts with whom a particular analyst exchanges his opinion irrespective of the working location. The size of the group $g2$ is determined by subtracting this number of actual counterparts for the exchange of opinion from the number of all potential counterparts for the exchange of opinion, which is obtained by summing up the first three columns in table 3.4. On average, the size of group $g1$ equals $k = k_1 + k_2 + k_3 = 1.3 + 1.1 + 2.1 = 4.5$, while the mean size of group $g2$ turns out to be $N - k = (7.8 + 17.9 + 43.3) - (1.3 + 1.1 + 2.1) = 64.5$. Hence, from the perspective of a particular analyst, the size of group $g2$ is generally much greater than the size of group $g1$. As I

always consider group averages, the influence of a singular analyst in group $g2$ is therefore very small. This means that if a counterpart for the exchange of opinion is wrongly placed in group $g2$, his impact is diluted. Hence, under h_0, the estimated influence of group $g1$ still might be higher than the estimated influence of group $g2$, such that the difference $\alpha - \beta$ in equation 3.1 turns out to be positive, if there are enough other analysts correctly placed in group $g1$. Due to the group sizes, it is even sufficient from the perspective of most of the analysts that group $g1$ only contains one properly assigned analyst, in order to fulfil condition 3.2.
The overall probability $P(\alpha > \beta | h_0)$ for estimating the correct sign of $\alpha - \beta$ in equation 3.1 under h_0 equals 73.3%. This means that running 1,000 simulations of a random group assignment while taking the information from the survey into account, the sign of the difference $\alpha - \beta$ in equation 3.1 is expected to be estimated correctly in 733 cases under h_0.

3.4 Results

3.4.1 Geographical proximity

With this paper, I intend to shed light on the structure of the influence among analysts. In this context, I test the relevance of geographical proximity, the impact of the exchange of opinion and the temporal change induced by the economic crisis starting in 2008. Testing different configurations of the augmented Dickey-Fuller test, all price target time series turn out to be stationary. Hence, there is no risk of obtaining spurious results.
I start the analysis on the country level (see table 3.5). Therefore, the construction of the relevant peer groups is straight forward as analysts' working locations are known from the price target database, such that additional information from the survey is not yet needed. From the perspective of a particular analyst, all other analysts covering the same company are divided into those who work in the same country (group $g1$) and those who work in a different

Table 3.5: Regression results for the structure of influence on the country level

	P_{ict}	$\overline{P_{ct}^{(g1)}}$	$\overline{P_{ct}^{(g2)}}$	α	β	const	$\alpha - \beta$	N	R^2
(I)	all	domestic	foreign	0.5600***	0.4148***	1.0081***	0.1452***	12,186	0.8734
				(0.0124)	(0.0123)	(0.2117)	(0.0213)		
(II)	non German	domestic	foreign	0.3130***	0.6868***	0.8089***	-0.3738***	3,946	0.9130
				(0.0194)	(0.0203)	(0.3134)	(0.0343)		
(III)	only German	domestic	foreign	0.6453***	0.3250***	1.0027***	0.3203***	8,240	0.8556
				(0.0160)	(0.0155)	(0.2729)	(0.0271)		
(IV)	only German	domestic	foreign	0.5853***	0.3777***	1.2923***	0.2077***	6,446	0.8306
	without three largest German firms			(0.0191)	(0.0184)	(0.3342)	(0.0322)		
(V)	only German	domestic	foreign	0.6658***	0.3040***	0.9453***	0.3617***	8,673	0.8616
	time window of 45 days			(0.0165)	(0.0160)	(0.2591)	(0.0280)		
(VI)	only German	domestic	foreign	0.6189***	0.3554***	0.9324***	0.2635***	7,192	0.8404
	time window of 15 days			(0.0164)	(0.0159)	(0.3088)	(0.0277)		
(VII)	only German	domestic	foreign	0.4361***	0.2846***	0.3230***	0.1515***	8,240	0.1421
	normalised price targets			(0.0175)	(0.0208)	(0.0251)	(0.0299)		
(VIII)	non German	German	non German	0.5096***	0.4754***	1.3713***	0.0343	3,991	0.9131
				(0.0170)	(0.0166)	(0.3008)	(0.0289)		

The table provides the results of the basic regression 3.1 on the country level. From the perspective of a particular analyst group $g1$ contains domestic analysts, while group $g2$ is build of foreign analysts. This composition of the groups changes in specification VIII where group $g1$ contains German analysts and group $g2$ is constructed by all other analysts. Specification I includes all analysts. For specification II and VIII only analysts who work outside Germany are considered on the left hand side of equation 3.1. Specification III-VII only include Germany based analysts on the left hand side of equation 3.1 (group $g2$ still contains foreign, i.e. non German analysts). A detailed description of the specifications is provided in the text. The significance of coefficients is indicated by stars (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$). Standard deviations are provided in parentheses.

country (group $g2$). As time window, I consider the thirty days period before the publication of the price target of a particular analyst. This time window is so designed that an analyst can only be influenced by analysts whose price targets were observable prior his own publication. The length of thirty days guarantees that there are enough analysts to be included with their price targets, while the latter however are not too old. Estimating the coefficients of equation 3.1 yields a significant difference of 0.1452 (specification I). This result, however, might be biased by the fact that most of the price targets are published by Germany based analysts. Indeed, considering only analysts working outside Germany on the left hand side of equation 3.1 leads to a negative difference of -0.3738 (specification II). This implies that the difference for German analysts is actually higher than estimated by the first regression. In fact, this difference equals 0.3203 (specification III). This means that an individual German analyst increases his price target by 0.32 EUR *more* when other German analysts on average increase their price target by 1 EUR compared to the same increase of price targets by analysts working outside Germany. In order to provide some robustness checks for this result, several out-of sample regressions have been run. First, the three German firms that provided most of the price targets are excluded. This still leads to a significant difference of 0.2077 (specification IV). Next, the time window has been varied. Considering a time window of 45 as well as 15 days prior the publication of a particular analyst's price target yields significant differences of 0.3617 and 0.2635, respectively (specification V and VI). Finally, I aim to suppress the bias of potential heteroscedasticity. Therefore, I normalised price targets by the market price of the corresponding stock on the day prior the publication. The resulting difference is significant and equals 0.1515 (specification VII). This means that an individual German analyst increases his price target by 0.15% *more* when other German analysts increase their price target by 1% compared to the same proportional increase of price targets by analysts working outside Germany.

After having provided empirical evidence that the intra-country correlation of price targets only applies for Germany based analysts, one might assume that this correlation is not due to the common country but is caused by the fact that the companies of the examined stocks are also headquartered in Germany. Therefore, German analysts might have or might at least be assumed to have a better set of information such that foreign analysts are more strongly influenced by German analysts than by their domestic colleagues. In order to analyse the influence that is generated by German analysts from the perspective of an analyst working outside Germany, I built up a group of analysts that work in Germany (group $g1$) and a group of all other analysts (group $g2$). The difference between the estimated coefficients equals 0.0343 and turns out to be insignificant (specification VIII). Hence, an analyst who works outside Germany is not more strongly influenced by German analysts than by all other analysts. Nevertheless, a German analyst still might have a better set of information although this is not recognised by analysts working outside Germany. I contrast this alternative hypothesis by comparing the returns an investor would have realised, if he had followed the implicit investment recommendations provided by price targets. The returns are given by

$$r_{ict} = \left(\frac{p_{c,t+365} + d_{ct,t+365}}{p_{ct}} - 1 \right) \operatorname{sgn}\left(P_{ict} - p_{ct}\right), \tag{3.5}$$

where p_{ct} is the market price of stock c at time t and $p_{c,t+365}$ is the stock price one year there after. The dividends that are paid during the period are given by $d_{ct,t+365}$. If an analyst publishes a price target that is higher than the current market price, then he considers the stock to be under valuated and implicitly recommends buying the stock. However, an analyst would not necessarily recommend buying a stock when his price target is only little higher than the prevailing stock price. Therefore, I use several thresholds for my analysis. These are 1%, 3% and 5%. By including dividends in equation 3.5, r_{ict} represents a gross return. For the comparative analysis of German and non German analysts I consider gross as well as net returns, i.e. returns that are calculated by including and excluding dividend payments. The results are displayed in table 3.6. It can be seen that returns that result from the buy and sell recommendations of German analysts are slightly higher. However,

Table 3.6: Average performance of German and non German analysts

	Germany	not Germany	difference
gross return. threshold 1%	6.98%	6.11%	0.87%
	(53.65%)	(51.75%)	
net return. threshold 1%	5.46%	4.43%	1.03%
	(53.79%)	(51.78%)	
gross return. threshold 3%	7.18%	6.36%	0.81%
	(54.28%)	(52.39%)	
net return. threshold 3%	5.62%	4.66%	0.97%
	(54.38%)	(52.38%)	
gross return. threshold 5%	7.46%	6.62%	0.84%
	(54.33%)	(53.06%)	
net return. threshold 5%	5.81%	4.89%	0.93%
	(54.35%)	(53.07%)	

The table shows average hypothetical returns that result from German and non German analysts' implicit recommendation provided by their price targets. The different methods of calculation are explained in the text. Standard deviations are provided in parentheses.

Table 3.7: Regression results for the structure of influence on the city level

	P_{ict}	$\overline{P_{ct}^{(g1)}}$	$\overline{P_{ct}^{(g2)}}$	α	β	const	$\alpha - \beta$	N	R^2
(IX)	all	same city	other city	0.3245***	0.6576***	0.7394***	-0.3330***	10,329	0.8741
				(0.0147)	(0.0150)	(0.2332)	(0.0256)		
(X)	non German	same city	other city	0.3155***	0.6839***	0.8180***	-0.3685***	3,918	0.9123
				(0.0195)	(0.0203)	(0.3145)	(0.0343)		
(XI)	only German	same city	other city	0.3012***	0.6702***	0.6959**	-0.3691***	6,411	0.8510
				(0.0212)	(0.0212)	(0.3228)	(0.0365)		

The table provides the results of the basic regression 3.1 on the city level. From the perspective of a particular analyst group $g1$ contains analysts who work in the same city, while group $g2$ is build of analysts who work in different cities. Specification (IX) includes all analysts. For Specification (X) only analysts who work outside Germany are considered on the left hand side of equation 3.1. Specification (XI) only includes Germany based analysts on the left hand side of equation 3.1 (group $g2$ still contains analysts working in foreign cities). The significance of coefficients is indicated by stars (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$). Standard deviations are provided in parentheses.

none of the differences are significantly different from zero. Therefore, I can conclude that analysts working in Germany do not have better knowledge about DAX30 companies although they are also headquartered in Germany. This finding is in line with Bae et al. (2008), who show that local information advantage vanishes for large companies that operate globally and have a good disclosure policy.

Now turning to the city level, from the perspective of a particular analyst, all other analysts covering the same company are divided into those who work in the same city (group $g1$) and those who work in a different city (group $g2$). The resulting difference equals -0.3330 (specification IX). Hence, analysts are more strongly influenced by analysts who work in different cities compared to those who work in the same city. This result remains unchanged if only analysts working outside Germany or only German analysts are considered on the right hand side of equation 3.1 (specification X and XI). All regression results based on the city level are shown in table 3.7.

3.4.2 Exchange of opinion

Up to now, I considered the influence stemming from analysts' price targets that could actually have been observed. In the following, I like to determine the relevance of the exchange of opinion among analysts. Therefore, I enlarge the time window to ± 30 days. Hence, an analyst is considered to be also influenced by analysts who published their price targets later in time. The intuition behind is that analysts who exchange their opinions can influence each other without having to observe the finally published price target.

In chapter 3.2, I explained that I do not certainly know an analyst's counterparts for the exchange of opinion. However, the data of the survey can be used to get a good guess, if one randomly assigns the analysts to the group of analysts who exchange their opinions with analyst i (group $g1$) and the group of those who don't (group $g2$). The regression equation 3.1 can only be estimated, if the group $g1$ from the perspective of a particular analyst i is non empty. This comes because there has to be at least one other analyst who could have influence on analyst i by the exchange of opinion, if the resulting impact shall be estimated. In order to ensure this, I dropped all observation where analysts (on the left hand side of equation 3.1) answered not to exchange their opinion with any other analyst or did not participate in the survey at all. Therefore, there are analysts whose price targets appear on the right hand side of equation 3.1, but don't on the left hand side.

Under the null hypothesis h_0 that an analyst is more strongly (with equal intensity) influenced by those analysts with whom he exchanges his opinion, the probability for correctly estimating the sign of the difference $\alpha - \beta$ in equation 3.1 equals 73.3%. This value results, if the probability $P_i(\alpha > \beta | h_0)$ at the level of a single analyst is weighted by all price targets he has published during the period of analysis. However, an analyst might publish a price target in a period of time when no other analyst of those who are randomly assigned to group $g1$ published a price target. In this case, the observation also has to be dropped for the regression 3.1, because group $g1$ would be empty. Hence, the

Table 3.8: Regression results for the relevance of the exchange of opinion

$\overline{\alpha}$	$\overline{\beta}$	$\overline{const}$	$\overline{\alpha - \beta}$	$\overline{N}$	$\overline{P(\alpha > \beta \vert h_0)}$	$f_{rel}\,(\alpha - \beta > 0)$
0.4496	0.5465	0.8265	-0.0969	679	75.3%	43.0%
(0.3687)	(0.3570)	(1.6738)	(0.7250)			

The table provides the mean results of the simulation with 1,000 point estimates of the basic regression 3.1 that is used to determine the relevance of the exchange of opinion. From the perspective of a particular analyst group $g1$ contains analysts with whom he exchanges his opinion, while group $g2$ is build of other analysts. $\overline{P(\alpha > \beta|h_0)}$ is the average probability that for a random assignment of the groups the sign of the difference $\alpha - \beta$ can be correctly estimated under the null hypothesis. $f_{rel}\,(\alpha - \beta > 0)$ is the relative frequency of simulation runs where the difference $\alpha - \beta$ turned out to be positive. Standard deviations of the point estimates resulting from the simulation runs are provided in parentheses.

number of price targets published by this particular analyst is reduced. This in turn changes the weighting coefficients w_i in equation 3.4, which thus depend on the random composition of group $g1$ and $g2$. Therefore, the probability for estimating the correct sign of $\alpha - \beta$ under h_0 varies slightly. Table 3.8 provides the results of 1,000 simulations. It can be seen that the mean probability for a proper assignment equals 75.3%, which is slightly higher than using a naïve weighting with all price targets published by an individual analyst. The average difference $\overline{\alpha - \beta}$ is negative and the point estimate of this difference is positive in only 43.0% of the cases. Given the fact that under h_0, one would expect $\alpha - \beta$ to be greater than zero in 75.3% of the cases, h_0 has to be rejected. Thus, I have to conclude that the exchange of opinion has no or at least less relevance than observation.

3.4.3 Social influence in conjunction with the prevailing financial market environment

All afore presented results are obtained by using the whole database ranging from the beginning of 2005 to mid 2010. This is a time period where financial markets were subject to remarkable fluctuations. There was a bull market until the beginning of 2007 when the U.S. subprime crisis began to develop to a global financial crisis. The consequences for non financial companies arose with the delay of one year, when the financial crisis became an economic crisis. Most of the companies in the DAX30 are non financial companies, such that it is of interest to examine changes in analysts' behaviour before and during the economic crisis. The beginning is marked by the collapse of the investment bank Lehman brothers on September 15^{th} 2008. This date is quite exactly in the middle of the analysed period and thus allows separating the whole database into two sets of data with similar number of observations. In the following, I use these two temporal subsets in order to repeat the analyses on the country and city level as well as regarding the exchange of opinion.

The results referring to the effect of geographical proximity are shown in table 3.9. On the country level, I only consider German analysts, as prior results showed that the relevance of the country only applies for analysts who work in Germany. It can be seen that the difference $\alpha - \beta$ is considerably greater before the economic crisis than during it (specifications XII and XIII). Before the crisis, a German analyst increased his price target by 0.51 EUR *more*, when other German analysts on average increased their price target by 1 EUR compared to the same increase of the price target by other analysts. This difference is 0.34 EUR higher than during the crisis. On the city level, $\alpha - \beta$ is negative before as well as during the crisis (specifications XIV and XV). However, this difference is slightly greater, i.e. less negative before the crisis.

Table 3.10 shows the temporal differences for the exchange of opinion. During the economic crisis the mean difference $\overline{\alpha - \beta}$ is negative and only 33.9% of the simulation runs yielded a positive difference $\alpha - \beta$. This is in line with

Table 3.9: Regression results for the temporal change on the country and the city level

	P_{ict}	$\overline{P_{ct}^{(g1)}}$	$\overline{P_{ct}^{(g2)}}$	α	β	const	$\alpha-\beta$	N	R^2
(XII)	only German	domestic	foreign	0.7414***	0.2354***	1.0673***	0.5060***	2,845	0.9372
	before econmic crisis			(0.0198)	(0.0186)	(0.3542)	(0.0330)		
(XIII)	only German	domestic	foreign	0.5646***	0.4000***	0.9497**	0.1647***	5,328	0.7665
	during econmic crisis			(0.0227)	(0.0226)	(0.3980)	(0.0389)		
(XIV)	all	same city	other city	0.3498***	0.6300***	1.0152***	-0.2802***	4,102	0.9376
	before econmic crisis			(0.0181)	(0.0180)	(0.2965)	(0.0312)		
(XV)	all	same city	other city	0.3189***	0.6658***	0.5414	-0.3469***	6,144	0.7874
	during econmic crisis			(0.0217)	(0.0227)	(0.3553)	(0.0382)		

The table provides the results of the basic regression 3.1 on the country and the city level. In specification XII and XIII, only German analysts are considered on the left hand side of equation 3.1. From the perspective of a particular analyst group $g1$ contains domestic analysts, while group $g2$ is build of foreign analysts. Specifications XIV and XV are based on all analysts. From the perspective of a particular analyst group $g1$ contains analysts who work in the same city while group $g2$ is build of analysts who work in different cities. The dataset is divided into two subsets with price targets being published before (specifications XII and XIV) and during the economic crisis (specifications XIII and XV). The significance of coefficients is indicated by stars (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$). Standard deviations are provided in parentheses.

Table 3.10: Regression results for the temporal change of relevance of exchange of opinion

	$\overline{\alpha}$	$\overline{\beta}$	$\overline{const}$	$\overline{\alpha-\beta}$	$\overline{N}$	$\overline{P(\alpha>\beta\|h_0)}$	$f_{rel}\,(\alpha-\beta>0)$
before economic crisis	0.5131	0.4173	4.2817	0.0958	262	63.4%	64.8%
	(0.1701)	(0.1737)	(1.7417)	(0.3425)			
during economic crisis	0.4001	0.7015	-3.4232	-0.3014	415	78.7%	33.9%
	(0.8471)	(0.8189)	(2.4488)	(1.6647)			

The table provides the mean results of the simulation with 1,000 point estimates of the basic regression 3.1 that is used to determine the relevance of the exchange of opinion. From the perspective of a particular analyst group $g1$ contains analysts with whom he exchanges his opinion, while group $g2$ is build of other analysts. The dataset is divided into two subsets with price targets being published before and during the economic crisis. $\overline{P(\alpha>\beta|h_0)}$ is the average probability that for a random assignment of the groups the sign of the difference $\alpha-\beta$ can be correctly estimated under the null hypothesis. $f_{rel}\,(\alpha-\beta>0)$ is the relative frequency of simulation runs where the difference $\alpha-\beta$ turned out to be positive. Standard deviations of the point estimates resulting from the simulation runs are provided in parentheses.

the previously obtained results by using the whole dataset. However, looking at the period before the economic crisis, $\overline{\alpha - \beta}$ turns out to be positive. The corresponding probability for correctly estimating the sign of $\alpha - \beta$ under h_0 equals 63.4%. The relative frequency of simulations runs where α is greater than β turns out to be 64.8%. This indicates that the influence from the exchange of opinion plays a considerable role for price targets published before the economic crisis.

3.5 Alternative explanation

The afore-presented results corroborate the hypothesis of local proximity for German analysts and the hypothesis that analysts are more strongly influenced by their counterparts for the exchange of opinion (at least before the economic crisis). However, there might be an alternative explanation for these findings. An often cited caveat in the literature of social interaction (see e.g. Manski (1993), Brock and Durlauf (2001), Moffitt (2001) and Blume et al. (2010)) is that individuals only appear to be influenced by peer group members. In truth, their actions are correlated, because peer group members have similar background characteristics that induce them to act analogously. For the first hypothesis this would mean that price targets of German analysts are only correlated, because all German analysts have for instance the same education and therefore use the same method for the evaluation of the market environment. For the second hypothesis, this would imply that analysts exchange their opinions with only those analysts who have a similar way of thinking about investment opportunities, such that price targets are correlated without any actual influence taking place. There are several aspects that can be used to argue against these alternative explanations. First of all, financial education nowadays follows international standards. There are even uniform certificates like the Chartered Financial Analyst (CFA)[12]. Therefore, it is not reasonable to assume that German analysts use a different tool box compared to their colleagues working outside Germany. Moreover, the structure of influence has been put in a temporal context. Hence, even if one does not trust the absolute results, there is a significant difference of behaviour before and during the economic crisis. This especially applies for the influence resulting from the exchange of opinion. If one still does not want to believe in the explanations of the structural patterns of influence, then there is at least a clear indicator that the influence among analysts is not homogenous as many authors assumed in their empirical studies.

3.6 Conclusion

The results can be summarised as follows. German DAX30 analysts are more sensitive to price targets of other Germany based analysts than to price targets published by analysts who work in other countries. This effect is not due to the fact that DAX30 companies are also headquartered in Germany. These finding are consistent with the hypothesis of local familiarity. However, on the city level no empirical evidence in favour of this hypothesis could be provided. Comparing the influence of pure observational learning with the influence that results from the exchange of opinion, I cannot find relevance of the latter while considering the whole period from 2005 to 2010. However, dividing the dataset into two subsets with price targets before and during the economic crisis starting in 2008 yields that before the crisis price targets of analysts who exchange their opinions systematically differ from those who don't. This tendency also applies for the analysis on the country level. Before the economic crisis, a German analyst is considerable more responsive to price targets of other German analysts than during the crisis.
Putting the results into perspective, one can draw the following conclusion.

[12]See www.cfainstitute.org for more information.

Before the economic crisis, analysts indented to differentiate from their peers. They tried to use research advantages provided by familiar analysts or those analysts with whom they regularly exchange their opinions. During the crisis in a time of great uncertainty, analysts were afraid of failing by providing estimates that were too far away from other analysts' results. Therefore, they rather aligned their price targets with the consensus such that the geographical influence and the influence from the exchange of opinion were not or at least less relevant.

On balance, I showed that the influence among analysts is dynamic and not homogenous. Therefore, it is reasonable to use an adequate structure of influence for further research of analysts' herding behaviour.

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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

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

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 $\tilde{\mathbf{Z}} = [\mathbf{\Gamma_t \hat{w}}_t, \mathbf{X}_t]$ 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

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

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 $\mathbf{Z} = [\mathbf{\Gamma_t}\mathbf{X}_t^{(1-6)}, \mathbf{X}_t]$ 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%**

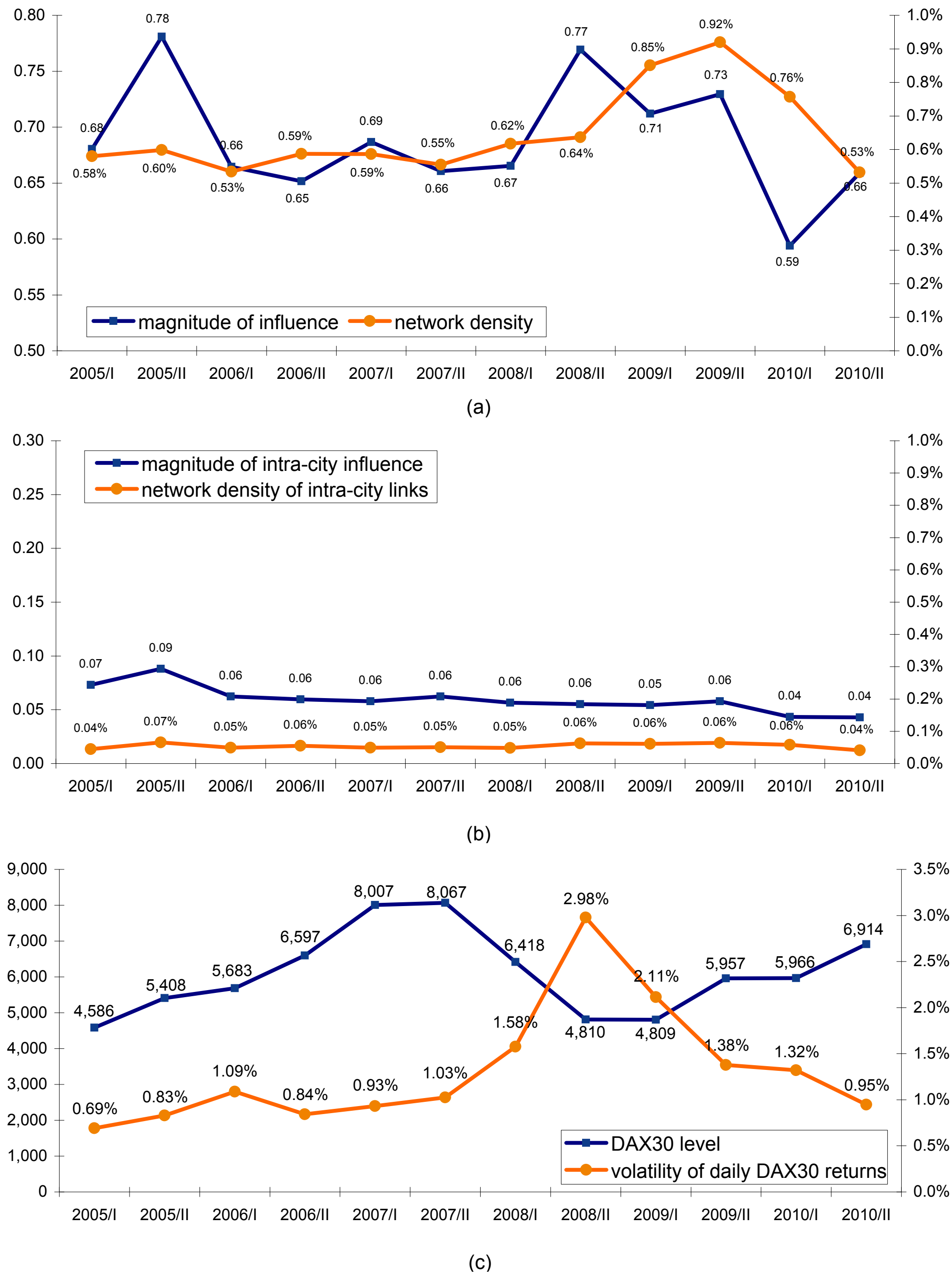
The first column displays the total network density. The second column shows the portion of network density that is generated by intra-city links. The third column also contains the portion of network density resulting from intra-city links, however, every link is weighted with the corresponding coefficient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