Essays in Applied Panel Data Econometrics

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Overview

The four studies in this dissertation cover two main topics using panel econometric methods.

The first topic is attributed to the first chapter and introduces a dynamic panel threshold model to investigate the non-linear impact of inflation on long-term economic growth. Most economists would agree that inflation has distortional effects on long-term economic growth if it gets too high. However, empirical evidence for "appropriate" inflation rates is still elusive. In the aftermath of the recent financial crisis, the long-time consensus on inflation targets for industrialized countries centering around 2% has been put up for discussion. For instance, Blanchard, DellAriccia and Mauro (2010) suggest an inflation target of 4% as it leaves more room for expansionary monetary policy in case of adverse shocks and is not likely to hamper growth. Applying the dynamic threshold model, the chapter provides new evidence on the inflation-growth nexus.

The second topic is dedicated to the remaining three chapters. They all analyze herding behavior of institutional traders in the stock market by employing a comprehensive panel data set. Herding behavior is the tendency of investors to accumulate on the same side of the market. This kind of trading pattern is one crucial factor for non-fundamental stock price movements associated with increasing price volatility. Hence, herding may lead or contribute to the financial and macroeconomic instability, see, e.g., Hwang and Salmon (2004). The second chapter focusses on the impact of data frequency and the use of anonymous data on the empirical assessment of herding. The third chapter investigates the causes and consequences of herding. Finally, chapter four tests predictions derived from the informational cascade model which provides rational for herding behavior.

Chapter 1 introduces a dynamic panel threshold model and re-examines the empirical relationship between inflation on long-term economic growth.

Advancing on Hansen (1999) and Caner and Hansen (2004), our model allows the estimation of threshold effects with panel data even in case of endogenous regressors. The study therefore overcomes a limitation of Hansen's model requiring all regressors to be exogenous. In growth regressions with panel data, the exogeneity assumption is particular severe, because initial income as a crucial variable is endogenous by construction. To ensure the adaptability of Hansen's distribution theory, we apply the forward orthogonal deviations transformation suggested by Arellano and Bover (1995), which in common with first-differencing eliminates fixed effects, but in contrast it does not introduce serial correlation in the transformed errors.

The empirical analysis is based on a large panel data set including 124 countries during the period from 1950 to 2004. Our empirical results strongly confirm earlier evidence in favor of inflation thresholds in the inflation-growth nexus. We also find notable differences between the results obtained for industrialized and non-industrialized countries. For industrialized countries, our results confirm the inflation targets of about 2% set by many central banks. For non-industrialized countries, we estimate that inflation hampers growth if it exceeds 17%. Below this threshold, however, the impact of inflation on growth remains insignificant. Therefore, our results do not support growth-enhancing effects of inflation in developing countries.

This chapter is based on a paper which is joint work with Alexander Bick and Dieter Nautz.

Chapter 2 employs a new and comprehensive panel data set to shed more light on the short-term character of herding by institutional traders in the stock market.

The previous evidence on herding is often impeded by data availability problems. In particular, positions taken by institutions on the stock market are reported only on a quarterly or semi-annually basis, if at all, see, e.g., Choi and Sias (2009). Several contributions, including Barber, Odean and Zhu (2009), attempt to overcome the problem of data frequency by using anonymous transaction data and simply define trades above a specific cutoff size as institutional.

The chapter therefore contributes to the empirical literature by applying a new, unique database that identifies all real-time transaction of financial institutions in the German stock market. Hence, the data set allows to overcome most of the problems of the previous literature, since it includes both higher frequent and investor-level data. The analysis provides new evidence on the herding behavior of financial institutions for a broad cross-section of stocks over the period from July 2006 to March 2009 in the German stock market. By using the prominent herding measures of Lakonishok, Shleifer and Vishny (1992) and Sias (2004), results show that herding by institutions occurs even on a daily basis. In order to investigate how the underlying data frequency may affect the empirical assessment of herding, we also evaluate herding measures at monthly and quarterly frequency. Neglecting the investor-related information contained in our data set, we also explore how herding measures are affected by the use of anonymous transaction data.

The empirical results suggest that basing analysis on low-frequent or anonymous transaction is likely to lead to delusive conclusions. In contrast to theoretical predictions and evidence of previous studies, the results with daily data do not confirm that short-term herding tends to be more pronounced in small stocks and in times of market stress. However, using quarterly data, herding measures increase in small capitalized stocks. We also demonstrate that herding measures based on anonymous transactions can cause misleading results about the behavior of institutional investors during the recent financial crisis, as herding measures significantly rise.

This chapter is based on a paper which is joint work with Dieter Nautz and which is forthcoming in the European Financial Management.

Chapter 3 applies fixed effects panel models to explore the causes of herding and its consequences for the stock market.

Generally, herding is divided into intentional herding and unintentional herding, see, e.g., Bikhchandani and Sharma (2001). Unintentional herding arises because institutions may examine the same factors and receive correlated information, leading them to arrive at similar conclusions regarding individual stocks, see, e.g., Hirshleifer, Subrahmanyam and Titman (1994). In contrast, intentional herding involves the imitation of other market participants, resulting in simultaneous buying or selling of the same stocks regardless of prior beliefs or information sets. With regard to the consequences, herding may either be stabilizing, as quickly incorporating information into stock prices, or destabilizing, as leading to divergence of prices away from fundamentals.

Previous studies employing quarterly data are limited in the investigation of the causes and the price impact of herding. For instance, there is no resolution on intra-quarter covariances of trades and returns and thus, these studies fail to conclude whether institutions are *reacting* to or *causing* stock price movements, see Lakonishok et al. (1992). Moreover, a destabilizing effect of herding is more likely to be detected in the short horizon since the market will dissipate deviations from fundamental values through the actions of arbitrageurs, see Puckett and Yan (2008). This chapter therefore contributes to the empirical literature on herding by using higher frequency investor-level data. Advancing on previous descriptive approaches, the availability of daily, investor-specific data enables us to perform a panel econometric analysis of the causes of herding and its consequences for the stock market.

The estimation results reveal that financial institutions do herd but that this herding is rather of the unintentional type. Herding depends on stock characteristics as well as on past returns and stock volatility. In particular, panel regressions reveal that herding may result from the common use of risk measures that drives correlated sell activities after a rise in volatility. Yet, even this unintentional herding may have a destabilizing stock price impact. In fact, evidence of return reversals based on panel estimations suggest a destabilizing impact of sell herding. Since those sell herds result from the common reaction on risk measures, this evidence supports a macro-prudential view on risks by regulators. In line with the predictions of Persaud (2000) or Daníelsson (2008), regulators and risk modeling institutions should take into account the endogeneity of risks induced by similar market sensitive risk management systems.

Chapter 4 applies intra-day data in order to investigate to what extent and under what circumstances institutions follow other institutions within a trading day.

According to the models of Bikhchandani, Hirshleifer and Welch (1992), Banerjee (1992) and Avery and Zemsky (1998) correlated trading might be a result of informational cascades, where investors ignore their own noisy information and imitate other market participants, since they infer (from observed trading behavior) that others have relevant information.

In highly developed financial markets, correlated trading driven by informational cascades can mainly be an intra-day phenomenon as the arrival of public information stops cascading, see Patterson and Sharma (2010). This chapter therefore use intra-day information of transactions made by financial institutions in the German stock market. Using the method developed by Sias (2004), our estimation results reveal that transactions of financial institutions are actually correlated within a trading day. When decomposing the correlation, we found that the correlation stems from both sources: Institutions following own trades, as they may split transactions, as well as institutions following other institutions.

Models of informational cascades predict that herd behavior and the correlation of trades should be more pronounced in times of uncertainty. Hence, we test three hypothesis derived from this prediction. Our empirical results show that the observed correlation of trades cannot be explained by informational cascades. In particular, we find only weak evidence for higher correlations in the crisis period. Moreover, the correlation among trades is found to be particularly strong in times of low analyst dispersion and at market openings when a lot of new information flows into the market.

Zusammenfassung

Einleitung Die Dissertation besteht aus vier Studien, die sich aus unterschiedlichen Perspektiven mit Panel-ökonometrischen Methoden beschäftigen. Panel Daten und Methoden finden dabei auf zwei Themengebieten Anwendung.

Im ersten Themengebiet und gleichzeitig ersten Kapitel der Dissertation werden die realen Effekte von Inflation mittels eines dynamischen Panel Schwellenwert-Modells untersucht. Das eingeführte Modell basiert auf dem Schwellenwert-Modell von Hansen (1999) und entwickelt die Methode hin zu einem dynamischen Modell fort. Das Modell wird zur Schätzung des nicht-linearen Einflusses von Inflation auf das Wirtschaftswachstum angewendet. Beide Variablen sind Anknüpfungspunkt makroökonomischer Politikziele. Die Finanzkrise hat jedoch Zweifel am bisherigen Konsens für niedrige Inflationsraten und die gängigen Inflationsziele von 2% der Zentralbanken aufgeworfen. Blanchard, DellAriccia und Mauro (2010) empfehlen beispielsweise eine Zielinflationsrate von 4% und bezweifeln etwaig resultierenden volkswirtschaftlichen Schaden. Das Kapitel zeigt durch die Nutzung des Schwellenwert-Modells neue empirische Evidenz zu dem Inflations-Wachstums Zusammenhang auf.

Das zweite Themengebiet der Dissertation wird in den übrigen drei Kapiteln ausgeführt und behandelt das Herdenverhalten von institutionellen Investoren auf dem deutschen Aktienmarkt. Herdenverhalten bezeichnet eine gleichförmige Verhaltenstendenz von Marktteilnehmern, die sich in korrelierten Kauf- oder Verkaufsaktionen manifestiert. Auf diese Weise können sich besonders auf Finanzmärkten Kursübertreibungen in beide Richtungen verstärken, was zur Abweichung der Preise von fundamentalen Werten (sogenannte spekulative Blasen) führt. Durch solche Ungleichgewichte können sich Implikationen für die Finanzstabilität und die makroökonomische Stabilität ergeben. Während die empirische Bestimmung von Herdenverhalten auf Finanzmärkten bisher insbesondere aufgrund der Datenverfügbarkeit problembehaftet war, analysiert diese Arbeit das gleichgerichtete Handeln unter Verwendung eines neuen, umfassenden Datensatzes. Das zweite Kapitel untersucht dabei den Einfluss der Datenfrequenz und der Nutzung anonymisierter Transaktionsdaten auf die Messung des Herdenverhaltens. Das dritte Kapitel analysiert die Ursachen und die Auswirkungen dieser Handlungsweisen. Ein wesentlicher Erklärungsansatz für rationales Herdenverhalten wird in dem Modell der Informationskaskaden beschrieben. Das vierte Kapital fokussiert sich auf dieses Modell und überprüft hieraus abgeleitete theoretische Implikationen.

Kapitel 1 entwickelt ein dynamisches Panel Schwellenwert-Modell zur Untersuchung des nicht-linearen Zusammenhangs zwischen Inflation und langfristigem Wirtschaftswachstum.

Hansen (1999) konzipierte ein Schwellenwert-Modell und die dazugehörige asymptotische Theorie für Panel Daten mit individuellen Effekten, welches erlaubt, die Schwellenwerte und die regime-spezifischen marginalen Einflüsse zu schätzen. Voraussetzung des Modells ist jedoch die Exogenität aller Regressoren. In Wachstumsregressionen mit Panel Daten ist die Exogenitätsannahme jedoch problematisch, da das Anfangskapital einer Volkswirtschaft als wesentliche Einflussvariable per Konstruktion endogen ist. Das in diesem Kapitel entwickelte Modell trägt der Endogenität Rechnung. Die notwendige Bereinigung um die individuellen Effekte wird mit der Methode der orthogonalen Abweichungen (forward orthogonal deviation) von Arellano and Bover (1995) vorgenommen. Diese Vorgehensweise erlaubt die Adaption von Hansen's Verteilungstheorie, da sie – im Gegensatz zur Bildung erster Differenzen (first differencing) – nicht zur Autokorrelation der Fehlerterme führt.

Untersuchungsgegenstand ist ein Panel von 124 Industrie- und Entwicklungsländern für die Zeitperiode von 1950 bis 2004, wobei Fünf-Jahres-Durchschnitte der Glättung von Konjunkturschwankungen dienen. Die Ergebnisse bestätigen den nicht-linearen Einfluss von Inflation auf Wachstum. Für Industrieländer wird ein Schwellwert in Höhe von 2.5% geschäzt. Während Inflationsraten unterhalb dieses Schwellenwertes einen positiven statistisch signifikanten Wachstumseffekt aufweisen, ist der Einfluss von Inflation über diesem Niveau negativ. Dieses Ergebnis bestätigt damit gängige Inflationsziele von Zentralbanken von 2%. Bezüglich Entwicklungsländern wird ein Schwellenwert von 17% ermittelt. Inflationseffekte auf Wachstum sind überhalb dieses Wertes signifikant negativ. Wachstumssteigernde Einflüsse von niedrigeren Inflationsraten können jedoch hier nicht bestätigt werden.

Der diesem Kapitel zugrundeliegende Aufsatz wurde in Zusammenarbeit mit Alexander Bick und Dieter Nautz verfasst.

Kapitel 2 verwendet einen neuen Datensatz bestehend aus Transaktionsdaten von Finanzinstituten, um die kurzfristigen Aspekte von Herdenverhalten auf dem Aktienmarkt zu untersuchen.

Die statistische Bestimmung von Herdenverhalten auf Finanzmärkten war bisher insbesondere aufgrund der Datenverfügbarkeit problembehaftet. Frühere empirische Studien nutzen hauptsächlich Positionsdaten von institutionellen Anlegern, aus deren Veränderung Informationen über getätigte Transaktionen abgeleitet werden, siehe zum Beispiel Choi und Sias (2009). Solche Daten sind jedoch überwiegend nur quartalsweise oder sogar nur halbjährlich verfügbar. Herdenverhalten, das sich innerhalb dieser Perioden manifestiert, ist nicht messbar. Andere Studien versuchen dieser Problematik durch die Nutzung von Transaktionsdaten Rechnung zu tragen. Allerdings sind diese Daten anonym. Die Untersuchung kann daher nicht Investor-spezifisch erfolgen. Es ist weder die Anzahl der Investoren erkennbar, noch ist eine Kategorisierung nach Investorengruppen möglich. Diese Studien grenzen daher die Transaktionen aufgrund des Volumens ab und betrachten Geschäfte über einer bestimmten Größe als institutionelle Transaktionen, siehe zum Beispiel Barber, Odean und Zhu (2009). Allerdings können institutionelle Investoren ihre Handelsentscheidung aufgeteilt auf mehrere Transaktionen realisiseren, was durch diese Methode nicht erfasst wird.

Dieses Kapitel trägt den genannten Problematiken Rechnung und analysiert Herdenverhalten mittels eines neuen Datensatzes, der einzelne Trasaktionen mit Investor-spezifischen Informationen umfasst. Zur Ermittlung der gleichgerichteten Handelstätigkeit verwendet die Studie die in der Literatur gängigen Methoden von Lakonishok, Shleifer und Vishny (1992) und Sias (2004). Die Ergebnisse zeigen, dass Herdenverhalten von institutionellen Investoren tatsächlich auf täglicher Basis erfolgt. Um den Einfluss der Datenfrequenz auf die Messung des Herdenverhaltens zu untersuchen werden die Berechnungen auch mittels Monats- und Quartalsdaten durchgeführt. Zudem simuliert die Studie die Auswirkungen der Nutzung von anonymisierten Daten, indem die Investor-spezifischen Informationen vernachlässigt werden.

Die empirischen Ergebnisse zeigen, dass sowohl Analysen mit niedrig frequentierten Daten als auch mit anonymen Daten nach beiden Messmethoden irreführende Schlussfolgerungen nach sich ziehen können. Die Resultate auf täglicher Basis dokumentieren, entgegen den theoretischen Implikationen und Ergebnissen früherer Studien, dass Herdenverhalten in Krisenzeiten und in Aktien mit geringerer Marktkapitalisierung nicht ausgeprägter ist. Unter Nutzung von monatlichen oder vierteljährlichen Daten steigt das gemessene Herdenverhalten in Aktien mit geringer Marktkapitalisierung jedoch an. Dieses Resultat deutet auf eine Überschätzung des gleichgerichteten Verhaltens in "kleineren" Aktien hin. Die Simulation mit anonymisierten Daten verdeutlicht ebenfalls eine Überschätzung. Insbesondere werden hohe Werte von Herdenverhalten in der Finanzkrise gemessen, was durch tägliche Daten nicht bestätigt werden kann.

Der diesem Kapitel zugrundeliegende Aufsatz, welcher in Zusammenarbeit mit Dieter Nautz entstanden ist, wird in der Fachzeitschrift *European Financial Management* veröffentlicht.

Kapitel 3 wendet Panel Modelle mit individuellen Effekten an, um die Ursachen und die Konsequenzen von Herdenverhalten zu untersuchen.

Korrelierte Handelstätigkeit auf Finanzmärkten kann aus unterschiedlichen Beweggründen resultieren. Bewusstes Herdenverhalten erfolgt, wenn Anleger eigene Informationen ignorieren und sich an den beobachteten Handelsaktionen anderer Marktteilnehmer orientieren. Gleichgerichtetes Handelsverhalten auf Aktienmärkten tritt jedoch auch unbewusst, d.h. unabhängig von den Handlungen anderer, auf. Zum Beispiel können öffentlich verfügbare Informationen korrelierte Handelsentscheidungen und damit gleichgerichtete Aktionen hervorrufen.

Bisherige Studien, die sich hauptsächlich auf Quartalsdaten stützen, sind in der Analysemöglichkeit der Determinanten und der Auswirkungen des gleichförmigen Handelsverhaltens beschränkt. Es können keine intraperiodischen Korrelationen berücksichtigt werden. Damit kann zum Beispiel nicht gefolgert werden, inwieweit Institute auf Aktienkursschwankungen reagieren oder diese hervorrufen, siehe Lakonishok, Shleifer und Vishny (1992). Zudem sind destabilisierende Effekte von Herdenverhalten, insbesondere in entwickelten Märkten, möglicherweise kurzfristiger Natur, da Ungleichgewichte durch Arbitrageure abgebaut werden, siehe Puckett und Yan (2008). Durch die Nutzung von täglichen Daten und Panel Schätzmodellen zeigt dieses Kapitel neue Ergebnisse bezüglich der Einflussgrössen und der Konsequenzen des Herdenverhaltens von institutionellen Investoren.

Die Ergebnisse dokumentieren, dass gleichgerichtetes Verhalten insbesondere bei den größten Instituten ausgeprägt ist. Allerdings implizieren die Schätzungen, dass die korrelierte Handelstätigkeit hauptsächlich unbewusster Natur ist. Die Panelregressionen zeigen, dass Herdenverhalten von Kursvolatilitäten und vergangenen Preisbewegungen beeinflusst wird. Kursvolatilitäten haben einen positiven signifikanten Effekt auf simultane Verkäufe der Institute. Auf der Kaufseite ist der Einfluss jedoch signifikant negativ. Da Kursvolatilität als Risikomaß genutzt wird und wesentliche Auswirkungen auf den Value-at-Risk der Portfolien hat, impliziert dieses Resultat, dass marktsensitive Risikomanagementsysteme gleichgerichtete Handelsaktionen forcieren. Bezüglich der Marktauswirkungen zeigen die Regressionsergebnisse, dass sich der sofortige negative Effekt korrelierter Verkaufstätigkeit nach wenigen Tagen umkehrt. Dieses Ergebnis impliziert einen destabilisierenden Einfluss von Verkaufs-Herden auf die Aktienkurse. Da diese gleichförmige Verkaufstätigkeit durch marktsensitive Risikomanagementsysteme verursacht oder verstärkt wird, unterstützen die Ergebnisse die Schlussfolgerungen von

Persaud (2000) oder auch Daníelsson (2008). Demnach induzieren marktsensitive Risikomanagementsysteme die Endogenität von Risiken, was von Aufsichtbehörden und risikomodellierenden Instituten berücksichtigt werden sollte.

Kapitel 4 untersucht die korrelierte Handelstätigkeit von institutionellen Investoren innerhalb eines Handelstages und testet Implikationen des Informationskaskadenmodells.

Eine mögliche Erklärung für rationales Herdenverhalten liefern die Modell zu Informationskaskaden von Bikhchandani, Hirshleifer und Welch (1992), Banerjee (1992) sowie Avery and Zemsky (1998). Informationskaskaden entstehen, wenn es für einen Entscheidungsträger optimal ist, dem Verhalten anderer Marktteilnehmer zu folgen und dabei die eigenen Informationen zu ignorieren. Der Investor trifft dabei eine Handelsentscheidung, die im Gegensatz zu dem eigenen Handelssignal steht, da die (beobachteten) Aktionen der Vorgänger ein starkes Gewicht im individuellen Wahrscheinlichkeitsurteil haben. Vorausetzung ist, dass der Entscheidungsträger unvollständige Informationen besitzt und die Entscheidung unter Unsicherheit trifft.

Allerdings sind Informationskaskaden nach diesen Modellen fragil und gegenüber neuen externen Informationen anfällig. Gerade in entwickelten Märkten sind Informationskaskaden daher möglicherweise ein kurzfristiges Phänomen, siehe Patterson und Sharma (2010). Das Kapitel untersucht korrelierte Handelstätigkeit im Aktienmarkt daher mittels halbstündlichen Zeitintervallen innerhalb eines Handelstages. Das Kapitel verwendet die Methode nach Sias (2004), wonach Korrelationen zwischen Kauf- oder Verkaufstätigkeiten gemessen werden. Die Untersuchung profitiert dabei von den Investor-spezifischen Informationen des Datensatzes. Bei Berechnung der Korrelation kann unterschieden werden, inwieweit die Investoren tatsächlich anderen Handelsteilnehmern folgen, oder eine Vielzahl eigener Transaktionen sequenziell getätigt werden. Bisherige Studien auf Basis hoch frequentierter Daten können diese Differenzierung aufgrund der Anonymität der Datensätze nicht vornehmen.

Die Ergebnisse zeigen, dass Transaktionen von institutionellen Investoren korreliert sind. Die gemessenen Korrelationen auf Basis von halbstündigen Intervallen sind dabei höher als die Ergebnisse auf Tagesbasis oder aus vorherigen Studien mit Daten von geringer Frequenz. Allerdings resultiert mehr als die Hälfte der Korrelation aus sequenziellen Transaktionen der Investoren selbst.

Zur Überprüfung, inwieweit die Korrelationen unter den Investoren tatsächlich aus Informationskaskaden resultieren, werden drei Hypothesen getestet, die sich aus den theoretischen Modellen ableiten lassen. Informationskaskaden bilden sich, sofern keine oder nur wenige öffentlich zugängliche Informationen voliegen, bei Informationsunsicherheit und Informationsasymmetrie. Demnach sollten Informationskaskaden insbesondere auftreten (1) in Zeiten von Marktturbulenzen, (2) bei geringem Informationsstand und (3) bei abweichenden Marktmeinungen als Indikation für die Unsicherheit des Marktwertes.

Die Ergebnisse zeigen jedoch, dass Korrelationen der Transaktionen unter den Investoren in Krisenzeiten nicht wesentlich ausgeprägter sind. Zudem sind die Korrelationen am höchsten zur Marktöffnung der Deutschen oder New Yorker Börse, wenn neue Informationen in den Markt fließen. Zuletzt zeigen sich eröhte Korrelationen, wenn die Streuung der Analystenempfehlungen gering ist und damit Makteinschätzungen nicht abweichen. Somit können die beobachteten Korrelationen nicht auf Informationskaskaden zurückgeführt werden.

1 Inflation and Growth: New Evidence from a Dynamic Panel Threshold Analysis

1.1 Introduction

Most economists would agree that inflation has distortional effects on long-term economic growth if it gets "too high". Yet how high is too high? In the aftermath of the recent financial crisis, the long-time consensus on inflation targets for industrialized countries centering around 2% has been put up for discussion. Following e.g. Blanchard, DellAriccia and Mauro (2010), the effects of inflation on growth are difficult to discern, so long as inflation remains in the single digits. As a consequence, they suggest that an inflation target of 4% might be more appropriate because it leaves more room for expansionary monetary policy in case of adverse shocks. For developing countries, the appropriate level of the inflation target is unclear as well. Bruno and Easterly (1998), for example, showed in a cross-sectional setting that inflation has only a detrimental impact on long-term economic growth if inflation exceeds a critical level of 40% — a rather large value which may be of only limited relevance for monetary policy of many countries.[1]

[1] For example, the Southern African Development Community (SADC) convergence criteria requires a low single digit inflation rate, see Regional Indicative Strategic Development Plan available at `http://www.sadc.int/attachment/download/file/74`. Recent empirical work by Goncalves and Salles (2008) and Lin and Ye (2009) suggests that inflation targeting in developing countries can lead to significant improvements in terms of inflation and output volatility.

The theoretical literature offers various channels through which inflation may distort or even foster economic growth, see Temple (2000). If these different channels overlap or offset each other, or unfold an economic meaningful impact only for certain ranges of inflation, the relationship between inflation and economic growth might be characterized by inflation thresholds, see Vaona (2010).[2] A natural starting point for the empirical analysis of inflation thresholds is the panel threshold model introduced by Hansen (1999) which is designed to estimate threshold values instead of imposing them. Yet, the application of Hansen's threshold model to the empirical analysis of the inflation-growth nexus is not without problems. The most important limitation of Hansen's model is that all regressors are required to be exogenous. In growth regressions with panel data, the exogeneity assumption is particular severe, because initial income as a crucial variable is endogenous by construction. Caselli, Esquivel and Lefort (1996) already demonstrated for linear panel models of economic growth that the endogeneity bias can be substantial. So far, dynamic versions of Hansen's panel threshold model have not been available. Therefore, with a view to the central role of initial income for the convergence debate of the economic growth literature, most empirical studies on growth-related thresholds applying the Hansen methodology decided to ignore the potential endogeneity bias, see Khan and Senhadji (2001), Cuaresma and Silgoner (2004), Foster (2006) and Bick (2010). In contrast, Drukker, Gomis-Porqueras and Hernandez-Verme (2005) excluded initial income from their growth regressions to avoid the endogeneity problem. Both ways to deal with the endogeneity of initial income can lead to biased estimates of the inflation thresholds and to misleading conclusions about the impact of inflation on growth in the corresponding inflation regimes.[3]

This paper introduces a dynamic version of Hansen's panel threshold model to shed more light on the inflation-growth nexus. By applying the forward orthogonal

[2] Similar non-linear effects of inflation have been documented by Bick and Nautz (2008) for relative price variability in the US and by Khan, Senhadji and Smith (2006) for financial depth in a large cross-country panel data set.

[3] Note that alternative approaches to estimate a non-linear relationship between inflation and growth face the same problem: they either exclude initial income (Omay and Kan (2010)) or do not control for its endogeneity (Burdekin, Denzau, Keil, Sitthiyot and Willet (2004), Hineline (2007), Vaona and Schiavo (2007)).

deviations transformation suggested by Arellano and Bover (1995), we combine the instrumental variable estimation of the cross-sectional threshold model introduced by Caner and Hansen (2004) with the panel threshold model of Hansen (1999). In the dynamic model, the endogeneity of important control variables is no longer an issue. This permits us to estimate the critical level of inflation for economic growth for industrialized and non-industrialized countries albeit the endogeneity problem of initial income.

Our empirical results strongly confirm earlier evidence in favor of inflation thresholds in the inflation-growth nexus. In accordance with Khan and Senhadji (2001), we find notable differences between the results obtained for industrialized and non-industrialized countries. For industrialized countries, the estimated inflation threshold is about 2.5% which provides strong support for the inflation targets of many central banks. In particular, inflation rates below/above 2.5% are associated with higher/lower long-term economic growth in industrialized countries. For developing countries, the estimated inflation threshold is 17.2%. Inflation rates exceeding this critical value, i.e. if it gets "too high", come along with significantly lower economic growth with a magnitude similar to industrialized countries. In contrast, there is no significant association between inflation and long-term economic growth in developing countries when inflation is below 17.2%.

Given the lack of a standard theory on the relationship between inflation and long-term economic growth, our empirical results on the inflation-growth nexus have to be interpreted with caution. Strictly speaking, our estimates may only reflect correlations and do not necessarily imply causality from inflation to growth. Yet, reduced form estimates may still serve as a benchmark and a first guideline for the discussion on the optimal level of inflation targets.

The rest of the paper is organized as follows. In Section 1.2, we discuss the econometrics of the dynamic panel threshold model. Section 1.3 introduces the data and the control variables employed in our empirical application. In Section 1.4 the dynamic panel threshold model is applied to the inflation-growth nexus in industrialized and non-industrialized countries. Section 1.5 concludes.

1.2 A Dynamic Panel Threshold Model

1.2.1 The Econometric Model

This section develops a dynamic panel threshold model that extends Hansen's (1999) original static set up by endogenous regressors. In our empirical application where we analyze the role of inflation thresholds in the relationship between inflation and economic growth ($y_{it} = dgpd_{it}$), the endogenous regressor will be initial income (gdp_{it-1}). Our model extension builds on the cross-sectional threshold model of Caner and Hansen (2004) where GMM type estimators are used in order to allow for endogeneity. To that aim, consider the following panel threshold model

$$y_{it} = \mu_i + \beta_1' z_{it} I(q_{it} \leq \gamma) + \beta_2' z_{it} I(q_{it} > \gamma) + \varepsilon_{it}, \tag{1.1}$$

where subscripts $i = 1, \ldots, N$ represents the country and $t = 1, \ldots, T$ indexes time. μ_i is the country specific fixed effect and the error term is $\varepsilon_{it} \overset{iid}{\sim} (0, \sigma^2)$. $I(\cdot)$ is the indicator function indicating the regime defined by the threshold variable q_{it} and the threshold level γ. z_{it} is a m-dimensional vector of explanatory regressors which may include lagged values of y and other endogenous variables. The vector of explanatory variables is partitioned into a subset z_{1it}, of exogenous variables uncorrelated with ε_{it}, and a subset of endogenous variables z_{2it}, correlated with ε_{it}. In addition to the structural equation (1.1) the model requires a suitable set of $k \geq m$ instrumental variables x_{it} including z_{1it}.

1.2.2 Fixed-Effects Elimination

In the first step of the estimation procedure, one has to eliminate the individual effects μ_i via a fixed-effects transformation. The main challenge is to transform the panel threshold model in a way that eliminates the country-specific fixed effects without violating the distributional assumptions underlying Hansen (1999) and Caner and Hansen (2004), compare Hansen (2000). In the dynamic model (1.1), the standard within transformation applied by Hansen (1999) leads to inconsistent estimates because the lagged dependent variable will always be correlated with the mean of the individual errors and thus all of the transformed individual errors. First-differencing of the dynamic equation (1.1) as usually done in the context of dynamic panels implies negative serial correlation of the error terms such that the distribution theory developed by Hansen (1999) is not applicable anymore to panel data.[4]

In view of these problems, we consider the forward orthogonal deviations transformation suggested by Arellano and Bover (1995) to eliminate the fixed effects.[5] The distinguishing feature of the forward orthogonal deviations transformation is that serial correlation of the transformed error terms is avoided. Instead of subtracting the previous observation from the contemporaneous one (first-differencing) or the mean from each observation (within transformation), it subtracts the average of all future available observations of a variable. Thus, for the error term, the forward orthogonal deviations transformation is given by:

$$\varepsilon_{it}^{*} = \sqrt{\frac{T-t}{T-t+1}}[\varepsilon_{it} - \frac{1}{T-t}(\varepsilon_{i(t+1)} + ... + \varepsilon_{iT})]. \tag{1.2}$$

Therefore, the forward orthogonal deviation transformation maintains the uncorrelatedness of the error terms, i.e.

$$Var(\varepsilon_i) = \sigma^2 I_T \;\Rightarrow\; Var(\varepsilon_i^*) = \sigma^2 I_{T-1}.$$

In accordance with Hansen (2000), this ensures that the estimation procedure derived by Caner and Hansen (2004) for a cross-sectional model can be applied to the dynamic panel equation (1.1).

1.2.3 Estimation

Following Caner and Hansen (2004), we estimate a reduced form regression for the endogeneous variables, z_{2it}, as a function of the instruments x_{it}. The endogenous variables, z_{2it}, are then replaced in the structural equation by the predicted

[4] Note that in Hansen (1999) the within-transformation also implies negative serial correlation of the transformed error terms. However, this is not a problem because of the idempotency of the transformed error matrix, see Equation A.12 Hansen (1999, p366).

[5] We are grateful to Jörg Breitung for this suggestion.

values $\hat{z}_{2it}$. In step two, Equation (1.1) is estimated via least squares for a fixed threshold γ where the z_{2i}'s are replaced by their predicted values from the first step regression. Denote the resulting sum of squared residuals by $S(\gamma)$. This step is repeated for a strict subset of the support of the threshold variable q from which in a third step the estimator of the threshold value γ is selected as the one associated with the smallest sum of squared residuals, i.e. $\hat{\gamma} = \underset{\gamma}{\operatorname{argmin}}\ S_n(\gamma)$.

In accordance with Hansen (2000) and Caner and Hansen (2004), the critical values for determining the 95% confidence interval of the threshold value are given by

$$\Gamma = \{\gamma : LR(\gamma) \leq C(\alpha)\},$$

where $C(\alpha)$ is the 95% percentile of the asymptotic distribution of the likelihood ratio statistic $LR(\gamma)$. The underlying likelihood ratio has been adjusted to account for the number of time periods used for each cross section, see Hansen (2000). Once $\hat{\gamma}$ is determined, the slope coefficients can be estimated by the generalized method of moments (GMM) for the previously used instruments and the previous estimated threshold $\hat{\gamma}$.

1.3 Data and Variables

Our empirical application of the dynamic panel threshold model to the inflation-growth nexus is based on an unbalanced panel-data set of 124 countries. Industrialized and non-industrialized countries are identified in accordance with the International Financial Statistics (IFS) and shown in Tables 1.3, 1.4, and 1.5 in the Appendix 1.6.1. Using data from 1950 to 2004 we extend the samples by Khan and Senhadji (2001) (1960 to 1998) and Drukker et al. (2005) (1950 to 2000). As a consequence, our sample contains more information about the growth effects of low inflation.

For each country, annual growth rates of real GDP per capita in constant 2000 prices (*dgdp*) are obtained from Penn World Table 6.2. Inflation is computed as the annual percentage change of the Consumer Price Index (π) collected from

IFS. In line with the empirical growth literature, our results on the determinants of long-term economic growth will be based on five-year averages which gives us 988 observations, 227 for industrialized and 761 for non-industrialized countries.

1.3.1 Control Variables

Any empirical analysis of inflation's impact on economic growth has to control for the influence of other economic variables that are correlated with the rate of inflation. Following Khan and Senhadji (2001) and Drukker et al. (2005), we consider the percentage of GDP dedicated to investment (*igdp*), the population growth rate (*dpop*), the initial income level (*initial*) measured as GDP per capita from the previous period and openness (*open*) measured as the logged share of exports plus imports in GDP. These variables are obtained from Penn World Table 6.2. The annual percentage change in the terms of trade (*dtot*) is measured as exports divided by imports. Export and import data are taken from Penn World Table 6.1 until 2000 and for the later years from the World Trade Organization (WTO) database. We also included the standard deviations of the terms of trade (*sdtot*) and of openness (*sdopen*). More information about the control variables is contained in Table 1.2 in the Appendix. All these variables passed the robustness tests of Levine and Renelt (1992) and Sala-i-Martin (1997).

1.3.2 Inflation

Inflation has been lower in industrialized countries with an average annual inflation rate over the sample period of 5.86% as opposed to 33.63% for non-industrialized countries. For both set of countries, the dispersion of inflation rates is considerable, see Figures 1.1 and 1.3 in the Appendix 1.6.2. In this case, Ghosh and Phillips (1998) strongly suggest the use of logged inflation rates to avoid that regression results are distorted by a few extreme inflation observations. Moreover, using logged inflation rates has the plausible implication that multiplicative, not additive, inflation shocks will have identical growth effects. Since our sample contains negative inflation rates, we follow Drukker et al. (2005) and Khan and Senhadji (2001) by employing a semi-log transformation of the inflation rate π_{it}

$$\tilde{\pi}_{it} = \begin{cases} \pi_{it} - 1, & \text{if } \pi_{it} \leq 1 \\ ln(\pi_{it}), & \text{if } \pi_{it} > 1, \end{cases}$$

where inflation rates below one are re-scaled for sake of continuity. In sharp contrast to the highly skewed and leptokurtic inflation data of industrialized and non-industrialized countries, the distributions of semi-logged inflation rates are much more symmetric and in line with the normal distribution, see Figures 1.2 and 1.4 in Appendix 1.6.2.

1.4 Inflation Thresholds and Growth

Let us now apply the dynamic panel threshold model to the analysis of the impact of inflation on long-term economic growth in industrialized and non-industrialized countries. To that aim, consider the following threshold model of the inflation-growth nexus:

$$dgdp_{it} = \mu_i + \beta_1 \tilde{\pi}_{it} I(\tilde{\pi}_{it} \leq \gamma) + \delta_1 I(\tilde{\pi}_{it} \leq \gamma) + \beta_2 \tilde{\pi}_{it} I(\tilde{\pi}_{it} > \gamma) + \phi' z_{it} + \varepsilon_{it}. \quad (1.3)$$

In our application, inflation $\tilde{\pi}_{it}$ is both, the threshold variable and the regime dependent regressor. z_{it} denotes the vector of partly endogenous control variables, where slope coefficients are assumed to be regime independent. Following Bick (2010), we allow for differences in the regime intercepts (δ_1).[6] Initial income is considered as endogenous variable, i.e. $z_{2it} = initial_{it} = gdp_{it-1}$, while z_{1it} contains the remaining control variables.[7]

Following Arellano and Bover (1995), we use lags of the dependent variable ($dgdp_{it-1}, \ldots, dgdp_{it-p}$) as instruments. Empirical results may depend on the

[6] Including time dummies in Equation (1.3) will not change our main results.

[7] The empirical model could be easily extended by allowing for the endogeneity of further control variables. In our application, however, standard Hausman tests indicate that the endogeneity of the remaining control variables is not an issue. Results of Hausman tests are not presented but are available on request.

number (p) of instruments, see Roodman (2009). In particular, there is a bias/efficiency trade-off in finite samples. Therefore, we considered two empirical benchmark specifications. On the one hand, we use all available lags of the instrument variable ($p = t$) to increase efficiency, see Table 1.1. On the other hand, we reduced the instrument count to one ($p = 1$) to avoid an overfit of instrumented variables that might lead to biased coefficient estimates. According to Table 1.6 in the Appendix, the choice of instruments has no relevant impact on our results.

Table 1.1 shows the results obtained for industrialized and non-industrialized countries. The upper part of the table displays the estimated inflation threshold and the corresponding 95% confidence interval. The middle part shows the regime-dependent coefficients of inflation on growth. Specifically, $\widehat{\beta}_1$ ($\widehat{\beta}_2$) denotes the marginal effect of inflation on growth in the low (high) inflation regime, i.e. when inflation is below (above) the estimated threshold value. The coefficients of the control variables are presented in the lower part of the table.

1.4.1 The Inflation-Growth Nexus in Industrialized Countries

The results for the empirical relation between inflation and growth in industrialized countries based on the first benchmark specification are presented in the first column of Table 1.1. The estimated inflation threshold of 2.53% as well as the marginal effects of inflation on growth strongly support the prevailing inflation targets of many central banks. First, the 95% confidence interval ([1.94, 2.76]) of the threshold value includes 2% but does not contain 4%, the alternative inflation target recently suggested by Blanchard et al. (2010). Second, both regime-dependent coefficients of inflation are significant and plausibly signed. Inflation is positively correlated with economic growth in industrialized countries if below the threshold ($\widehat{\beta}_1 = 1.37$), while the opposite is true for higher inflation ($\widehat{\beta}_2 = -0.391$). The absolute size of the inflation coefficients suggests that correlation between inflation and economic growth of industrialized countries is stronger when inflation is low. According to the 95% confidence intervals, this conclusion holds at least for inflation rates "below but close to 2%".

Table 1.1: Inflation Thresholds and Growth

	Industrialized Countries	Non-Industrialized Countries
Threshold estimates		
$\widehat{\gamma}$	2.530%	17.228%
95% confidence interval	[1.94, 2.76]	[12.85, 19.11]
Impact of inflation		
$\widehat{\beta}_1$	1.374^{***} (0.436)	-0.121 (0.117)
$\widehat{\beta}_2$	-0.391^{*} (0.220)	-0.434^{**} (0.222)
Impact of covariates		
$initial_{it}$	-1.371 (0.950)	-1.800^{**} (0.858)
$igdp_{it}$	0.107^{***} (0.036)	0.157^{***} (0.045)
$dpop_{it}$	0.290 (0.341)	-0.503^{**} (0.257)
$dtot_{it}$	-0.162^{***} (0.036)	-0.072^{***} (0.025)
$sdtot_{it}$	-0.036 (0.041)	-0.007 (0.020)
$open_{it}$	-0.882 (1.080)	0.768 (0.640)
$sdopen_{it}$	0.426^{**} (0.213)	0.046 (0.169)
$\widehat{\delta}_1$	-0.384 (0.511)	0.745 (1.077)
Observations	227	761
N	23	101

Notes: This table reports results for the dynamic panel threshold estimation as described in Section 1.2 using all available lags of the instrument variable, i.e. $\{dgdp_{it-1},\ dgdp_{it-2},\ \ldots, dgdp_{i0}\}$. Following Hansen (1999), each regime contains at least 5% of all observations. For industrialized countries, feasible inflation thresholds are, therefore, between 1.146 and 15.668% and for non-industrialized countries between 1.002 and 66.146%. Standard errors are given in parentheses.

It is worth emphasizing that our results are robust with respect to the choice of instruments, see Table 1.6 in the Appendix. The only notable exception refers to the confidence interval of the inflation threshold. If the instrument count is reduced to one, estimation is less efficient and the 95% confidence interval of the inflation threshold widens to [1.38, 5.50]. As a consequence, the evidence on the long-run growth effects of inflation rates around 4% must be viewed with caution.

1.4.2 The Inflation-Growth Nexus in Non-Industrialized Countries

The results for non-industrialized countries are shown in the second column of Table 1.1. They differ from those obtained for industrialized countries in two important aspects. First, the estimated threshold level of inflation (17.2%) is definitely higher than in industrialized countries. The 95% confidence interval indicates that the critical value of inflation for non-industrialized countries is clearly lower than the 40% proposed by Bruno and Easterly (1998). According to our estimates, even inflation rates above 12.85% may already be seen as "too high". The higher inflation threshold for non-industrialized countries could be explained by the widespread use of indexation systems, which many non-industrialized countries have adopted due to a long history of inflation. These indexation systems may partially reduce the adverse effects of inflation. Following e.g. Khan and Senhadji (2001), higher inflation thresholds in non-industrialized countries may also be related to a convergence process and the Balassa-Samuelson effect. The coefficient of inflation ($\widehat{\beta}_2$=-0.434) is significant and plausibly signed when inflation gets above its threshold. Therefore we find clear evidence suggesting that high inflation rates in non-industrialized countries come along with lower growth rates.[8]

The second important difference between the empirical results obtained for industrialized and non-industrialized countries refers to the correlation between growth and inflation when inflation is below its threshold. While the inflation coefficient

[8] By contrast, Drukker et al. (2005) find significant inflation thresholds but no significant impact of inflation on growth in any regime.

in industrial countries has been significant for low inflation rates and large in absolute terms relative to high inflation, this is not true for the low-inflation regime in developing countries. The corresponding estimate, $\widehat{\beta}_1 = -0.12$, is small and far from significant for non-industrialized countries.

For non-industrialized countries, the effect of the instrument variables on the estimated inflation thresholds is negligible, see Table 1.6. The reduction of the instrument count only affects the estimates for the control variables where the standard errors slightly increase.

Finally, it is worth noting that our results on the empirical inflation-growth nexus obtained from a dynamic panel threshold model broadly confirm earlier findings based on models that should have suffered from an endogeneity bias, compare Khan and Senhadji (2001) and Bick (2010). Apparently, in our application accounting for the endogeneity of control variables does not have a major impact on the estimated thresholds. In other application, however, avoiding the endogeneity bias in a panel threshold model may lead to very different conclusions.

1.5 Concluding Remarks

This paper provides new evidence on the non-linear relationship between inflation and long-term economic growth. To that aim, we built on Hansen (1999) and Caner and Hansen (2004) and developed a dynamic threshold model that allows for endogeneous regressors in a panel setup. Applying the forward orthogonal deviations transformation suggested by Arellano and Bover (1995) ensured that the original distribution theory of the threshold model applied to static panels as in Hansen (1999) is still valid in a dynamic context.

Applying the dynamic panel threshold model to the analysis of thresholds in the inflation-growth nexus, confirmes the general consensus among economists. In particular, our empirical results suggest that inflation distorts economic growth provided it exceeds a certain critical value. However, there are important differences for industrialized and non-industrialized countries concerning both the level of the estimated inflation threshold and the impact of inflation in the various inflation regimes.

For industrialized countries, our results support the inflation targets of about 2% which are more or less explicitly announced by many central banks. Contributing to the recent discussion on the appropriate level of inflation targets stirred by Blanchard et al. (2010), we estimated that inflation rates exceeding a critical value of 2.5% are negatively correlated with economic growth while the opposite is true below that level.

For non-industrialized countries, the estimated inflation threshold is much higher, about 17%. Inflation rates above this threshold come along with significantly lower growth rates for non-industrialized countries but not vice versa. Thus, our results do not support growth-enhancing effects of moderate inflation rates below the threshold value. However, policy conclusions based on reduced form estimates have to be viewed with caution. In particular, the estimated inflation-growth nexus does not necessarily reflect causality but rather correlation. Yet, significant inflation thresholds in the empirical relationship between inflation and growth may provide a useful guideline for further research on the impact of inflation on growth.

The empirical setup of the current study controlled for the effect of further variables on growth but assumed that the level of the inflation threshold only depends on whether a country is industrialized or not. In particular for the very heterogenous group of non-industrialized countries, this assumption may be too restrictive. Lin and Ye (2009), for instance, show that the performance of inflation targeting in developing countries can be affected by further country characteristics. Accordingly, inflation thresholds in developing countries and, thus, the appropriate level of the inflation target might be also country-specific. The identification of country-specific inflation thresholds in the inflation-growth nexus might provide useful information about the appropriate location and width of an inflation targeting band. We leave this extension of our analysis for future research.

1.6 Appendix

1.6.1 Tables

Table 1.2: List of Variables

dgdp	Five-year average of the annual growth rate of real GDP per capita in constant 2000 prices
dpop	Five-year average of the annual growth rate of population
dtot	Five-year average of the annual percentage change in the terms of trade, where the terms of trade are measured as exports divided by imports
igdp	Five-year average of the annual percentage of GDP dedicated to investment
initial	Five-year average of GDP per capita in 2000 constant prices, from the previous period, in logs
open	Five-year average of log of openness, where openness is measured as the share of exports plus imports in the GDP
π	Five-year average of the annual percentage change of the CPI index
$\tilde{\pi}$	Semi-log transformed π
sdtot	Five-year standard deviation of the terms of trade
sdopen	Five-year standard deviation of openness
x	Vector of control variables: $initial, igdp, dpop, dtot, sdtot, open, sdopen$

Table 1.3: Sample Industrialized Countries

Country	t	$\underset{mean}{\pi}$	$\underset{mean}{dgdp}$	Country	t	$\underset{mean}{\pi}$	$\underset{mean}{dgdp}$
Australia	10	5.26	2.13	Japan	10	3.64	4.43
Austria	10	3.54	3.27	Luxembourg	10	3.49	3.18
Belgium	10	3.73	2.65	Netherlands	10	3.87	2.29
Canada	10	4.14	2.22	New Zealand	10	6.30	1.66
Denmark	10	5.28	2.28	Norway	10	5.03	2.89
Finland	10	5.71	2.86	Portugal	10	9.42	3.71
France	10	5.08	2.79	Spain	10	8.07	3.52
Germany	8	2.60	2.22	Sweden	10	5.21	2.14
Greece	9	10.34	3.23	Switzerland	10	2.95	1.81
Iceland	10	17.84	2.83	United Kingdom	10	5.97	2.22
Ireland	10	6.42	3.74	United States	10	4.02	2.28
Italy	10	6.71	3.06				

Notes: Average of annual inflation rates and average of annual growth rates of GDP in percent over the period 1955-2004. Source: IFS, Penn World Table 6.2.

Table 1.4: Sample Non-Industrialized Countries (1)

Country	T	$\underset{mean}{\pi}$	$\underset{mean}{dgdp}$	Country	T	$\underset{mean}{\pi}$	$\underset{mean}{dgdp}$
Algeria	7	10.58	1.40	Malawi	7	18.82	1.35
Argentina	10	199.63	1.08	Malaysia	9	3.18	4.62
Bahamas	6	4.46	1.30	Mali	7	4.76	2.02
Bahrain	6	3.54	0.71	Malta	6	3.60	5.34
Barbados	7	6.99	1.24	Mauritania	5	6.94	0.24
Benin	2	4.19	2.11	Mauritius	9	8.08	3.12
Bolivia	10	291.40	4.04	Mexico	10	22.79	2.05
Botswana	6	10.43	5.44	Morocco	10	5.05	2.37
Brazil	7	346.25	2.10	Mozambique	4	40.12	3.23
Burkina Faso	8	4.78	1.29	Namibia	5	11.24	0.61
Burundi	8	9.81	0.91	Nepal	8	8.12	1.43
Cameroon	7	7.40	1.19	Netherlands Ant.	6	4.37	0.42
Cape Verde	5	7.33	4.28	Nicaragua	7	791.09	-1.53
Central African Rep.	6	5.68	-0.13	Niger	8	5.33	0.84
Chad	7	3.12	0.98	Nigeria	10	15.83	0.96
Chile	9	52.03	2.40	Pakistan	9	.67	2.70
China	7	5.01	7.30	Panama	10	2.30	2.95
Colombia	10	16.83	1.66	Papua New Gui.	6	7.95	2.45
Congo	7	7.65	1.40	Paraguay	9	12.55	1.46
Costa Rica	10	12.41	1.66	Peru	10	266.10	1.10
Cote d‘Ivoire	8	6.94	0.66	Philippines	10	9.15	1.75
Cyprus	6	4.82	5.09	Poland	6	46.97	2.03
Dominica	6	5.72	2.56	Romania	7	38.33	3.35
Dominican Rep.	9	12.61	2.96	Rwanda	7	10.04	1.88
Ecuador	9	23.27	1.63	Samoa	6	8.45	0.96
Egypt	9	9.08	2.89	Saudi Arabia	6	2.99	-1.84
El Salvador	10	8.19	1.05	Senegal	7	6.22	0.15
Equatorial Guinea	5	12.60	10.96	Sierra Leone	6	39.54	-1.80
Ethiopia	8	6.22	1.68	Singapore	8	2.91	4.98
Fiji	6	5.83	1.10	Solomon Islands	6	10.35	-0.36
Gabon	8	5.78	0.30	South Africa	10	8.13	1.48
Gambia	8	9.56	1.02	Sri Lanka	10	7.59	3.27

Continued on next page.

Table 1.5: Sample Non-Industrialized Countries (2)

Country	T	$\underset{mean}{\pi}$	$\underset{mean}{dgdp}$	Country	T	$\underset{mean}{\pi}$	$\underset{mean}{dgdp}$
Ghana	8	32.65	7.34	St, Lucia	6	5.26	2.68
Grenada	5	4.20	2.61	St,Vincent & Grenad.	6	4.795	4.21
Guatemala	10	7.96	1.07	Sudan	6	43.18	0.48
Guinea-Bissau	3	25.81	1.30	Suriname	6	43.03	3.76
Haiti	6	13.99	0.42	Swaziland	6	11.68	2.75
Honduras	10	8.81	0.89	Syria	8	10.35	1.85
Hong Kong	8	5.98	4.72	Tanzania	8	18.27	1.69
Hungary	6	12.46	2.27	Thailand	10	4.72	4.42
India	10	7.22	2.75	Togo	7	6.43	-1.46
Indonesia	8	53.61	3.53	Tonga	6	8.63	4.13
Iran	9	14.27	2.10	Trinidad & Tobago	10	7.23	3.55
Israel	9	39.92	2.75	Tunisia	7	4.73	3.27
Jamaica	9	15.29	0.80	Turkey	10	36.64	2.46
Jordan	7	6.81	-0.47	Uganda	5	48.62	1.63
Kenya	9	10.19	0.28	Uruguay	10	45.95	0.92
Korea	7	8.85	6.07	Venezuela	10	17.90	0.56
Kuwait	6	2.77	0.94	Zambia	7	35.67	0.21
Lesotho	6	12.93	3.25	Zimbabwe	8	37.10	0.54
Madagascar	8	12.46	-1.23				

Notes: Average of annual inflation rates and average of annual growth rates of GDP in percent over the period 1955-2004. Source: IFS, Penn World Table 6.2.

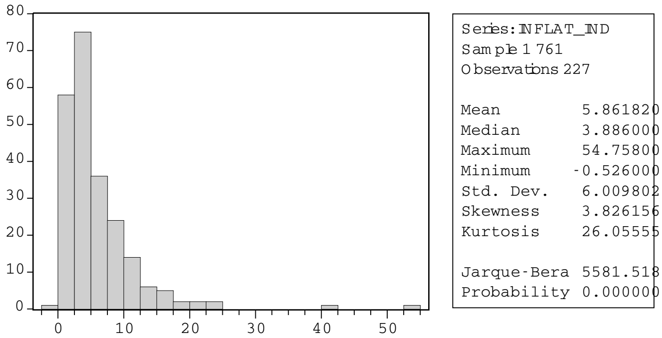
Table 1.6: Inflation Thresholds and Growth - Estimation with Reduced Instrument Count

	Industrialized Countries	Non-Industrialized Countries
Threshold estimates		
$\widehat{\gamma}$	2.530%	17.228%
95% confidence interval	[1.38, 5.50]	[12.87, 19.11]
Impact of inflation		
$\widehat{\beta}_1$	1.280^{***} (0.520)	-0.141 (0.121)
$\widehat{\beta}_2$	-0.531^{*} (0.312)	-0.494^{**} (0.221)
Impact of covariates		
$initial_{it}$	-3.543 (2.731)	-1.761 (1.240)
$igdp_{it}$	0.093^{***} (0.030)	0.156^{***} (0.048)
$dpop_{it}$	0.101 (0.387)	-0.503 (0.350)
$dtot_{it}$	-0.150^{***} (0.043)	-0.072^{***} (0.028)
$sdtot_{it}$	-0.003 (0.057)	-0.006 (0.023)
$open_{it}$	1.361 (3.311)	0.733 (0.866)
$sdopen_{it}$	0.287 (0.288)	0.050 (0.188)
$\widehat{\delta}_1$	-0.523 (0.607)	0.753 (1.199)
Observations	227	761
N	23	101

Notes: Results for the dynamic panel threshold model (see Section 1.2) using only one instrument lag ($dgdp_{it-1}$). Each regime contains at least 5% of all observations. For industrialized countries, feasible inflation thresholds are, therefore, between 1.146 and 15.668% and for non-industrialized countries between 1.002 and 66.146%. Standard errors are given in parentheses.

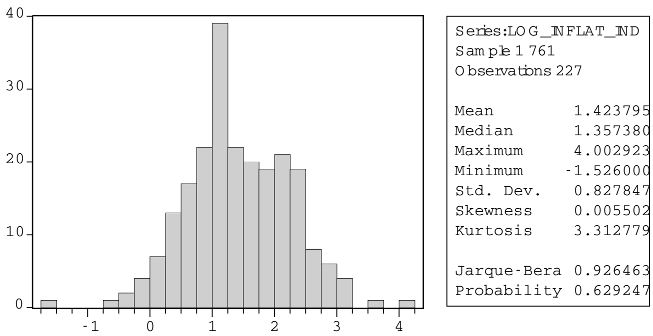
1.6.2 Figures

Figure 1.1: Distribution of Inflation Rates - Industrialized Countries



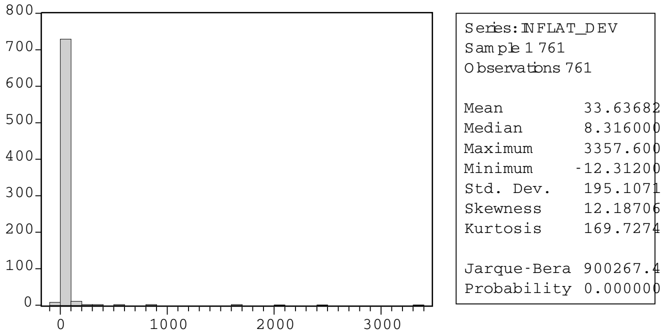
Notes: Five-year average of annual inflation rates (percentage points) for industrial countries, 1955-2004. Source: IFS.

Figure 1.2: Distribution of Log Inflation Rates - Industrialized Countries



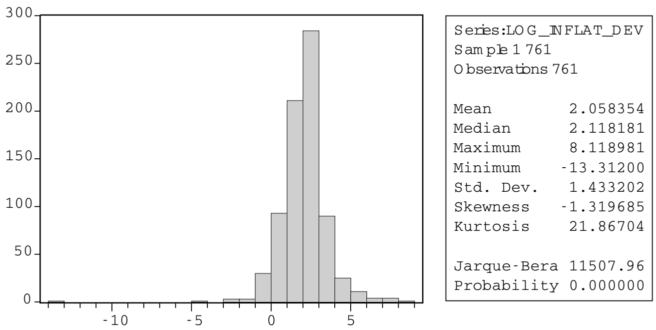
Notes: Five-year average of annual inflation rates (percentage points) after the semi-log transformation for industrial countries, 1955-2004, see Section 2.1. Source: IFS.

Figure 1.3: Distribution of Inflation Rates - Non-Industrialized Countries



Notes: Five-year average of annual inflation rates (percentage points) for non-industrial countries, 1955-2004. Source: IFS.

Figure 1.4: Distribution of Log Inflation Rates - Non-Industrialized Countries



Notes: Five-year average of annual inflation rates (percentage points) after the semi-log transformation for non-industrial countries, 1955-2004, see Section 2.1. Source: IFS.

2 Short–Term Herding of Institutional Traders: New Evidence from the German Stock Market

2.1 Introduction

Herding behavior of investors, defined as the tendency to accumulate on the same side of the market, is often viewed as a significant threat for the stability and the efficiency of financial markets, see Hirshleifer and Teoh (2003) and Hwang and Salmon (2004). The empirical literature on herding behavior in financial markets is particularly interested in the investment behavior of institutional investors, i.e., of banks and other financial institutions, see, e.g., Barber, Odean and Zhu (2009). Yet, the evidence on herding behavior of institutional investors is mixed and partly elusive.

The evidence on herding is often impeded by data availability problems. In particular, positions taken by institutions on the stock market are reported only infrequently, if at all. For example, U.S. mutual funds reports of holdings are available only on a quarterly basis, see, e.g., Choi and Sias (2009). Evidence for German mutual funds even had to be based on semi-annual data, see Walter and Weber (2006). In high-developed financial markets, however, herding might also occur within shorter time intervals.

Several contributions, including Barber et al. (2009), attempt to overcome the problem of data frequency by using anonymous transaction data instead of reported holdings. Since those data do not identify the trader, researchers usually separate trades by size and then simply define trades above a specific cutoff size as institutional. However, even though large trades are almost exclusively the province of institutions, institutions with superior information might split their trades to hide their informational advantage. While low-frequency data may still contain useful information about longer-term herding, the interpretation of herding measures based on anonymous transactions is not without problems. In particular, it is not clear whether the strategic trading behavior of institutional investors tends to increase or decrease the evidence on herding.

The current paper sheds more light on the empirical relevance of short-term herding by introducing a new and comprehensive data set on German stock market transactions that includes both high-frequency and investor-level data. Our analysis provides new evidence on the herding behavior of financial institutions for a broad cross-section of stocks over the period from July 2006 to March 2009 in the German stock market. In order to investigate how the underlying data frequency may affect the empirical assessment of short-term herding, we evaluate herding measures at daily, monthly, and quarterly frequency. Neglecting the investor-related information contained in our data set, we explore how herding measures are affected by the use of anonymous transaction data.

The empirical results suggest that previous studies based on low-frequent or anonymous transaction data might have overestimated the extent of short-term herding. This conclusion holds irrespective of the herding measure applied. Confirming the results obtained with the static herding measure proposed by Lakonishok, Shleifer and Vishny (1992), the dynamic measure of Sias (2004) shows that institutional trades are correlated over time. However, although there are investors who follow other traders, the main part of the correlation results from institutions that follow their *own* trading strategy. We find that daily herding measures typically contradict implications of herding theory. In particular, it is not confirmed that short-term herding is more pronounced in smaller and less liquid stocks. Moreover, our results do not indicate that short-term herding increases in times of market stress, i.e., during the recent financial crisis. It is worth noting, however, that conclusions concerning the impact of the financial crisis on the trading behavior of institutional investors would have been misleading if herding measures were based on anonymous transaction data.

The rest of the paper is structured as follows: Section 2.2 briefly reviews the literature on herding. Section 2.3 discusses the role of data availability on the herding measure. Section 2.4 introduces the applied herding measures. Section 2.5 presents the empirical results and Section 2.6 offers some conclusions.

2.2 Herding: A Brief Review of the Literature

2.2.1 Types of Herding

Following e.g. Bikhchandani and Sharma (2001), herding describes the tendency of institutions or individuals to show similarity in their behavior and thus act like a herd. Recent economic theory distinguishes between intentional herding and unintentional, or spurious herding.[1] *Unintentional herding* is mainly fundamental driven and arises because institutions may examine the same factors and receive correlated private information, leading them to arrive at similar conclusions regarding individual stocks, see, e.g., Hirshleifer, Subrahmanyam and Titman (1994). Moreover, professionals may constitute a relatively homogenous group: they share a similar educational background and professional qualifications and tend to interpret informational signals similarly.

In contrast, *intentional herding* is more sentiment-driven and involves the imitation of other market participants, resulting in simultaneous buying or selling of the same stocks regardless of prior beliefs or information sets. This type of herding can lead to asset prices failing to reflect fundamental information, exacerbation of volatility, and destabilization of markets, thus having the potential to create, or at least contribute, to bubbles and crashes on financial markets, see,

[1] For a comprehensive survey of the theoretical and empirical herding literature, see, e.g., Hirshleifer and Teoh (2003).

e.g., Morris and Shin (1999) and Persaud (2000). Yet, several economic theories including models of information cascades (Avery and Zemsky (1998)) and reputation (Scharfstein and Stein (1990)) show that even intentional herding can be rational from the trader's perspective.

Models of intentional herding typically assume that there is only little reliable information in the market and that traders are uncertain about their decisions and thus follow the crowd. In contrast, in the case of unintentional herding, traders acknowledge public information as reliable, interpret it similarly and thus they all end up on the same side of the market. For both types of herding, the degree of herding is linked to the uncertainty or availability of information.

2.2.2 Determinants of Herding

2.2.2.1 Size Effects and the Development of the Market

The empirical literature explores the determinants of herding via the link between herding and information availability. Lakonishok et al. (1992) segregate stocks by size because market capitalization of firms usually reflects the quantity and quality of information available. Thus, one would expect higher levels of herding in trading small stocks as evidence of intentional herding. In line with theoretical predictions, they find evidence of herding being more intense among small companies compared to large stocks. Further empirical evidence on the link between herding and size is provided by Wermers (1999) and Sias (2004).[2]

Based on semi-annual data, Walter and Weber (2006) and Oehler and Wendt (2009) report significant positive and higher levels of herding for German mutual funds compared to those found in U.S.-based research. Walter and Weber (2006) link the finding of herding to the stage of development of the financial market.

[2] An alternative, less direct approach to analyze herding behavior is proposed by Christie and Huang (1995), where herding is measured for the whole market and not for a specific group of market participants. Assuming that herding occurs when individual investors neglect their own information and simply follow the crowd, herding implies that the dispersion of cross-sectional returns decreases in times of higher uncertainty, i.e., when the volatility of returns is large, see Chiang and Zheng (2010).

They argue that the German market is not as highly developed as the U.S. and U.K. capital markets. There is also evidence for higher herding levels in emerging markets compared to developed ones.[3] High herding in emerging markets may be attributed to incomplete regulatory frameworks, especially in the area of market transparency. Deficiencies in corporate disclosure and information quality create uncertainty in the market, throw doubt on the reliability of public information, and thus impede fundamental analysis, Antoniou, Ergul, Holmes and Priestley (1997) and Gelos and Wei (2002). Kallinterakis and Kratunova (2007) argue that in such an environment it is reasonable to assume that investors will prefer to base their trading on their peers' observed actions. Thus, intentional herding through information cascades is more likely to occur in less developed markets. In the current paper, we assume that the degree of market transparency increases with the size of the traded stocks. As a result, less herding in larger stocks may also appear because the corresponding markets are higher developed and, thus, more transparent.

2.2.2.2 State of the Market

The extent of herding may depend on the state of the overall market. Choe et al. (1999) find higher herding levels before the Asian crisis of 1997 than during the crisis for the Korean stock market. Using data from the Jakarta Stock Exchange, Bowe and Domuta (2004) show that herding by foreigners increased following the outbreak of the crisis. Analyzing the relationship between the cross-sectional dispersion of returns and their volatility, Chiang and Zheng (2010) conclude that herding behavior appears to be more apparent during the period in which the financial crisis occurs. In contrast, using data from U.S. and South Korean stock markets, Hwang and Salmon (2004) find higher herding measures during relatively quiet periods than during periods when the market is under stress. In order to

[3] For example, Lobao and Serra (2007) document strong evidence of herding behavior for Portuguese mutual funds. Significant herding is reported for Indonesia (Bowe and Domuta (2004)), Poland (Voronkova and Bohl (2005)), Korea (Choe, Kho and Stulz (1999), Kim and Wei (2002)) and South Africa (Gilmour and Smit (2002)).

account for the state of the market, the following empirical analysis allows for different herding intensities before and during the recent financial crisis.

2.3 Data

2.3.1 Data Issues

2.3.1.1 Low Frequency

Most empirical studies on herding in financial markets identify institutional transactions as changes in reported positions in a stock. However, positions are reported very infrequently. For example, the bulk of the literature considers the trading behavior of U.S. mutual funds who generally report only on a quarterly basis. For German mutual funds, even half-year reports are required.[4] Semi-annual and even quarterly data provide only a crude basis for inferring trades and this frequency might be too low in a rapidly changing stock market environment. Interestingly, the overall effect of the data-frequency on the resulting herding measure is not obvious. On the one hand, herding might be understated, since trades that are completed within the period are not captured. In markets with frequent public information flows and high turnover that lead to the timely incorporation of information, herding behavior caused by informational cascades is likely to occur only in the short-term, that is, before public information becomes available. On the other hand, however, herding might also be overstated when looking at a long time interval, since buys at the beginning of the period that are not completed within the period and buys of others at the end are regarded as herding. In order to explore the impact of data frequency on the herding measure, we calculated herding measures based on daily, monthly and quarterly data.

[4] There are also studies that rely on yearly ownership data, see, e.g., Kim and Nofsinger (2005) who investigate herding of financial institutions in Japan. Puckett and Yan (2008) used weekly data to overcome the low frequency problem.

2.3.1.2 Identification of Traders

In view of these problems, the recent empirical literature, including Barber et al. (2009), attempts to overcome the lack of high-frequency data by using anonymous transaction data.[5] In these contributions, institutional trades are identified by use of a cutoff approach. Transactions above a specific cutoff size are considered as a proxy for institutional trades, since large trades are typically the province of institutions. For example, Lee and Radhakrishna (2000) suggest a cutoff of $50,000 for larger stocks. However, this approach can be misleading if institutions split their trades to hide a superior information advantage. In this case, the most informative institutional trades are probably not the largest ones. Our data confirms that although institutions trade often during a day, those trades are not necessarily large. Herding measures based on anonymous transactions may tend to over- or to understate the true extent of herding. In order to shed more light on the total effect of anonymous transaction data on the herding measure, we ignore the information about the investor contained in our data and calculate the herding measures for various cutoff levels.

2.3.2 The BaFin Datasource

Our data set includes all real-time transactions carried out on German stock exchanges. The data are provided by the German Federal Financial Supervisory Authority (BaFin). Under Section 9 of the German Securities Trading Act, all credit institutions and financial services institutions are required to report to BaFin any transaction in securities or derivatives which are admitted to trading on an organized market.

These records enable the identification of all relevant trade characteristics, including the trader (the institution), the particular stock, time, number of traded shares, price, and the volume of the transaction. Moreover, the records identify

[5] Because the dynamic Sias herding measure additionally requires the identification of the trader over time, empirical work relying on anonymous transactions employs the static herding measure introduced by Lakonishok et al. (1992).

on whose behalf the trade was executed, i.e., whether the institution traded for its own account or on behalf of a client that is not a financial institution. Since the aim of our study is the investigation of institutional trades, particularly those of financial institutions, we focus on the trading of own accounts, i.e., those cases when a bank or a financial services institution is clearly the originator of the trade.[6] Using data from July 2006 until March 2009 (a total of 698 trading days), we cover market upturns as well as the recent market downturn.

The analysis focuses on shares listed on the three major German stock indices: the DAX 30 (the index of the 30 largest and most liquid stocks), the MDAX (a mid-cap index of 50 stocks that rank behind the DAX 30 in terms of size and liquidity), and the SDAX (a small-cap index of 50 stocks that rank behind the MDAX components).[7] Calculating herding measures for these different stock market segments, we explore whether there are differences in the trading behavior in small and large stocks.

Overall, we have 167,422,502 records of proprietary transactions by 1,120 institutions in those stocks on German stock exchanges. For each institution, we compute the daily trade imbalance. Among these 1,120 traders, 1,044 institutions trade on the DAX 30 stocks, 742 on the MDAX stocks and 512 on the SDAX stocks. On average, about 25 of these institutions trade every day in those stocks, justifying the use of daily data. The institutions have an average daily market share of DAX 30 stocks of about 46%. Interestingly, the market share declined after the start of the financial crisis, implying a retraction from trading business, see Figure 2.1 in the Appendix. In the period from July 1, 2006 until August 8, 2007, the proportion constituted 66%, shrinking to 32% after August 9, 2007. Table 2.4 in the Appendix provides further information on the institutions under investigation.

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[6] Therefore, we exclude institutions trading exclusively for the purpose of market making. We also exclude institutions that are formally mandated as designated sponsors, i.e., liquidity providers, for a specific stock.

[7] The stocks were selected according to the index compositions at the end of the observation period on March 31, 2009. The time series of five stocks on the MDAX and five stocks on the SDAX are not complete for the whole period. We have therefore an unbalanced panel of stocks and days, totaling 88,435 observations.

2.4 Herding Measures

In this section, we briefly review the two herding measures predominantly applied in the literature.

2.4.1 The LSV Measure

The first herding measure had been introduced by Lakonishok et al. (1992) (LSV measure). According to the LSV measure, herding is defined as the tendency of traders to accumulate on the same side of the market in a specific stock and at the same time, relative to what would be expected if they traded independently.

The LSV herding statistic is given by

$$HM_{it} = |br_{it} - \bar{br}_t| - E_t[|br_{it} - \bar{br}_t|], \tag{2.1}$$

where br_{it} is the the number of institutions buying stock i at time t as proportion of all institutions trading in i at t. $\bar{br}_t$ is the period average of the buyer ratios over all stocks, which is a proxy for the expected value of the buyer ratio at t, $E_t[br_{it}]$, and thus accounts for an overall signal in the market at time t. Hence, the first term of Equation (2.1) captures the deviation of the buyers ratio in i at t from the overall buy probability at time t, i.e. captures herding as excess dispersion of what would be expected for that time. The second term, $E_t[|br_{it} - \bar{br}_t|]$, ensures that the herding measure HM_{it} will be zero if the trades are independent.

Following Lakonishok et al. (1992), the empirical literature calculates the mean herding measure $\overline{HM}$ as the mean of HM_{it} across all stocks and all periods. A positive and significant value of $\overline{HM}$ indicates the average tendency of the investigated group to accumulate in their trading decisions. The higher the $\overline{HM}$, the stronger the herding. For example, $\overline{HM} = 2\%$ indicates that out of every 100 transaction, two more traders trade on the same side of the market than would be expected if each trader had decided randomly and independently. However, it should be noted that the maximum value of $\overline{HM}$ is not equal to one, even if all traders buy stock i at time t, since HM_{it} is defined as excess or additional herding over the overall trend $\bar{br}_t$. Thus, only stock-picking herding and similar trading patterns beyond market trends are analyzed.

2.4.2 The Sias Measure

The LSV herding measure is a static measure that detects contemporaneous buying or selling within the same time period. In contrast, the dynamic approach proposed by Sias (2004) explores whether the buying tendency of traders persists over time. The focus of the Sias herding measure is on whether institutional investors follow each others' trades by examining the correlation between institutional trades over time. Similar to the LSV measure, the starting point of the Sias measure is the number of buyers as a fraction of all traders. According to Sias (2004), the ratio is standardized to have zero mean and unit variance:

$$\Delta_{it} = \frac{br_{it} - \bar{br}_t}{\sigma(br_{it})}. \tag{2.2}$$

$\sigma(br_{it})$ is the cross sectional standard deviation of buyer ratios across I stocks at time t. The Sias herding measure is defined as the correlation between the standardized buyer ratios in consecutive periods:

$$\Delta_{it} = \beta_t \Delta_{i,t-1} + \epsilon_{it}. \tag{2.3}$$

The cross-sectional regression is estimated for each day t and then the time-series average of the coefficients is calculated: $\hat{\beta} = \frac{\sum_{t=2}^{T} \beta_t}{T-1}$. A high buyer ratio would usually result in a higher LSV measure (if higher than on average) but not necessarily to a higher Sias measure as this depends on the ratio at the next trading day.

The Sias methodology further differentiates between investors who follow the trades of others (i.e., *true herding* according to Sias (2004)) and those who follow their own trades. For this purpose, the correlation is decomposed into two components:

$$\beta = \rho(\Delta_{it}, \Delta_{i,t-1}) = \left[\frac{1}{(I-1)\sigma(br_{it})\sigma(br_{i,t-1})}\right] \sum_{i=1}^{I} \left[\sum_{n=1}^{N_{it}} \frac{(D_{nit} - \bar{br}_t)(D_{ni,t-1} - \bar{br}_{t-1})}{N_{it} N_{i,t-1}}\right]$$
$$+ \left[\frac{1}{(I-1)\sigma(br_{it})\sigma(br_{i,t-1})}\right] \sum_{i=1}^{I} \left[\sum_{n=1}^{N_{it}} \sum_{m=1, m \neq n}^{N_{i,t-1}} \frac{(D_{nit} - \bar{br}_t)(D_{mi,t-1} - \bar{br}_{t-1})}{N_{it} N_{i,t-1}}\right], \quad (2.4)$$

where N_{it} is the number of institutions trading stock i at time t and I is the number of stocks traded. D_{nit} is a dummy variable that equals one if institution n is a buyer in i at time t and zero otherwise. $D_{mi,t-1}$ is a dummy variable that equals one if trader m (who is different from trader n) is a buyer at day $t-1$. Therefore, the first part of the measure represents the component of the cross-sectional inter-temporal correlation that results from institutions following their own strategies when buying or selling the same stocks over adjacent days. The second part indicates the portion of correlation resulting from institutions following the trades of others over adjacent days. According to Sias (2004), a positive correlation that results from institutions following other institutions, i.e., the latter part of the decomposed correlation, can be regarded as first evidence for informational cascades.

The analysis on size effects on herding is complicated by large differences in the number of traders. There are typically more institutions trading in large capitalization stocks than in a small stocks and this will affect both the decomposition of the correlation coefficient and the cross-sectional correlation between the buyers ratios. Therefore, Sias (2004) introduces a modified decomposition of the correlation coefficient β that accounts for the number of traders in a market segment, see Appendix 2.7.1. We will employ these modified measures to assess to what extent correlated trading in different market segments is actually related directly to traders following the trades of others.

2.5 Empirical Evidence on Herding

2.5.1 Results on LSV Herding

2.5.1.1 Evidence from Daily Herding Measures

Our results obtained for the static LSV herding are summarized in Table 2.1. Following the empirical literature, HM_{it} is computed only if at least five traders are active in stock i at time t.[8] Let us first discuss the results obtained for daily investor-level data shown in the first row of each panel. For daily data, the mean value of the herding measure $\overline{HM}$ over the complete sample period and over all stocks is 1.40%. The value is statistically significant but small and slightly lower than found in previous studies using low-frequency data, including Lakonishok et al. (1992) and Walter and Weber (2006) who both found herding to be about 2.70%.

Theories on herding behavior typically predict that herding will be more pronounced in smaller and less liquid stocks, where informational problems should be particularly severe. Our results based on daily data do not confirm this prediction. In contrast, we find that herding for stocks in the DAX30 is 3.65%, i.e., about 2.5 times larger than the herding measure obtained for all stocks. In fact, the daily herding measure for the small stocks defining the SDAX is actually insignificant (t-statistic= -0.57).[9]

[8] Table 2.5 in the Appendix shows that results are robust with respect to different assumptions on minimum numbers of traders. In our application, the resulting loss of observations is not an issue. Table 2.4 in the Appendix shows that even on the SDAX on average 10.78 institutions are active each day in each stock. Out of the overall panel of stocks and days (88,435 observations), we calculated 87,839 herding measures, i.e., for 542 observations there were no trade imbalances by any institution. Due to the constraint to a minimum of five traders, we lose 3,997 observations for the sample of all institutional traders, i.e., 83,842 observations remain.

[9] In accordance with Lakonishok et al. (1992), empirical LSV herding measures below zero should be interpreted as evidence against herding. According to e.g. Bellando (2010), negatively signed LSV herding measures occur because the adjustment factor in Equation (2.1) can bias the LSV herding measure downwards if the trading intensity is low. This explains why negatively signed herding measures can be observed in case of small stocks. In our application, however, using only observations with a minimum number of 5 traders should ensure that the bias is only small. Notice further that our conclusions hold for different minimum numbers of traders, see Table 2.5 in the Appendix.

If information gets less reliable in times of market stress, herding measures should increase during a financial crisis. For each group of stocks, the two lower panels of Table 2.1 display the average herding measure for the crisis and the non-crisis period, i.e., before and after August 9, 2007 when tensions in the European money market lead to rapid increases in interest rates. For daily data, the evidence found on increased herding during the financial crisis is not very convincing. Short-term herding actually slightly increased in small and medium stocks over the crisis period. For large stocks, however, herding seemed to be more pronounced in the pre-crisis period.

2.5.1.2 Effects of Data Frequency and the Use of Anonymous Transaction Data

The bulk of the literature on herding had to rely either on lower frequency data or anonymous transaction data. In order to investigate the impact these data limitations have on the herding measure, we re-calculate the measures constraining our sample to quarterly data and to trades above a specific size.

Data Frequency

In a first step, we calculate herding measures for each institution based on quarterly trade imbalances. In each panel of Table 2.1, quarterly herding measures are displayed in the second row. With only a few exceptions, herding measures are higher on a quarterly horizon and in a range similar to that found in previous studies using quarterly data. With quarterly data, the degree of herding increases particulary for small-capitalized (SDAX) stocks. Yet, irrespective of the period under consideration and in line with the results obtained for daily data, the results do not suggest that herding is more pronounced in small stocks. Interestingly, in contrast to the daily measures, the quarterly herding measures have significantly increased in the crisis period for all market segments. For brevity, we only present results for quarterly data. Results obtained for monthly data are fully in line with the conclusions on quarterly data and are reported in Table 2.7 in the Appendix.

Table 2.1: LSV Herding Measures

	All Stocks	*DAX 30*	*MDAX*	*SDAX*
Sample period: July 2006 – March 2009				
Daily data	1.40	3.65	1.24	−0.03
	(0.02)	(0.04)	(0.04)	(0.05)
Observations	83,842	20,901	33,616	29,325
Quarterly data	2.29	3.59	2.14	1.63
	(0.15)	(0.26)	(0.23)	(0.27)
Observations	1,395	331	534	530
Anonymous transactions	4.58	4.39	5.27	3.90
	(0.02)	(0.04)	(0.04)	(0.06)
Observations	80,012	20,865	32,438	26,709
Crisis period (≥08/09/07)				
Daily data	1.60	3.17	1.41	0.34
	(0.03)	(0.06)	(0.05)	(0.07)
Observations	50,585	12,474	20,611	17,500
Quarterly data	2.69	3.95	2.46	2.12
	(0.20)	(0.35)	(0.31)	(0.38)
Observations	872	208	334	330
Anonymous transactions	5.99	5.68	5.99	4.97
	(0.04)	(0.05)	(0.04)	(0.08)
Observations	47,261	12,439	19,581	15,241

Notes: This table reports mean values of HM in percentage terms, calculated at daily frequency, quarterly frequency and with anonymous transaction data (i.e., all transactions below €34,000 for DAX stocks, €14,000 for MDAX stocks and €7,000 for SDAX stocks are dropped) for all stocks and various market segments. Standard errors are given in parentheses.

Anonymous Transaction Data

Following the empirical literature using cutoff approaches to identify institutional investors from anonymous transactions, we calculate herding measures for data where all institutional trades below a specific size have been dropped. Lee and Radhakrishna (2000) suggests cutoffs of $50,000, $20,000, and $10,000 for large, medium, and small stocks. Assuming the current level of exchange rates, we adopt that idea and consider only trades in DAX, MDAX, and SDAX stocks that have a volume of more than €34,000, €14,000, and €7,000, respectively. Out of our overall 167,422,502 records we exclude 118,307,150 due to this constraint. Ignoring trader identification, we treat every remaining transaction as independent. Consequently, if the same institution trades more than once during a day, its transactions are regarded as trades by different institutions.

For each panel, the resulting herding measures are displayed in the third line of Table 2.1. With some exceptions during the pre-crisis period, herding measures based on anonymous transactions are significantly higher than those obtained for investor-level data. This suggests that restricting the attention to large trades tends to exaggerate the actual degree of herding. More importantly, however, herding measures based on anonymous transaction data particularly overstate the extent of herding during the crisis period. In fact, in contrast to the results obtained for investor-level data, herding measures based on anonymous transactions seemingly indicate that the degree of herding has more than doubled in the crisis period for each market segment. Apparently, the identification of institutional traders through a cutoff approach is particulary difficult in the crisis period. In our application, evidence on herding based on anonymous transaction data leads to misleading conclusions about the influence of market stress for the degree of herding.

2.5.2 Results on Sias Herding

Table 2.2 displays the results obtained from the Sias herding measure. The upper part of the table reports the average correlation in percentage terms.[10] The estimated correlation at daily frequency over the complete period and over all

[10] Following Sias (2004) and in line with the calculation of the LSV measure, only observations with at least five traders active in i at time t are considered in the estimation. Table 2.6 in the Appendix display results with different minimum numbers of traders and reveal that results are robust with respect to the assumptions on minimum numbers of traders.

stocks is 18.01%, which is slightly higher than the value obtained by Sias (2004) but lower than the result of Puckett and Yan (2008) for weekly frequency. Similar to our results on LSV herding, Sias herding measures obtained from quarterly and anonymous transaction data tend to be higher than those obtained for daily investor-specific data.[11]

Correlated trading can only be attributed to herding behavior when the correlation in trades has occurred because traders actually followed *other* traders. The lower parts of Table 2.2 show the results for the partitioned correlation according to the decomposition proposed by Sias (2004), compare Equation (2.4). Since this decomposition requires the identification of the trader, it cannot be applied to anonymous transaction data. The results shown in the two lower panels of Table 2.2 reveal that institutions follow their own trades as well as those of others. However, in contrast to the static LSV measure, results obtained from the dynamic Sias measure crucially depend on the frequency of the data. While at a daily frequency, the main part of the correlation, about 56.19% (=0.1012/0.1801), results from institutions that follow their own trades, herding is much more pronounced for quarterly data. In line with Sias (2004) and Choi and Sias (2009), our quarterly estimates imply that nearly the whole correlation (92%=18.8/20.32) results from following other traders, i.e., herding.

Moreover, in sharp contrast to daily herding measures but very much in line with the empirical literature, quarterly herding measures tend to be higher for smaller stocks. This may indicate that the size-effects predicted by herding theory are more relevant for longer-term herding.

Finally, we investigated whether the evidence on Sias herding depends on the state of the market. Table 2.3 presents results for the average correlation and the decomposed correlation during the crisis-period. In particular for quarterly data, the Sias herding measures indicate a higher degree of herding during the crisis-period.

[11] Again results for monthly data are in line with our conclusions and are reported in Tables 2.8 and 2.9 in the Appendix.

Table 2.2: Sias Herding Measures for the Whole Sample Period

	All Stocks	*DAX 30*	*MDAX*	*SDAX*
Average Correlation				
Daily data	18.01	20.01	18.60	16.84
	(0.53)	(0.68)	(0.53)	(0.53)
Observations	83,585	20,715	33,342	29,528
Quarterly data	20.32	20.46	14.06	23.02
	(2.77)	(0.56)	(3.38)	(4.57)
Observations	1,260	300	483	477
Anonymous transactions	27.32	22.43	24.96	29.88
	(0.35)	(0.67)	(0.54)	(0.60)
Observations	77,295	20,575	31,745	24,975
Follow Own Trades				
Daily data	10.12	2.02	3.46	5.47
	(0.19)	(0.03)	(0.04)	(0.06)
Quarterly data	1.52	0.50	0.26	0.33
	(0.70)	(0.17)	(0.43)	(0.56)
Follow Trades of Others				
Daily data	7.89	0.32	0.26	0.14
	(0.23)	(0.03)	(0.04)	(0.06)
Quarterly data	18.80	2.50	2.67	3.13
	(1.54)	(0.17)	(0.43)	(0.56)

Notes: The upper part of the table reports results for the average correlation in percentage terms of the coefficient β calculated at daily and quarterly frequency and for anonymous transaction data. Below, the table reports the partitioned correlations that result from institutions following their own trades (panel 2) and institutions following the trades of others (panel 3), see Equation (2.4). Columns 2-4 of the table show the results from the computation of the cross-sectional average contribution from following their own trades (Equation (2.5)) and following others' trades (Equation (2.6)) for DAX 30, MDAX and SDAX stocks. Standard errors are given in parentheses.

Table 2.3: Sias Herding Measures for the Crisis period (≥08/09/07)

	All Stocks	*DAX 30*	*MDAX*	*SDAX*
Average Correlation				
Daily data	18.49 (0.43)	22.21 (0.87)	18.92 (0.68)	16.50 (0.74)
Observations	50,524	12,349	20,430	17,745
Quarterly data	25.64 (3.47)	28.95 (6.96)	18.04 (5.06)	26.80 (4.73)
Observations	773	90	297	296
Anonymous transactions	27.15 (0.45)	21.98 (0.88)	24.58 (0.70)	30.97 (0.80)
Observations	45,541	12,301	19,179	14,061
Follow Own Trades				
Daily data	8.99 (0.22)	1.90 (0.04)	3.16 (0.05)	5.05 (0.08)
Quarterly data	1.98 (0.47)	0.69 (0.20)	0.35 (0.60)	0.09 (0.90)
Follow Trades of Others				
Daily data	9.50 (0.22)	0.39 (0.04)	0.32 (0.05)	0.21 (0.08)
Quarterly data	23.66 (2.43)	2.51 (0.20)	2.43 (0.50)	3.46 (0.90)

Notes: This table reports correlations and decomposed correlations in percentage terms considering only the period from August 8, 2007 until March 30, 2009. See notes in Table 2.2 for further explanations.

2.6 Conclusions

This paper contributes to the empirical literature on the short-term herding behavior of financial institutions by analyzing high-frequency investor-level data that directly identifies institutional transactions. Applying Lakonishok et al.'s (1992) herding measure to a broad cross-section of German stocks over the period from August 2006 to April 2009, we find an overall level of herding of 1.44% for all investigated financial institutions, which is statistically significant but quite low. In the same vein, the dynamic herding measure of Sias (2004) shows that trades of institutions are correlated over time. However, the main part of this correlation stems from institutions that follow their own trades and is not a consequence of herding.

If herding behavior is amplified by insufficient information availability or information asymmetry, herding should be more pronounced in small stocks and in times of market stress. Using daily data, both theoretical predictions are not supported by herding measures obtained from investor-level data. In fact, we find that short-term herding is even more pronounced in large stocks and highly developed market segments. Moreover, daily herding measures have not increased since the beginning of the financial crisis.

Our data set allows us to explore the role of data availability for the evidence on herding. First, we calculate the herding measures for quarterly data. Interestingly, the resulting longer-term herding term measures partly lead to different conclusions. In line with the empirical literature using low-frequent data, quarterly herding measures are larger for smaller stocks. Moreover, the degree of quarterly herding has increased during the financial crisis. In a second exercise, we transform our data in anonymous transactions by ignoring all information about the investor. Following the empirical literature, we assume that institutional traders can be identified by large trades. According to our empirical results, herding measures based on anonymous transactions should be viewed with caution. The resulting herding measures not only exaggerate the degree of herding, they also provide spurious evidence in favor of increased short-term herding during the financial crisis.

2.7 Appendix

2.7.1 The Modified Sias Measure Capturing Size-Effects

With increasing number of investors, the "following other trades" term in the standard decomposition of the Sias herding measure will increase much faster than the "following their own trades" term. Moreover, the cross-sectional standard deviation of the buyers ratio tends to fall. Simply dividing the sample into larger and smaller stocks could therefore automatically result in a larger relative contribution of herding (following others) in large capitalization stocks. In order to capture the distorting effect of the average number of traders on the herding measure calculated for a specific market segment, Sias (2004) introduces a modified decomposition of the correlation coefficient. The size-adjusted contribution of traders "following own trades" is

$$\frac{(D_{nit} - \bar{br}_t)(D_{ni,t-1} - \bar{br}_{t-1})}{N_{it}^*}, \tag{2.5}$$

where N_{it}^* is the number of institutions trading stock i in both time periods $t-1$ and t. The average "herding contribution" for each stock i and time t only refers to traders who follow the trades of others:

$$\sum_{n=1}^{N_{it}} \sum_{m=1, m \neq n}^{N_{i,t-1}^*} \frac{(D_{nit} - \bar{br}_t)(D_{mi,t-1} - \bar{br}_{t-1})}{N_{it} N_{i,t-1}^*}, \tag{2.6}$$

where N_{it} is the number of institutions trading stock i in t and N_{it}^* is the number of other institutions trading stock i in time $t-1$. Note that the modified measures do not add to the overall correlation coefficient.

2.7.2 Tables

Table 2.4: Statistics on Trading of Institutions

	All	DAX 30	MDAX	SDAX
Average daily number of traders active				
Whole sample	25.14	50.79	23.41	10.78
<08/09/07	31.96	65.26	28.80	13.10
≥08/09/07	20.80	41.01	20.00	9.34
Average daily market share in percent				
Whole sample	51.00	45.97	51.00	54.30
<08/09/07	70.34	65.91	75.33	68.71
≥08/09/07	39.45	32.46	37.43	45.82

Notes: The first part of the table reports the average of investigated institutions active in a specific stock on a specific day. The numbers are computed according to the daily trade imbalance of the institutions. The second part of the table reports the share that the investigated institutions have in the trading volume of a specific stock on a specific day averaged over all stocks and days in percentage terms.

Table 2.5: Daily LSV Measures - Different Minimum Numbers of Trader Active

	AllStocks	*DAX30*	*MDAX*	*SDAX*
>0 trader	1.55 (0.02)	3.65 (0.04)	1.25 (0.04)	0.54 (0.05)
Observations	87,839	20,904	33,673	33,262
>5 trader	1.40 (0.02)	3.65 (0.04)	1.24 (0.04)	−0.03 (0.05)
Observations	83,842	20,901	33,616	29,325
>10 trader	1.71 (0.02)	3.63 (0.04)	1.30 (0.04)	0.06 (0.06)
Observations	69,474	20,900	31,864	16,710
>20 trader	2.57 (0.03)	3.62 (0.04)	1.74 (0.04)	0.77 (0.10)
Observations	42,385	20,201	19,116	3,068

Notes: This table reports mean values of daily HM in percentage terms for the whole sample of stocks, for the sub-sample of DAX 30, MDAX and SDAX stocks considering different minimum numbers of traders active (0, 5, 10 or 20) for each stock on each trading day. The herding measures are first computed over the whole sample stocks and over all trading days (but only for that cases were the respective minimum trader amount is given) and than averaged across the different sub-sample of stocks. Standard errors are given in parentheses.

Table 2.6: Daily Sias Measures - Different Minimum Numbers of Trader Active

	AllStocks	*DAX30*	*MDAX*	*SDAX*
>0 trader	17.61 (0.26)	20.13 (0.67)	19.02 (0.54)	16.20 (0.54)
Observations	87,839	20,904	33,673	33,262
>5 trader	18.01 (0.53)	20.01 (0.68)	18.60 (0.53)	16.84 (0.53)
Observations	83,842	20,901	33,616	29,325
>10 trader	19.64 (0.14)	20.12 (0.67)	19.84 (0.52)	18.10 (0.83)
Observations	69,474	20,900	31,864	16,710
>20 trader	18.72 (0.17)	20.02 (0.69)	19.29 (0.75)	14.04 (1.70)
Observations	42,385	20,201	19,116	3,068

Notes: This table reports values of the average correlation coefficient β according to Sias (2004) considering different minimum numbers of traders active (0, 5, 10 or 20) for each stock on each trading day. The correlations were first estimated with a cross-sectional regression for each day t and stocks i. The reported coefficients display the time-series average of the regression coefficients. The coefficients are estimated considering the whole sample of stocks as well as only DAX 30, MDAX, and SDAX stocks separately.

Table 2.7: LSV Herding Measures - Monthly Data

	All Stocks	*DAX 30*	*MDAX*	*SDAX*
Sample period: July 2006 – March 2009				
Monthly data	1.97 (0.07)	3.03 (0.16)	1.98 (0.14)	1.29 (0.17)
Observations	4,171	990	1,597	1,584
Pre-crisis period (<08/09/07)				
Monthly data	1.36 (0.12)	3.00 (0.22)	1.05 (0.18)	0.65 (0.22)
Observations	1,710	410	650	650
Crisis period (≥08/09/07)				
Monthly data	2.39 (0.13)	3.06 (0.23)	2.62 (0.20)	1.73 (0.24)
Observations	2,461	580	947	934

Notes: This table reports mean values of HM in percentage terms, calculated at monthly frequency, see Table 2.1 for further explanations.

Table 2.8: Sias Herding Measures for the Whole Sample Period - Monthly Data

	All Stocks	*DAX 30*	*MDAX*	*SDAX*
Average Correlation				
Monthly data	22.00	23.09	19.90	21.90
	(1.50)	(2.48)	(2.43)	(2.47)
Observations	4,005	928	1,546	1,531
Follow Own Trades				
Monthly data	4.60	1.31	0.98	1.19
	(0.45)	(0.10)	(0.23)	(0.53)
Follow Trades of Others				
Monthly data	17.40	1.95	2.22	2.98
	(1.23)	(0.15)	(0.33)	(0.53)

Notes: This table reports results for the Sias measure calculated at monthly frequency, see Table 2.2 for further explanations.

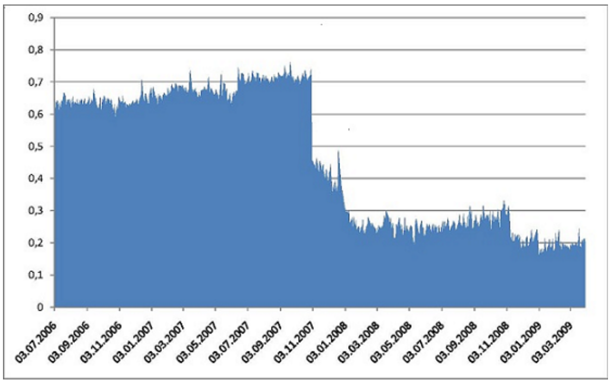
Table 2.9: Sias Herding Measures for the Crisis period (≥08/09/07) - Monthly Data

	All Stocks	*DAX 30*	*MDAX*	*SDAX*
Average Correlation				
Monthly data	24.96	30.91	22.27	23.38
	(1.95)	(4.06)	(3.12)	(3.16)
Observations	2,433	551	942	940
Follow Own Trades				
Monthly data	4.51	1.35	1.12	1.20
	(0.47)	(0.32)	(0.40)	(0.50)
Follow Trades of Others				
Monthly data	20.45	2.45	2.13	3.16
	(2.43)	(0.30)	(0.28)	(0.48)

Notes: This table reports results for the Sias measure calculated at monthly frequency, see Table 2.2 and Table 2.3 for further explanations.

2.7.3 Figures

Figure 2.1: Share of Institutional Investors in the Trading Volume of DAX 30



Notes: The figure shows the development of the share that institutions have in the trading volume averaged over DAX 30 stocks. Source: BaFin records and Datastream.

3 On the Causes and Consequences of Short-Term Herding by Institutional Traders

3.1 Introduction

A growing body of literature established the tendency of investors to accumulate on the same side of the market, known as herding behavior. Generally, herding is divided into sentiment-driven *intentional* herding and *unintentional* herding driven by the common reaction on public information and signals, see, e.g., Bikhchandani and Sharma (2001). Distinguishing the causes of herding is crucial for regulatory purposes and for discovering whether herding leads to market inefficiency and financial bubbles. According to Scharfstein and Stein (1990), Hirshleifer and Teoh (2003), or Hwang and Salmon (2004), *intentional* herding may destabilize stock prices and thus impair the well-functioning of financial markets. Yet, even *unintentional* herding may be inefficient, if the correlated trading is not driven by fundamental values.

The aim of this paper is to shed more light on the herding behavior of institutional investors, in particular banks. The predominant class of investors in the stock market has the power to move the market and impact prices, even more if they herd. This emphasizes the importance of discovering whether institutional investors herd and, if so, the *causes* and the *consequences* of herd behavior for stock prices.

To date, the literature on institutional herding has been severely handicapped by the unavailability of appropriate data. Empirical assessment of herding requires disaggregated investor-level data. In general, the positions taken by institutions on the stock market are reported *infrequently*, if at all. For example, for U.S. mutual funds or other institutional investors, reports of holdings are available only on a quarterly basis, see, e.g., Choi and Sias (2009), Wermers (1999). Studies employing this type of data are also limited in the investigation of the determinants and the price impact of herding. There is no resolution on intra-quarter covariances of trades and returns and thus, these studies fail to conclude whether institutions are *reacting* to or *causing* stock price movements, see Lakonishok et al. (1992).[1]

This paper contributes to the empirical literature on herding by using higher-frequency investor-level data that directly identify institutional transactions. The analysis therefore overcomes the data problems faced by previous studies and provides new evidence on the short-term herding behavior of financial institutions for a broad cross-section of stocks over the period from July 2006 to March 2009 in the German stock market.[2] Advancing on previous descriptive approaches, the availability of daily, investor-specific data enables us to perform a panel econometric analysis of the causes of herding and its consequences on stock prices.

The estimation results reveal that financial institutions do indeed herd and that this herding depends on stock characteristics as well as on past returns and stock volatility. In particular, we find –contradicting theories of *intentional* herding– that herding is more pronounced in larger and more liquid stocks. The mean herding measure for the 30 most professional institutions in DAX 30 stocks constitutes 5.17% according to the Lakonishok et al. (1992) measure. Panel regressions reveal further evidence that herding is rather of the *unintentional* type. For instance,

[1] A part of the empirical literature, e.g., Barber et al. (2009), attempts to overcome the problem of data frequency by using *anonymous transaction data* instead of reported holdings. However, those data do not identify the trader. Therefore, work on this front separates trades by size and then identifies trades above a specific cutoff size as institutional. Kremer and Nautz (2010), i.e. displayed in Chapter 2, show that evidence based on anonymous transaction data can lead to misleading conclusions.

[2] Walter and Weber (2006) analyzed herding for German mutual funds at a semi-annual frequency.

herding on the buy and sell side is inversely related to past returns. Interestingly, only herding on the sell side is positively related to past stock volatility. This finding can be explained by the common use of risk measures that drives correlated selling activities after a rise in volatility.

Even though herding can mainly be explained by *unintentional* causes, non-fundamental factors can result in a destabilizing impact. The literature explores a destabilizing stock price impact by investigating whether subsequent returns continue or reverse after herding activities. Destabilizing herding, that drives prices away from fundamental values, would result in subsequent return reversals, see, e.g., Choi and Sias (2009). In fact, we find evidence for a destabilizing impact of sell herds but not of buy herds: The negative impact of sell herding on stock returns reverse after a few trading days, while in case of buy herding the positive impact continuous.

Overall, our results provide evidence for a destabilizing impact of sell herds in the German stock market. Since those sell herds result from the common reaction on risk measures, this evidence supports a macro-prudential view on risks by regulators. In line with the predictions of Persaud (2000) or Daníelsson (2008), regulators and risk modeling institutions should take into account the endogeneity of risks induced by similar market sensitive risk management systems.

The rest of the paper is structured as follows: Section 3.2 reviews the theories behind herding behavior and summarizes the empirical literature. Section 3.3 introduces the data and Section 3.4 discusses the herding measures. Section 3.5 and 3.6 present the empirical analysis on the causes and the consequences of herding. Section 3.7 contains a summary of the main results and offers some concluding remarks.

3.2 Theory and Empirical Literature

3.2.1 The Rational behind Herding Behavior

The term "herding" describes the tendency of institutions or individuals to show similarity in their behavior and thus act like a "herd." There are several types of herd behavior, defined by various explanations for the co-movement. Generally, herding is divided into *i) intentional* herding and *ii) unintentional* or *spurious* herding, see, e.g., Bikhchandani and Sharma (2001).

Unintentional herding arises because institutions are attracted by stocks with certain characteristics such as higher liquidity (see, e.g., Falkenstein (1996)) or because institutions examine the same factors and receive correlated private information, leading them to arrive at similar conclusions regarding individual stocks (see, e.g., Hirshleifer et al. (1994)). Moreover, professionals may constitute a relatively homogenous group: they share a similar educational background and professional qualifications and tend to interpret informational signals similarly. A prominent example is the common reaction of financial institutions to similar risk measures.

In contrast, *intentional* herding is morse sentiment-driven and involves the imitation of other market participants, resulting in simultaneous buying or selling of the same stocks regardless of prior beliefs or information sets. There are two major theoretical models that explain the rational behind this behavior: According to the *information cascade model*, traders copy the investment activity of other market participants because they infer (from observed trading behavior) that others have relevant information, see Bikhchandani, Hirshleifer and Welch (1992), Banerjee (1992) and Avery and Zemsky (1998). The second explanation for herding behavior is derived by the *reputation based model* originally developed by Scharfstein and Stein (1990). According to this model, institutions or professional investors are subject to reputational risk when they act differently from the crowd.

Models of *intentional* herding typically assume that there is only little reliable information in the market. Therefore, traders are uncertain about their decisions and follow the crowd. In contrast, in the case of *unintentional* herding, traders acknowledge public information as reliable. Yet, since they interpret it similarly, they all end up on the same side of the market. Therefore, both types of herding are linked to the uncertainty or availability of information.

3.2.2 Revealing the Causes of Herding

Distinguishing between different causes or types of herding behavior is crucial for regulatory purposes and in determining whether herding leads to market inefficiency. Revealing the type of herding is difficult due to the large number of factors that may influence an investment decision and because the motives behind a trade are not discernable.

3.2.2.1 Market Transparency

The empirical literature explores the determinants of herding via the link between herding and information by considering variables that proxy, e.g., the availability of information.

Lakonishok et al. (1992) investigate herding within a quarterly time span using a sample of U.S. equity funds. They segregate stocks by size because *market capitalization* of firms usually reflects the quantity and quality of information available. Thus, one would expect higher levels of herding in trading small stocks as evidence in favor of *intentional* herding. Conversely, *unintentional* herding is more likely to occur in stocks with larger market capitalization because institutions have a higher commonality in information. In fact, Lakonishok et al. (1992) find evidence of herding being more intense among small companies compared to large stocks. Other studies, including Wermers (1999), Sias (2004) or Choi and Sias (2009), confirm higher herding in small stocks.

There is also evidence for higher herding levels in emerging markets compared to developed ones.[3] High herding in emerging markets may be attributed to incomplete regulatory frameworks, especially in the area of *market transparency*. Deficiencies in corporate disclosure and information quality create uncertainty in the market, throw doubt on the reliability of public information, and thus impede fundamental analysis, see Antoniou et al. (1997) and Gelos and Wei (2002). Kallinterakis and Kratunova (2007) argue that in such an environment it is reasonable to assume that investors will prefer to base their trading on their peers' observed actions. Thus, intentional herding through information cascades is more likely to occur in less developed markets.

3.2.2.2 Feedback Trading

As *unintentional* herding arises due to simultaneous reactions to common signals, a manifestation of this kind of herding is momentum investment, i.e., *positive feedback trading*. If herding is driven by past returns, this would be interpreted as evidence of unintentional herding, see, e.g., Froot, Scharfstein and Stein (1992) and Sias (2004). The evidence on feedback trading so far is mixed: While Lakonishok et al. (1992) show that past performances of stocks did not increase herding, Grinblatt, Titman and Wermers (1995) document positive feedback strategies contributing to herding. In contrast, Wylie (2005) finds that U.K. funds herd out of stocks that have performed well in the past. Even though herding caused by correlated positive feedback trading is considered to be *unintentional* herding according to the theory above, such herding might also have a destabilizing impact on financial markets, see, e.g., De Long, Shleifer, Summers and Waldmann (1990).

[3] For example, Lobao and Serra (2007) document strong evidence of herding behavior for Portuguese mutual funds. Significant herding is reported for Indonesia (Bowe and Domuta (2004)), Poland (Voronkova and Bohl (2005)), Korea (Choe et al. (1999), Kim and Wei (2002)) and South Africa (Gilmour and Smit (2002)). Based on semi-annual data, Walter and Weber (2006) as well as Oehler and Wendt (2009) report significant positive and higher levels of herding for German mutual funds compared to those found in U.S.-based research. Walter and Weber (2006) link the finding of herding to the stage of development of the financial market. They argue that the German market is not as highly developed as the U.S. and U.K. capital markets.

3.2.2.3 Risk Management Systems

Persaud (2000), Jorion (2002) or Daníelsson (2008) argue that market-sensitive risk management systems used by banks, such as Value at Risk (VaR) models, require banks to sell when volatility rises. Thus, banks act like a herd, all selling the same stocks at the same time in response to negative shocks. Although this kind of trading is considered to be *unintentional* herding, it leads to further slumps in prices. If financial regulation implies that institutions are increasingly using similar market-sensitive risk management systems, *unintentional* herding occurs because the diversity of decision rules is reduced.

3.2.3 The Consequences of Herding: Destabilizing Price Impacts

Institutional herds may induce price pressure and thus impact stock prices. However, this might not necessarily destabilize the market. In particular *unintentional* herding can be an efficient outcome, provided it results from the simultaneous reaction on fundamental values. In this case, it speeds up the adjustment of prices and makes the market more efficient, see Lakonishok et al. (1992). In contrast, both types of herding lead to inefficient outcomes if they are not based on fundamentals. In this case, asset prices fail to reflect fundamental information. Herding then causes a destabilization of markets, thus having the potential to create, or at least contribute, to bubbles and crashes on financial markets, see, e.g., Scharfstein and Stein (1990). In case of unintentional herding, a prominent example are positive feedback strategies that aggravate downward or upward pressures, see, e.g., De Long et al. (1990). Moreover, Daníelsson (2008) or Persaud (2000) particularly highlight the potential destabilizing effects of market sensitive risk regulation which forces the common reactions on volatility and thus the endogeneity of risks.

Scharfstein and Stein (1990) and Barberis and Schleifer (2003) suggest that if herding drives prices away from fundamentals, price movements should reverse subsequently. In order to reveal a destabilizing impact empirically, it is analyzed whether the impact of herding on prices continues or reverses in the future while the latter would be interpreted as destabilizing impact, see, e.g., Choi and Sias (2009).

Previous evidence on this issue is rather mixed: Early studies based on quarterly data, e.g., Lakonishok et al. (1992), Wermers (1999) or Sias (2004) do not find return reversals following herds. More recent studies, e.g. Puckett and Yan (2008) as well as Brown, Wei and Wermers (2010) provide evidence on return reversals. Puckett and Yan (2008) partially overcome the low-frequency problem of previous studies by using weekly data. They argue that a destabilizing effect of herding is more likely to be detected in the short horizon since the market will dissipate deviations from fundamental values through the actions of arbitrageurs. Note that the previous studies based on quarterly data are not able to detect destabilizing impacts over shorter horizons. In Section 3.6 we will investigate subsequent returns after herding activity and provide evidence on reversals or continuation of the impact of herding on subsequent returns.

3.3 The Data Set

The data set[4] employed in this paper avoids most of the problems that plague earlier work by including disaggregated high-frequency investor-level data. In fact, our data set includes *all* real-time transactions carried out on German stock exchanges. The data are provided by the German Federal Financial Supervisory Authority (BaFin). Under Section 9 of the German Securities Trading Act, all credit institutions and financial services institutions are required to report to BaFin any transaction in securities or derivatives which are admitted to trading on an organized market.

These records enable the identification of all relevant trade characteristics, including the trader (the institution), the particular stock, time, number of traded shares, price, and the volume of the transaction. Moreover, the records identify on whose behalf the trade was executed, i.e., whether the institution traded for

[4] The first three paragraphs of this section are already set out in Chapter 2, Section 2.3.2 of this thesis. The description is included in this chapter additionally for the sake of completeness.

its own account or on behalf of a client that is not a financial institution. Since the aim of our study is the investigation of institutional trades, particularly those of financial institutions, we focus on the trading of own accounts, i.e., those cases when a bank or a financial services institution is clearly the originator of the trade. Direct identification of the trading financial institution also enables us to create subgroups of institutions in order to examine differences in their behavior. We exclude institutions trading exclusively for the purpose of market making. We also exclude institutions that are formally mandated as designated sponsors, i.e., liquidity providers, for a specific stock.[5] Using data from July 2006 until March 2009 (a total of 698 trading days), we cover market upturns as well as the recent market downturn. We will investigate whether trading behavior has changed since the outbreak of the financial crisis.

The analysis focuses on shares listed on the three major German stock indices: the DAX 30 (the index of the 30 largest and most liquid stocks), the MDAX (a mid-cap index of 50 stocks that rank behind the DAX 30 in terms of size and liquidity), and the SDAX (a small-cap index of 50 stocks that rank behind the MDAX components).[6] These indices allow to investigate the trading behavior in small and large stocks.

Over the observation period, we have proprietary transactions by 1,120 institutions in those stocks on German stock exchanges.[7] For each institution, we compute the daily trade imbalance.

While Kremer and Nautz (2010) (see Chapter 2) investigate the sample of all those 1,200 financial institutions in the German stock market,[8] this paper focuses

[5] For each stock, there are usually about two institutions formally mandated as market maker. The institutions are not completely dropped from the sample (unless they are already dropped due to purely engaging in market maker business), but only for those stocks for which they act as designated sponsors. The particular designated sponsors for each stock are published at www.deutsche-boerse.com.

[6] The stocks were selected according to the index compositions at the end of the observation period on March 31, 2009. The time series of five stocks on the MDAX and five stocks on the SDAX are not complete for the whole period. We have therefore an unbalanced panel of stocks and days, totaling 88,435 observations. We require at least five institutions active each day, decreasing the sample to 83,842 remaining observations.

[7] Among these 1,120 traders, 1,044 institutions trade on the DAX 30 stocks, 742 on the MDAX stocks and 512 on the SDAX stocks.

on particularly important subgroups of institutions from the overall institutional sample. The theory of *unintentional* herding predicts higher herding levels among institutions that share the same investment style and the same professional qualifications, see Hirshleifer et al. (1994). Moreover, according to the reputation based model, higher *intentional herding* can be expected in a more homogenous group of professionals who are evaluated against each other, see Scharfstein and Stein (1990). The overall sample of 1,120 institutions is comprised of a large heterogeneous group. Among those institutions, the 30 most active traders, according to their trading volume in the investigated shares, account for 80% of the entire trading volume over all institutions and can thus be regarded as the most professional and most important for the stock market. Hence, the detection of any destabilizing impact would suggest a high potential threat to financial stability. Moreover, these professionals can be considered as belonging to the same peer group.

We therefore built a subsample based on the 30 most active traders.[9] This subgroup also includes several foreign institutions. We therefore create an additional subsample comprising only the 40 most active German banks that are engaged in proprietary trading on stock markets.[10] The German banks are all subject to the same regulatory regime and oversight by the financial authority. Although the regulatory framework and risk management systems for the foreign banks are expected to be similar, for these German banks we were able to ensure –by means of an investigation of the risk reports included in their annual reports– that they all use VaR models and implement regulatory or internal VaR limits.

[8] Kremer and Nautz (2010) focus on the impact of data frequency on herding measures, but not on causes and consequences of herding.

[9] Note that considering a subgroup of 30 institutions instead of, e.g., 10 ensures that enough traders are active in a specific stock on a specific day. Nevertheless, 14,879 observations are lost, i.e., 68,963 observations remain.

[10] We select those institutions according to their trading volume over the observation period in the selected stocks. We select only German institutions based on the definition of same in Section 1 Paragraph 1 of the German Banking Act. Note that we now use 40 instead of 30 to ensure that enough traders are active in a specific stock on a specific day. The sample is than comprised of 69,257 observations.

3.4 Do Institutions Herd?

3.4.1 The Herding Measure

Following the bulk of the empirical literature, our analysis builds on the herding measure introduced by Lakonishok et al. (1992) (LSV measure).[11] According to the LSV measure, herding is defined as the tendency of traders to accumulate on the same side of the market in a specific stock and at the same time, relative to what would be expected if they traded independently.[12]

The LSV measure assumes that under the null hypothesis of no herding, the decision to buy or to sell is a bernoulli distributed random variable with equal success probability for all stocks at a given time.[13] Consider a number of N_{it} institutions trading in stock i at time t. Out of these N_{it} transactions, a number of b_{it} are buy transactions. The buyer ratio br_{it}, the prominent variable in the LSV measure, is then defined as $br_{it} = \frac{b_{it}}{N_{it}}$.

The second import variable is $\bar{br}_t$, i.e. the average of the buyer ratio over all stocks at time t. This variable accounts for an overall signal in the market at t.

In line with the definition of herding above, the LSV herding statistic is given by

$$HM_{it} = |br_{it} - \bar{br}_t| - E_t[|br_{it} - \bar{br}_t|]. \tag{3.1}$$

[11] The LSV measure is already set out in Section 2.4.1 of this thesis. The description is included in this chapter additionally for the sake of completeness. Note the extension at the end of this section.

[12] An alternative measure used in the literature is that constructed by Sias (2004). This dynamic measure quantifies the degree to which institutions follow institutional trades of the prior period. The Sias herding measure captures the degree of correlation of the fraction of buyers between different periods. We will show results on the Sias measure in the Appendix, see Table 3.9. The results do not effect our main conclusions. When revealing determinants and consequences of herding in this study we will focus on the LSV herding measure, since previous studies (and also Sias (2004)) use static measures capturing intra-period herds for determining price impacts.

[13] One implication of this assumption is that short selling must be possible. This assumption is not problematic for our investigated institutions, for which short selling is in general feasible. In contrast, most mutual funds investigated by previous studies are not allowed to engage in short sales. Thus, if they have no holding in stock i, they can act only as buyer and the action would not be binomially distributed.

The first term captures the deviation of the buyers ratio in stock i at t from the overall buy probability at time t. Thus, herding is measured as excess dispersion of what would be expected for that time. Therefore, the measure captures similar trading patterns beyond market trends and eliminates the influence of market-wide herding. The second term $E_t[|br_{it} - \bar{br}_t|]$ is the expected value of the difference between the buyer ratio and period-average buyer ratio. Subtracting this term accounts for the possibility to observe more variation in the buyers ratio in stocks with only a few trades. This adjustment factor ensures that the herding measure HM_{it} will be zero if the trades are independent.[14]

The empirical literature following Lakonishok et al. (1992), calculates the mean across all stocks and all periods, leading to the mean herding measure $\overline{HM}$. A positive and significant value of $\overline{HM}$ indicates the average tendency of the investigated group to accumulate in their trading decisions. The higher the $\overline{HM}$, the stronger the herding. For example, $\overline{HM} = 2\%$ indicates that out of every 100 transaction, two more traders trade on the same side of the market than would have been expected if each trader had decided randomly and independently. Note that the maximum value of $\overline{HM}$ is not equal to 100%, even if all traders buy stock i at time t, since HM_{it} is defined as excess or additional herding over the overall trend $\bar{br}_t$. Thus, only stock-picking herding and similar trading patterns *beyond* market trends are analyzed.

The herding measure HM_{it} gauges herding without regard to the direction of the trades (buy or sell). Following Grinblatt et al. (1995) and Wermers (1999), we also distinguish between "buy herding" BHM_{it} and "sell herding" SHM_{it}, to discover whether institutions buy or sell a stock i in herds, where

$$BHM_{it} = HM_{it} \quad if \quad br_{it} > \bar{br}_t, \tag{3.2}$$

$$SHM_{it} = HM_{it} \quad if \quad br_{it} < \bar{br}_t. \tag{3.3}$$

[14] Following previous studies, e.g., Wermers (1999), HM_{it} is computed only if at least five traders are active in i at time t, however, the loss of observations is not relevant, see Section 4.3. Estimations with different minimum numbers of traders (up to 20) reveal that results are robust with respect to the assumptions on minimum numbers of traders. Results are available on request.

Note that $br_{it} = \bar{br}_t$ is not captured by BHM_{it} or by SHM_{it} because in this case no herding occurs, i.e., there is no herding on either the buy or on the sell side.[15]

BHM_{it} and SHM_{it} capture asymmetries in institutions' behavior when buying or selling. The separate measurement of herding *into* stocks and *out* of stocks will be important when analyzing the causes of trading behavior in Section 3.5.2.

3.4.2 Herding of Institutions in the German Stock Market

Table 3.1: Daily LSV Herding Measures of 30 Most Active Traders (1)

	All Stocks			DAX 30		
	HM	BHM	SHM	HM	BHM	SHM
Whole sample	2.48	2.67	2.30	5.18	5.28	5.08
	(0.03)	(0.05)	(0.05)	(0.06)	(0.08)	(0.08)
Observations	68,963	35,806	33,130	20,853	10,692	10,154
<08/09/07	2.93	3.55	2.15	5.84	6.26	5.35
	(0.05)	(0.07)	(0.08)	(0.08)	(0.12)	(0.12)
Observations	30,362	16,868	13,494	8,427	4,546	3,881
≥08/09/07	2.14	1.87	2.41	4.73	4.55	4.92
	(0.05)	(0.07)	(0.07)	(0.08)	(0.12)	(0.12)
Observations	38,601	18,938	19,636	12,426	6,146	6,273

Notes: This table reports mean values of HM, BHM and SHM in percentage terms for the whole sample of stocks and for DAX 30 stocks considering only the 30 most active institutions in the sample. These 30 institutions are identified according to their overall trading volume over the whole sample period and all sample stocks. The measures are calculated considering a minimum number of 5 traders for each stock on each trading day. The herding measures are first computed over the whole sample stocks and over all trading days and than averaged across the different time spans and the sub-sample of stocks.

[15] Comparing the observations in, e.g., Table 3.3, the resulting loss of data is not empirically relevant.

Results provided in Table 3.1 reveal higher herding measures for the 30 most active traders compared to the findings of Kremer and Nautz (2010) for all institutions. The mean daily herding measure across all stocks is 2.48%. Considering only DAX 30 stocks, the herding measure significantly rises to 5.18%, a high level of herding compared to previous findings. For MDAX and SDAX stocks, the herding measure is small, see Table 3.6 in the Appendix. This result does not support the theory of *intentional* herding, which predicts higher herding levels in stocks with less information availability and asymmetry. This suggests that herding behavior is more likely of the *unintentional* type.

There is no evidence for increased herding during the crisis period. Herding on the buy side is more pronounced in the non-crisis period, whereas sell side herding is higher than buy herding during the crisis. This might be a result of higher volatility of stocks during the financial crisis. Our panel econometric analysis in Section 3.5.2 shall provide more insights into this issue.

The results for the sample of 40 most active German banks are shown in Table 3.7 and Table 3.8 in the Appendix. The findings are very similar to those for the subgroup of 30. Again, the herding measure is much higher in DAX 30 stocks, with a mean of 5.21%, confirming the hypothesis that herding might be more of the unintentional type.[16]

3.5 Why do Institutions Herd?

3.5.1 Potential Causes of Herding

In this Section we investigate the potential causes of the herding behavior detected in the previous Section within a panel estimation framework. According to the theory discussed in Section 4.2 herding behavior centers around information in the market. On the one hand, *intentional* herding results from information asymmetry

[16] Results on the Sias measure displayed in Table 3.9 and Table 3.10 in the Appendix do not effect those conclusions. In fact, results show that the main part of the estimated correlation of trades stems from institutions that follow their own trades rather than following others.

or information uncertainty. On the other hand, *unintentional* herding is related to reliable public information. The following empirical analysis therefore focuses on empirical proxies to measure information availability, information asymmetry or uncertainty in the market. Moreover, the focus is on determinants that may imply a destabilizing pro-cyclicality.

Information Availability

Following the previous literature on herding, we consider firm size ($Size$) as possible determinant of herding. Small firms are usually less transparent, i.e., less public information is available. The model of intentional herding would therefore predict an inverse relation between herding and firm size. Conversely, unintentional herding is more likely to occur in larger stocks because institutions have a higher commonality in information. Firm size is measured by the logarithm of the previous day's closing market capitalization of the specific stock.

Information Asymmetry

A factor also related to herding could be the trading volume (Vol) of a specific stock. A vast literature highlights the relation between information quality, market liquidity and information asymmetries. In particular, Diamond and Verrecchia (1991) predict higher information asymmetry in less liquid markets. Suominen's (2001) model suggests that higher trading volume indicates better information quality. We therefore use market volumes of stocks[17] as a proxy for information asymmetry. Intentional herding theory implies that lower trading volumes are associated with higher herding levels. Conversely, a positive relation could be explained by herding of institutions that are attracted by stocks with higher liquidity, see, e.g., Falkenstein (1996).

[17] Leuz and Verrecchia (2000) and Welker (2006) argue that market liquidity can be measured by transaction volumes or bid-ask spreads.

Uncertainty vs. Risk Measures

Additionally, we compute stock return volatility (Std) based on the standard deviation of the past 250 daily stock returns and on the last 90 and 30 stock returns. On the one hand, stock return volatility is assumed to reflect the extent of disagreement among market participants, thus proxying the degree of uncertainty in the market. Intentional herding models would therefore predict higher herding in stocks that experienced a higher degree of volatility. Note that higher information uncertainty should induce herding in a symmetric way, i.e., on both the buy and sell side. On the other hand, higher levels of herding in more volatile stocks might also be related to a common use of risk measures. VaR models or other volatility sensitive models employed for risk management purposes and regulatory requirements induce common sell activity, see e.g. Persaud (2000). The minimum observation period according to Basel II market risk standards is one year, i.e., 250 trading days. Therefore, we expect to see more sell herding in stocks with higher past year standard deviation of stock returns, since those regulated institutions highly engaged in trading generally use such risk management models or at least built on past volatility as risk measure.[18] A positive impact of volatility on sell herding but not on buy herding could then be considered as evidence of unintentional herding.

Feedback Trading

We further consider past returns of stocks (r). As unintentional herding occurs due to the simultaneous reaction to common signals, a manifestation of this kind of herding is momentum investment. De Long et al. (1990) argue that institutions follow short-term strategies based on positive feedback trading and thus show procyclical behavior. Such a trading pattern could result in herding, i.e., if all react to the same price signals, see Froot et al. (1992).

[18] For all German banks in the sample, we can ensure that VaR models and implement regulatory or internal VaR limits are used according to statements in their risk reports included in annual reports.

Table 3.2 summarizes the theoretical predictions on the determinants of herding. Note that the role of stock return volatility, *Std*, may differ for buy and sell herding.

Table 3.2: Theoretical Predictions on the Determinants of Herding

	Intentional	Unintentional
$Size$	−	+
Vol	−	+
r	0	+/−
Std	+ (for buy and sell herding)	− (only for sell herding)

Notes: This table classifies the predicted impact of firm size ($Size$), trading volume (Vol), stock returns (r) and volatility (Std) on the herding measure. "-", "+" and "0" denotes a negative, positive and insignificant impact, respectively.

3.5.2 On the Causes of Herding: Empirical Results from Panel Regressions

3.5.2.1 Empirical Determinants of Herding Behavior

In order to examine the relation between institutional herding and its possible determinants, we estimate the following fixed effects panel regression model:

$$HM_{it} = a + bSize_{i,t-1} + cVol_{it} + d|r_{i,t-1}| + eStd_{it} + \alpha_i + \gamma_t + \epsilon_{it}, \qquad (3.4)$$

where HM_{it} is the LSV herding measure of the 30 most active traders as calculated according to Equation (3.1).[19] $Size_{i,t-1}$ is measured by the logarithm of the previous day's closing market capitalization of stock i. Vol_{it} captures the logarithm of the trading volume of stock i during trading day t. $|r_{i,t-1}|$ is the absolute value of the return of stock i measured from the closing prices on day $t-1$ and $t-2$.[20] The absolute value is used since HM_{it} does not discriminate between the buy and sell sides. Std_{it} is the volatility, measured as the standard deviation of the past 250 daily stock returns.[21] α_i are stock-specific effects and γ_t are time dummies.[22]

Let us first look at the results for the regression with the unsigned herding measure HM, which are displayed in the first column of Table 3.3. The coefficient estimate for $Size$ is positive but insignificant and the coefficient for Vol is positive and statistically significant. This suggests that the evidence of higher herding levels for DAX 30 stocks in Section 3.4.2 is more likely the result of these stocks' higher liquidity than due to higher market capitalization. However, the size effect might already be captured by the fixed effects in the regression, since market capitalization changes only slightly over time.[23] Second, since higher trading volume is related to lower information asymmetry and higher information quality, this result suggests that these large financial institutions are less likely to engage in *intentional* herding. The positive relation could be an indication of *unintentional* herding, whereby the institutions are attracted by stocks with specific characteristics like higher trading volume, see Falkenstein (1996).

The parameter estimate for volatility of returns Std indicates that there is more herding for more volatile stocks. Volatility in the market is related to uncertainty and thus, at first glance, this estimate hints at the existence of *intentional* herding. However, the estimate could also be related to the common use of risk measures

[19] Results considering the herding measures for the 40 German banks are very similar. For brevity results are not displayed but are available on request.

[20] We include further lagged return measures to check robustness.

[21] We include different volatility measures to check robustness.

[22] An F-test strongly suggests the inclusion of time dummies γ_t in the regressions and a Breusch-Pagan Lagrange multiplier test on $H_0 : \sigma_i^2 = 0$ indicates the existence of individual effects α_i.

[23] In a pooled OLS regression, market capitalization has a positive significant impact. Results are available on request.

Table 3.3: Causes of Herding - Panel Regression

	HM_{it}	BHM_{it}	SHM_{it}
Regressors			
$Size_{i,t-1}$	0.0020 (0.0027)	0.0029 (0.0020)	0.0016 (0.0019)
Vol_{it}	0.0069^{***} (0.0012)	0.0023^{***} (0.0007)	0.0082^{***} (0.0008)
$\lvert r_{i,t-1}\rvert$	-0.0001 (0.0003)		
$r_{i,t-1}$		-0.0015^{***} (0.0002)	0.0008^{***} (0.0002)
Std_{it}	0.0031^{***} (0.0012)	-0.0096^{***} (0.0009)	0.0020^{***} (0.0012)
$Dummy^b_{it}$		0.0156^{***} (0.0011)	
$Dummy^s_{it}$			0.0111^{***} (0.0002)
Diagnostics			
$Wooldridge$	$F = 0.346$ ($Prob{>}F$=0.5573)	$F = 0.251$ ($Prob{>}F$=0.6170)	$F = 0.666$ ($Prob{>}F$=0.4159)
$Cook - Weisberg$	$\chi^2 = 3383.14$ ($Prob{>}\chi^2$=0.0000)	$\chi^2 = 4924.52$ ($Prob{>}\chi^2$=0.0000)	$\chi^2 = 1290.95$ ($Prob{>}\chi^2$=0.0000)
$Sargan - Hansen$	$\chi^2 = 10.343$ ($Prob{>}\chi^2$=0.0350)	$\chi^2 = 16.422$ ($Prob{>}\chi^2$=0.0353)	$\chi^2 = 17.536$ ($Prob{>}\chi^2$=0.0036)
Observations	65,846	34,130	31,691

Notes: The herding measure HM_{it} for the subgroup of 30 most active traders is regressed on variables $Size_{i,t-1}$, Vol_{it}, $|r_{i,t-1}|$ and Std_{it}. The buy and sell herding measures BHM_{it} and SHM_{it} are regressed on variables $Size_{i,t-1}$, Vol_{it}, $r_{i,t-1}$ and Std_{it}. The variable $Size_{i,t-1}$ is the logarithm of market capitalization, Vol_{it} is the logarithm of the trading volume of stock, $r_{i,t-1}$ is the daily stock return and $|r_{i,t-1}|$ is its absolute value. Std_{it} measures the standard deviation of past 250 daily stock returns. $Dummy^b_{it}$ ($Dummy^s_{it}$) is a dummy variable, that equals one, if buy herding (sell herding) occurred also on the previous day $t-1$, and zero otherwise. The statistical significance at 1%, 5% and 10% is represented as ***, **, and * respectively. Standard errors are given in parentheses in the upper part of the table. The lower part of the table reports test statistics and p-values in parentheses. $Wooldridge$ and $Cook - Weisberg$ are tests on serial correlation and heteroscedasticity of error terms. $Sargan - Hansen$ displays the overidentification test on the independence of random effects.

that recommend selling the more volatile stocks. Results on buy and sell herding discussed below shed more light on this issue.

3.5.2.2 Buy and Sell Herding

The variables described above might affect buy and sell herding differently. We therefore estimate Equation (3.4) separately for herding on the buy and sell side using the same set of explanatory variables. The only exception is that the absolute return $|r|$ is replaced by the signed return r as the direction of the recent price movement will affect whether momentum investors herd more on the buy or sell side:

$$BHM_{it} = a^b + b^b Size_{i,t-1} + c^b Vol_{it} + d^b r_{i,t-1} + e^b Std_{it} + e^b Dummy^b_{it} + \alpha^b_i + \gamma^b_t + \epsilon^b_{it} \tag{3.5}$$

$$SHM_{it} = a^s + b^s Size_{i,t-1} + c^s Vol_{it} + d^s r_{i,t-1} + e^s Std_{it} + e^s Dummy^s_{it} + \alpha^s_i + \gamma^s_t + \epsilon^s_{it} \tag{3.6}$$

In these regressions we also include a dummy variable $Dummy^b_{it}$ ($Dummy^s_{it}$), equal to one, if buy herding (sell herding) also occurred on the previous day $t-1$; zero otherwise.[24]

The results for the fixed effects regressions on buy and sell herding are reported in the second and third columns of Table 3.3. Estimates for Vol reveal that herding on the buy and sell sides is positively related to the liquidity of stocks. In line with Sias (2004), the small but significant impact of the dummy variables shows that herding is persistent over time.

The results obtained for r and Std are particularly interesting. First, the signs of Std differ between the buy and sell herding regression. In the case of sell-side

[24] These dummies partly account for persistence of herding on either the buy or sell side. To account for a correlation is suggested by the evidence on the Sias measure in Table 3.9. We include dummy variables rather than the lagged endogenous variable to avoid too many missing observations. Note also that the exclusion of those dummies would not impact our main results since it would not change the significance or the signs of the other covariates.

herding *Std*, has a significant positive impact. Hence, the higher the volatility of a stock, the more herding occurs on the sell side. However, the coefficient estimate for *Std* on buy herding is significantly negative. This asymmetric effect is not compatible with the theory of *intentional* herding. It is unlikely that the herding behavior is based on uncertainty in the market, since this should affect buy and sell herding in the same way. Apparently, institutions share the preference to sell (buy) stocks that have shown a high (low) volatility. This is a clear indication for *unintentional* herding that might be a result of common risk management practices, see Daníelsson (2008).[25]

The estimated impact of returns r is statistically significant for buy and sell herding regressions. As in the case of *Std*, the coefficient estimates are of opposite signs – i.e., buy herding is significantly negatively related to past returns, while past returns have a positive impact on sell herding. This contradicts the conclusion drawn in previous studies (e.g. Grinblatt et al. (1995), Wermers (1999) or Walter and Weber (2006)) that institutions are momentum investors and follow positive feedback strategies. In contrast, in our sample, institutions share a preference for buying past losers and selling past winners. Overall, the results indicate that herding occurs mostly *unintentionally* and is due to shared preferences and investment styles.[26]

The lower part of Table 3.3 presents the relevant test statistics and p-values of diagnostic tests. The three models Equations (3.4) - (3.6) were estimated as fixed effects panel regressions using the within estimator, i.e., the Ordinary Least Squares (OLS) of deviations from stock-specific means, which is feasible according

[25] The results are robust with respect to shorter periods for the calculation of the standard deviation. Using the past 90 daily stock returns or the past 30 daily stock returns (often used as internal risk measures) does not change the results significantly. For brevity, these results are not presented, but are available on request.

[26] We also included lagged returns up to five trading days, $r_{i,t-2}$,..,$r_{i,t-5}$, in the regressions to check whether further past returns influence herding. Our results do not change qualitatively. The coefficient estimates of all past returns have the same sign, i.e., are all negative in the buy herding regression and all positive in the sell herding regression. However, coefficient estimates of returns prior to $t-2$ are insignificant. Moreover, instead of measuring daily $r_{i,t-1}$ with regard to the closing prices on day $t-1$ and $t-2$, we also use a weekly cumulative return measure, i.e., calculated from closing prices on $t-1$ and $t-6$. Our results in all regressions do not change qualitatively. For brevity, these results are not presented, but are available on request.

to the tests employed.[27] We account for heteroscedasticity in the error terms, by using heteroscedasticity-robust standard errors, see Stock and Watson (2008).

3.6 On the Consequences of Herding on Stock Prices

3.6.1 Empirical Results from Panel Regressions

Our evidence implies that institutions rather herd unintentionally. However, even unintentional herding may contribute to destabilization if not based on fundamental information. In order to examine whether herding is stabilizing or destabilizing, theoretical predictions (see Section 3.2.3) and previous empirical studies (see e.g. Sias (2004)) suggest to analyze whether the relation of herding and subsequent prices continues or reverses.

If herding does reflect the incorporation of fundamental information into asset prices, a positive (negative) correlation of buy (sell) herding and subsequent returns should continue. In contrast, if herding drives stock prices away from fundamental values, as it is not information based, we would expect evidence of reversals in subsequent periods. To investigate the impact of herding and subsequent returns, we estimate the following fixed effects panel regression models:

$$\begin{aligned} r_{i,t,t+n} &= a^n + b^n BHM_{it} + c^n SHM_{it} + d^n Size_{it} \\ &+ e^n BM_{it} + f^n r_{i,t-5,t} + g^n Std_{it} + \alpha_i^n + \gamma_t^n + \epsilon_{it}^n, \end{aligned} \tag{3.7}$$

where $r_{i,t,t+n}$ denotes the cumulative return of stock i from time t to $t+n$. Cumulative returns are calculated for $n = 1, 2, ..., 20$ trading days, i.e., the one day ahead return ($n = 1$), and cumulative returns during subsequent two, three,.., or 20 days. In line with Puckett and Yan (2008) and Barber et al. (2009), we

[27] According to a Hausman test on endogeneity of the regressors, the null hypothesis of exogeneity cannot be rejected. However, results are consistent with respect to Generalized Method of Moments (GMM) estimations.

include in Equation (3.7) control variables $Size_{it}$, measured by the logarithm of closing market capitalization of stock i, the book-to-market ratio BM_{it} of stock i, $r_{i,t-5,t}$, the past cumulative return of stock i measured from the closing prices on day t and $t-5$ and Std_{it}, measured as the standard deviation of the past 250 daily stock returns.[28] Heterogenous stock-specific effects α_i and time dummies γ_t are also included in the regression.[29]

Table 3.4: Consequences of Herding - Panel Regression (1)

	$r_{i,t,t+1}$	$r_{i,t,t+2}$	$r_{i,t,t+3}$	$r_{i,t,t+5}$	$r_{i,t,t+10}$	$r_{i,t,t+20}$
BHM_{it}	0.216	0.633***	0.872***	1.002***	1.348***	1.600***
	(0.146)	(0.256)	(0.302)	(0.039)	(0.239)	(0.734)
SHM_{it}	−0.445***	−0.641***	−0.751***	−0.587**	0.674	0.698
	(0.182)	(0.295)	(0.258)	(0.289)	(0.429)	(0.662)

Notes: This table presents results of regressions of future stock returns on institutional herding. Six regressions of Equation (3.7) with different cumulative future returns (up to $n = 20$ trading days) as dependent variable are estimated. The subsequent cumulative return is regressed on the buy herding measure BHM_{it}, the sell herding measure SHM_{it} and control variables $Size_{it}$, BM_{it}, Vol_{it}, $r_{i,t-5,t}$ and Std_{it}, see Table 3.3 for explanation. The statistical significance at 1%, 5%, and 10% is represented as ***, **, and * respectively. Standard errors are given in parentheses. Results for the complete set of regressors are displayed in Table 3.11 in the Appendix.

To account for endogenous returns $r_{i,t-5,t}$, we estimate the regression with GMM using lagged variables as instruments. Hansen J statistics confirm the validity. However, due to the large T, the endogeneity bias is negligible and results are again consistent across estimation methods.[30] We account for heteroscedasticity and autocorrelation in the error terms by using robust standard errors, see Stock and Watson (2008). The lower part of Table 3.11 in the Appendix presents test statistics and p-values of diagnostic tests.

[28] Again, we include 90 and 30 days Std to check robustness. We also test again for alternative lagged return specifications, with $r_{i,t-1}$ up to $r_{i,t-5}$. Results do not change qualitatively and are available upon request.

[29] A Breusch-Pagan Lagrange multiplier test on $H_0 : \sigma_i^2 = 0$ indicates the existence of individual effects α_i. The inclusion of time dummies γ_t does not change the results.

[30] For brevity, OLS results are not presented, but are available on request.

We perform the panel regressions of Equation (3.7) twenty times, i.e., for each n. The six columns in Table 3.4 display the results for the different cumulative returns n= $1, 2, 3, 5, 10, 20$ as dependent variables. First, the coefficients on BHM_{it} are positive and significant over the complete time horizon. In line with Puckett and Yan (2008) this finding does not imply any destabilizing reversal after buy herding. In the short-term for the first subsequent days, coefficients on SHM_{it} are significantly negative. However, for the cumulative returns after 10 trading days, the sign changes to positive and the coefficient estimate becomes insignificant.[31] In accordance with Puckett and Yan (2008) this reversal in the relation of sell herding and cumulative returns imply a destabilizing effect of sell herding by institutions.

Findings on the remaining control variables, displayed in Table 3.11 in the Appendix, are consistent with earlier findings, e.g., Puckett and Yan (2008): Subsequent returns are negatively related to prior returns $r_{i,t-5,t}$ and firm size $Size_{i,t}$, implying that small stocks outperform large stocks. Moreover, past volatility Std_{it} has also a negative effect on subsequent returns.

3.6.2 Portfolio Formation Results

In order to demonstrate the robustness of our findings, we follow Wermers (1999) and related empirical literature and investigate subsequent abnormal returns of stock that institutions have heavily bought and sold in herds. For each day, all stocks are categorized into buy-herding or sell-herding stocks. For both groups, stocks quintile portfolios are formed based on their daily herding measures. Thus, portfolio B1 (B5) consists of stocks that have a small (high) value of BHM_{it}, while stocks in S1 (S5) have a small (high) value of SHM_{it}. For each of the ten constructed portfolios daily subsequent mean abnormal returns ar_{t+n} were calculated with Fama-French factor alphas.[32] In line with Puckett and Yan (2008),

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[31] In fact, the coefficient estimate decrease at $n = 5$, gets insignificant at $n = 7$, and the change of the sign occurs at $n = 9$. Results are not reported for brevity, but are available on request.

[32] Using the following regression:

$$r_{p,t} = \alpha_p + \beta_{1p} RMRF_t + \beta_{2p} SMB_t + \beta_{3p} HML_t + \epsilon_{pt}.$$

Table 3.5: Consequences of Herding - Portfolio Abnormal Returns

	ar_1	ar_2	ar_3	ar_5	ar_{10}	ar_{20}
Buy Herding						
B1	-0.024	0.001	0.008	-0.001	-0.006	0.022
B2	0.014	0.014	0.021	0.019	0.003	0.001
B3	0.029	0.004	-0.011	0.001	-0.003	-0.006
B4	0.048	0.049	0.029	0.020	0.013	0.006
B5	0.046	0.046	0.053	0.036	0.015	0.017
Sell Herding						
S1	0.012	-0.006	-0.009	-0.006	-0.005	-0.004
S2	-0.021	-0.003	-0.019	-0.016	-0.014	-0.005
S3	-0.021	-0.027	-0.021	-0.002	0.078	0.003
S4	-0.045	-0.037	-0.032	-0.021	-0.021	0.009
S5	-0.043	-0.044	-0.018	-0.012	0.001	0.011

Notes: For each time period t, all stocks are sorted by institutional buying-herding measures BHM_{it}, forming portfolios B1 to B5, or by selling-herding measures SHM_{it}, forming portfolios S1 to S5. Then we calculate the mean abnormal returns for the 10 herding-sorted portfolios. B5 (S5) represents the portfolio where stocks are heavily bought (sold) by herd while B1 (S1) represents the portfolio where stocks are lightly bought (sold) by herd. For each of the ten constructed portfolios daily abnormal returns ar_{t+n} were calculated with Fama-French factor alphas. Finally, the time-series average abnormal return for each portfolio is computed for $n = 1, 2, ..., 20$ days. Abnormal returns are calculated and are presented in percentage terms.

daily abnormal returns were calculated and then averaged for $n = 1, 2...20$ days, i.e. ar_{20} represents the average abnormal daily return during the first 20 trading days.

Factors $RMRF_t$, SMB_t and HML_t are calculated following the portfolio construction procedure described by Fama and French. To calculate excess market return $RMRF_t$, we use daily returns of the Composite DAX (CDAX), covering all stocks in the general and prime standard. As risk free rate, we use daily data on annualized 3-month money market rates in Germany available from the Deutsche Bundesbank.

Results presented in Table 3.5 confirm conclusions of the panel regression analysis. The six columns in the table display the results for the different average abnormal returns for days n= $1, 2, 3, 5, 10, 20$. The highest buy herding portfolios show on average up to 20 trading days positive daily abnormal returns. However, abnormal daily returns strongly decrease after three days. In fact, the factor alphas according to the Fama-French regression get insignificant but are still positive after the fourth day.[33] For the highest sell herding portfolios (S4 and S5) daily abnormal returns are negative for the first few days after herding. Again, the effect decreases. Factor alphas get insignificant and change to positive values after five trading days. Towards ten trading days even the average of the daily abnormal returns as shown in the fifth column of Table 3.5 change to positive values.

3.7 Conclusions

This paper contributes to the empirical literature on herding by using higher-frequency investor-level data that directly identify institutional transactions. The analysis therefore overcomes the data problems faced by previous studies and provides new evidence on the short-term herding behavior of financial institutions. Applying Lakonishok et al.'s (1992) herding measure to a broad cross-section of German stocks over the period from August 2006 to April 2009, we explore causes and consequences of herding by financial institutions.

Contradicting the theory on intentional herding, our results do not confirm that small capitalization stocks are more vulnerable to herding behavior. We find that herding is more pronounced in DAX 30 shares with a herding level of 5.17% for the 30 most active institutions. These results suggest that herding behavior is not the result of insufficient information availability or information asymmetry but is rather unintentional.

[33] Results for the single Fama-French regressions are not displayed for brevity, but are available on request.

A panel econometric analysis confirms this conclusion and provides further insight into the causes of herding. Herding depends on past volatility and past returns of the specific stock. Herding on the buy side is negatively related whereas herding on the sell side is positively related to past returns. Most important, we find that rising stock volatility leads to more sell-side herding by financial institutions. This result indicates, that herding results also from the common reaction of institutions on risk measures.

Regarding the consequences of herding, we show that sell-side herding is attributed to a destabilization of stock prices in the short-term, as indicated by subsequent return reversals after sell herding.

The empirical results of the paper therefore support the predictions of Daníelsson (2008) and Daníelsson, Shin and Zigrand (2009), who argue that the common use of VaR models and other volatility sensitive risk measures reduce the diversity of decision rules resulting in herding behavior by banks with potential destabilizing implications. Therefore, regulators and risk modeling institutions need to be aware of how risk management systems induce risk endogeneity and affect macro-prudential aspects of risks.

3.8 Appendix

Table 3.6: Daily LSV Herding Measures of 30 Most Active Traders (2)

	MDAX			SDAX		
	HM	BHM	SHM	HM	BHM	SHM
Whole sample	1.18 (0.05)	1.39 (0.07)	0.96 (0.07)	1.59 (0.09)	1.86 (0.12)	1.28 (0.14)
Observations	31,668	16,439	15,211	16,442	8,675	7,765
<08/09/07	1.78 (0.07)	2.67 (0.11)	0.65 (0.10)	1.85 (0.12)	2.39 (0.16)	1.14 (0.20)
Observations	12,749	7,137	5,612	9,186	5,185	4,001
≥08/09/07	0.76 (0.07)	0.40 (0.09)	1.15 (0.10)	1.25 (0.14)	1.07 (0.21)	1.43 (0.20)
Observations	18,919	9,302	9,599	7,256	3,490	3,764

Notes: This table reports mean values of HM, BHM and SHM in percentage terms for MDAX and SDAX stocks considering the 30 most active institutions in the sample. See Table 3.1 for further information.

Table 3.7: Daily LSV Herding Measures of 40 Most Active German Banks (1)

	All Stocks			DAX 30		
	HM	BHM	SHM	HM	BHM	SHM
Whole sample	2.16 (0.03)	2.11 (0.05)	2.31 (0.05)	5.21 (0.05)	5.05 (0.08)	5.30 (0.08)
Observations	69,274	34,573	34,694	20,897	10,132	10,764
<08/09/07	1.96 (0.05)	2.07 (0.04)	1.85 (0.08)	4.78 (0.08)	5.65 (0.09)	4.86 (0.12)
Observations	27,635	13,728	13,907	8,425	4,044	4,381
≥08/09/07	2.39 (0.04)	2.13 (0.07)	2.45 (0.07)	5.48 (0.04)	5.41 (0.12)	5.73 (0.10)
Observations	41,639	20,845	20,787	12,472	6,088	6,383

Notes: This table reports mean values of HM, BHM and SHM in percentage terms for the whole sample of stocks and for DAX 30 stocks considering the 40 largest German banks that are engaged in proprietary trading. See Table 3.1 for further information.

Table 3.8: Daily LSV Herding Measures of 40 Most Active German Banks (2)

	MDAX			SDAX		
	HM	BHM	SHM	HM	BHM	SHM
Whole sample	1.22 (0.05)	1.29 (0.07)	1.15 (0.07)	0.22 (0.08)	0.11 (0.12)	0.34 (0.12)
Observations	31,630	16,050	15,575	16,747	8,391	8,355
<08/09/07	1.25 (0.07)	1.40 (0.11)	1.10 (0.10)	0.14 (0.12)	0.31 (0.18)	0.63 (0.17)
Observations	12,072	6,043	6,029	7,138	3,641	3,497
≥08/09/07	1.21 (0.07)	1.22 (0.09)	1.18 (0.08)	0.50 (0.11)	0.04 (0.16)	1.05 (0.16)
Observations	19,558	10,007	9,546	9,609	4,750	4,858

Notes: This table reports mean values of HM, BHM and SHM in percentage terms for MDAX and SDAX stocks considering the 40 largest German banks that are engaged in proprietary trading. See Table 3.1 for further information.

Table 3.9: Mean Sias Measure of 30 Most Active Traders

	Average Correlation	Partitioned Correlation	
		Follow Own Trades	Follow Trades of Others
Whole sample	16.42 (0.34)	11.40 (0.27)	5.02 (0.26)
<08/09/07	19.61 (0.57)	12.01 (0.40)	7.60 (0.24)
≥08/09/07	14.25 (0.52)	10.98 (0.38)	3.27 (0.23)
Buy Herding			
Whole sample	6.23 (0.23)	4.35 (0.14)	1.88 (0.15)
<08/09/07	7.65 (0.37)	4.74 (0.23)	2.91 (0.15)
≥08/09/07	5.27 (0.35)	4.09 (0.19)	1.18 (0.15)
Sell Herding			
Whole sample	10.19 (0.24)	7.06 (0.20)	3.13 (0.12)
<08/09/07	11.96 (0.33)	7.26 (0.29)	4,70 (0.12)
≥08/09/07	8.98 (0.35)	6.90 (0.28)	2.08 (0.13)

Notes: This table reports results of the Sias measure for all stocks in the samples considering the 30 most active institutions. The upper part of the table reports values of the average correlation in percentage terms of the coefficient β. The correlations were first estimated with a cross-sectional regression for each day t and stocks i. The reported correlations display the time-series average of the regression coefficients in percentage terms. The second and third column report the partitioned correlations that result from institutions following their own trades and institutions following the trades of others, see Sias (2004). In the lower parts of the table the correlation is partitioned into those stocks institutions purchased at the previous day (buy herding) and those institutions sold (sell herding). Standard errors are given in parentheses.

Table 3.10: Mean Sias Measure of 40 Most Active German Banks

	Average Correlation	Partitioned Correlation	
		Follow Own Trades	Follow Trades of Others
Whole sample	15.46 (0.36)	10.19 (0.23)	5.27 (0.26)
<08/09/07	15.54 (0.59)	11.51 (0.29)	4.03 (0.24)
≥08/09/07	15.33 (0.47)	9.32 (0.28)	6.01 (0.23)
Buy Herding			
Whole sample	5.73 (0.23)	3.75 (0.11)	1.98 (0.15)
<08/09/07	5.59 (0.37)	4.04 (0.21)	1.55 (0.15)
≥08/09/07	5.83 (0.35)	3.56 (0.15)	2.27 (0.15)
Sell Herding			
Whole sample	9.73 (0.24)	6.45 (0.15)	3.28 (0.12)
<08/09/07	9.95 (0.33)	7.47 (0.26)	2.48 (0.12)
≥08/09/07	9.50 (0.35)	5.76 (0.18)	3.74 (0.13)

Notes: This table reports results of the Sias measure for all stocks in the samples but considering the 40 largest German banks. See Table 3.9 for further explanation.

Table 3.11: Consequences of Herding - Panel Regression (2)

	$r_{i,t,t+1}$	$r_{i,t,t+2}$	$r_{i,t,t+3}$	$r_{i,t,t+5}$	$r_{i,t,t+10}$	$r_{i,t,t+20}$
Regressors						
BHM_{it}	0.216 (0.146)	0.633^{***} (0.256)	0.872^{***} (0.302)	1.002^{***} (0.039)	1.348^{***} (0.239)	1.600^{***} (0.734)
SHM_{it}	-0.445^{***} (0.182)	-0.641^{***} (0.295)	-0.751^{***} (0.258)	-0.587^{**} (0.289)	0.674 (0.429)	0.698 (0.662)
$Size_{it}$	-0.172^{***} (0.056)	-0.314^{***} (0.085)	-0.561^{***} (0.096)	-1.029^{***} (0.084)	-2.300^{***} (0.123)	-3.172^{***} (0.155)
BM_{it}	0.146^{***} (0.036)	0.340^{***} (0.056)	0.522^{***} (0.064)	1.030^{***} (0.030)	1.540^{***} (0.121)	2.075^{***} (0.141)
Vol_{it}	0.019 (0.013)	0.026 (0.020)	0.053^{*} (0.029)	0.030 (0.030)	0.006 (0.041)	0.012 (0.041)
$r_{i,t-5,t}$	-0.032^{***} (0.003)	-0.065^{***} (0.005)	-0.065^{**} (0.006)	-0.048^{***} (0.008)	-0.045^{***} (0.010)	-0.026^{*} (0.014)
Std_{it}	-0.223^{***} (0.022)	-0.458^{***} (0.027)	-0.602^{***} (0.032)	-1.122^{***} (0.041)	-2.162^{***} (0.056)	-4.166^{***} (0.096)
Diagnostics						
$Wool.$	$F = 13.91$ $(P>F=0.00)$	$F = 145.91$ $(P>F=0.00)$	$F = 703.34$ $(P>F=0.00)$	$F = 68.83$ $(P>F=0.00)$	$F = 269.21$ $(P>F=0.00)$	$F = 112.18$ $(P>F=0.00)$
$C.-W.$	$\chi^2 = 9125.6$ $(P>\chi^2=0.00)$	$\chi^2 = 12966$ $(P>\chi^2=0.00)$	$\chi^2 = 13244$ $(P>\chi^2=0.00)$	$\chi^2 = 14152$ $(P>\chi^2=0.00)$	$\chi^2 = 16661$ $(P>\chi^2=0.00)$	$\chi^2 = 19318$ $(P>\chi^2=0.00)$
$S.-H.$	$\chi^2 = 36.80$ $(P>\chi^2=0.00)$	$\chi^2 = 18.39$ $(P>\chi^2=0.00)$	$\chi^2 = 8.93$ $(P>\chi^2=0.01)$	$\chi^2 = 12.53$ $(P>\chi^2=0.00)$	$\chi^2 = 25.22$ $(P>\chi^2=0.00)$	$\chi^2 = 36.29$ $(P>\chi^2=0.00)$

Notes: This table presents the results of the complete set of regressors for regressions of future stock returns on institutional herding. Six regressions of Equation (3.7) with different cumulative future returns (up to $n = 20$ trading days) as dependent variable are estimated. The subsequent cumulative return is regressed on the buy herding measure BHM_{it}, the sell herding measure SHM_{it} and control variables $Size_{it}$, BM_{it}, Vol_{it}, $r_{i,t-5,t}$ and Std_{it}. The statistical significance at 1%, 5%, and 10% is represented as ***, **, and * respectively. Standard errors are given in parentheses. The lower part of the table reports test statistics and p-values in parentheses ($Wool.$, $C.-W.$, and $S.-H.$ display $Wooldridge$, $Cook-Weisberg$, and $Sargan-Hansen$ tests, see Table 3.3 for more explanation.

4 Can Correlated Trades in the Stock Market be Explained by Informational Cascades? Empirical Results from an Intra-Day Analysis

4.1 Introduction

Increasing empirical literature provides evidence on "correlated trading" of institutional investors, see, e.g., Sias (2004). However, the rational behind this trading behavior and its consequences for the functioning of financial markets are still unclear. On the one hand, correlated trading can occur as investors react commonly on the same public information or e.g. risk measures, see Chapter 3. On the other hand, correlated trading might be a result of informational cascades, where investors ignore their own noisy information and imitate other market participants, since they infer (from observed trading behavior) that others have relevant information, see Bikhchandani et al. (1992) and Avery and Zemsky (1998). As a result, correlated trading driven by informational cascades should be particularly pronounced in times of uncertainty. This paper uses a comprehensive data set to test this theoretical prediction.

Informational cascades occur in the short-term and are more of an intra-day phenomenon, especially in developed markets. The arrival of public information and consequent price adjustments will dominate information from observed behavior and stop incorrect cascades, see Christoffersen and Tang (2009) and Patterson and Sharma (2010). Hence, the empirical assessment of cascades requires a fine-grade analysis of disaggregated investor-level data. Yet, the literature on institutional herding has been handicapped by the unavailability of appropriate data. The previous literature, using the measures developed by Lakonishok et al. (1992) or Sias (2004), focusses on institutions' changes in quarterly holdings which cannot account for the short-term character of informational cascades. Recently, Patterson and Sharma (2010) analyze cascades in the U.S. market in the 1998-2001 period within an intra-day context.[1] Their proposed method is based on counting runs of buy or sell trades. The intuition is that longer sequences of buy and sell trades are evidence for informational cascades. They consider trade data that do not differentiate at investor level. Hence, it is not possible to differentiate between traders that indeed follow predecessors and traders that simply follow themselves, because they split their trades; a differentiation accounted for by Sias (2004).

This paper contributes to the literature by analyzing higher frequent investor-level data that directly identify transactions by each trader. The data are provided by the German Federal Financial Supervisory Authority (BaFin) and include all real-time transactions carried out by banks and financial services institutions trading for their own account on German stock exchanges. We analyze the transactions of financial institutions in stocks included in the major German stock index DAX 30 over the period from July 2006 to March 2009. To test for the formations of informational cascades we use the method developed by Sias (2004), testing for positive correlations of the fraction of institutions buying in time intervals within a day. The method allows for the division of the correlation into its components, i.e. whether the institutions follow their own trades or whether the correlation in fact results from institutions follow other institutions into and out of the same stocks. Since our data allow for the direct identification of the trader, we are, to our knowledge, the first applying this measure in the intra-day context.

Our estimation results reveal that transactions of financial institutions are actually correlated within a trading day. When decomposing the correlation, we find that

[1] Lin, Tsai and Sun (2009) apply the same methodology analyzing the Taiwan stock market.

the correlation stems from both sources: Institutions following own trades as well as following other institutions. Hence, our findings support the use of investor-level data to account for sequential trades by single institutions.

According to the informational cascade models of Bikhchandani et al. (1992), Banerjee (1992), and Avery and Zemsky (1998), an important precondition for cascades in the stock market with flexible prices is uncertainty about the value of an asset and the accuracy of information. In order to analyze whether the "following other institutions" behavior indeed can be regarded as formation of informational cascades, we test three theoretical predictions centering around this prediction: First, cascades should be observed in times of market stress, as associated with higher uncertainty. However, our results show only weak evidence for higher correlations in the market turbulence during the crisis. Second, cascades should be observed in times with fewer information in the market. Yet, our estimation results reveal that correlation of trades is significantly higher in the opening intervals and the afternoon session when new information enters into the German market due to the opening of the U.S. market. Third, cascades will be observed in times with higher analyst dispersion as a measure of uncertainty about the asset value. However, we rather find a negative relationship between the Sias measure and analyst dispersions. Overall, our evidence does not support the theory of informational cascades. Our results are more in line with Lin, Tsai and Sun (2009) and also confirm the conclusions in Chapter 3 suggesting correlated trading activity rather resulting unintentionally, probably through the common reaction on information.

The rest of the paper is structured as follows: Section 4.2 reviews the theory on informational cascades. Section 4.3 and 4.4 introduce the data and discuss the Sias herding measure. Section 4.5 presents the empirical results on the testable hypotheses. Section 4.6 contains a summary of the main results and offers some concluding remarks.

4.2 The Theory of Informational Cascades

4.2.1 Informational Cascade Models

Informational cascades occur as a sequence of decisions where rational investors disregard their own information and preferences in favor of following the decisions of investors ahead. Hence, investors rationally copy actions irrespective of their own private information. According to the information cascade model of Bikhchandani et al. (1992), a group of investors decide in sequence whether to adopt or reject a possible action; i.e. whether to invest in the stock or not. The decision makers have two sources of information: Each investor observes the trade decisions of all investors ahead. Additionally, each investor has information regarding the value of the asset, but this information is incomplete and noisy. However, the two sources of information may present conflicting signals. All investors follow Bayesian rationality. If the decision maker's own information is limited, he may put more weight on the information derived from the observation of others' actions. Hence, investors may ignore their own signal and follow the behavior of the preceding deciders only, resulting in an informational cascade. The underlying message of the informational cascades theory is that the influence of others' actions can be substantial that it dominates the own information, as this own information is uncertain. Hence, uncertainty in the decision makers own information is the key factor driving informational cascades.

The model of Avery and Zemsky (1998) extends the assumption of Bikhchandani et al.'s (1992) model by introducing a market maker adjusting prices. The flexible prices reduce the likeliness of cascades compared to the original model. The market maker incorporates all publicly available information in the prices. In this setting it is optimal to trade based on own information than upon observed behavior of predecessors. However, if the market maker has information disadvantages, prices are not adjusted effectively. Thus, according to Avery and Zemsky (1998) cascades occur more infrequently and require additional uncertainty compared to the model of only Bikhchandani et al. (1992). Conditions for the cascades in this setting are the uncertainty about the value of the stock, the uncertainty about the accuracy of information and information asymmetry.

The empirical approaches examining cascade behavior can be divided into analyzes of market data and laboratory experiments. Laboratory experiments have the advantage that they directly allow to control for public and private information. Hence theoretical predictions are explicitly testable, see, e.g., Alevy, Haigh and List (2007). Early laboratory experiments indeed detect informational cascading behavior, see, e.g., Anderson and Holt (1997) as first application. However, more recent evidence from experiments questions a distinct imitative behavior. Alevy, Haigh and List (2007) experimented explicitly with market professionals. They find that market professionals tend to make use of their private signal to a greater degree and base their decisions on the quality of the public signal to a greater extent, than do students with which experiments usually are conducted. Also, results of Weizsäcker (2010) indicate that people assign much more weight on their own information relative to the publicly observable decisions. Additionally, Drehmann, Oechssler and Roider (2005) do not find evidence for imitative behavior in their financial market experiment. In contrast, participants rather show contrarian behavior against the market trend as they mistrust the decisions of others.

Analysis on market data have, in contrast to laboratory experiments, the disadvantage that the motives behind a financial decision are not directly discernable. A large number of factors may influence an investment decision and controlling for underlying fundamentals is difficult. Hence, empirically, a direct link between theoretical predictions and behavior is problematic, see Alevy et al. (2007) and Bikhchandani and Sharma (2001).

4.2.2 Testable Hypotheses

To capture this link within our analysis to the extent possible, we follow e.g. Patterson and Sharma (2010) and make use of the theoretical implications. Overall, the above summarized models in general imply cascades to be observed in cases of lower information quantity and precision and higher information uncertainty and asymmetry. Hence, the theory of informational cascades leads to the following testable predictions:

H1: Informational cascades will be observed in times of market turbulence. This prediction derives from the assumption that times of market stress are associated with increased uncertainty and investor anxiety, see Patterson and Sharma (2010). We will test the hypothesis by estimating correlations separately for the crisis and non-crisis period.

H2: Informational cascades will be observed in times with fewer public information in the market. This prediction directly indicates the theoretical relation between informational cascades and lower information quantity, see Lin, Tsai and Sun (2009). The hypothesis is tested by accounting for time intervals during the day in which information flows into the market.

H3: Informational cascades will be observed in times when analysts opinions disperse. This prediction derives from the assumption that dispersions of analyst options capture the magnitude of beliefs heterogeneity. Higher dispersions indicate higher information uncertainty and asymmetry, see Brown et al. (2010) and Christoffersen and Tang (2009). We will test the hypothesis by classifying the standard deviation of analyst recommendations in tertiles and estimating correlations accordingly.

4.3 Data and Sample

The paper employs disaggregated high-frequency investor-level data covering *all* real-time transactions carried out in the German stock market in shares included in the DAX 30, i.e., the index of the 30 largest and most liquid stocks.[2]

[2] Kremer and Nautz (2010), displayed in Chapter 2, have shown, that herding in the short-term rather occurs in larger than in small stocks. Thus, this analysis focuses on the largest shares. Kremer and Nautz (2010) use the data as first and show the impact of data-frequency on herding levels by comparing quarterly, monthly and daily calculations. The data are provided by the German Federal Financial Supervisory Authority (BaFin). Under Section 9 of the German Securities Trading Act, all credit institutions and financial services institutions are required to report to BaFin any transaction in securities or derivatives which are admitted to trading on an organized market.

These records allow for the identification of all relevant trade characteristics, including the trader (the institution). The information also include e.g. the particular stock, time, number of traded shares, price, and the volume of the transaction. Moreover, the records identify on whose behalf the trade was executed, i.e., whether the institution traded for its own account or on behalf of a client that is not a financial institution. Since the aim of our study is the investigation of institutional trades, particularly those of financial institutions, we focus on the trading of own accounts, i.e., those cases when a bank or a financial services institution is clearly the originator of the trade. We exclude institutions trading exclusively for the purpose of market making. We also exclude institutions that are formally mandated as designated sponsors, i.e., liquidity providers, for a specific stock.[3]

The study covers data from July 2006 until March 2009 (a total of 698 trading days).[4] Over this observation period 1,044 institutions traded in DAX 30 stocks on German stock exchanges. For our analysis, we divide each trading day into 18 half-hour intervals as displayed in Table 4.1. The third and fourth column of Table 4.1 show the average trading activity during one trading day. The number of institutions trading is relatively stable over the different intervals, while most traders are active at the opening (about 25) and closing interval. Nevertheless, in each interval, enough institutions are active to perform the intra-day analysis. The fourth column of Table 4.1 provides for information regarding the dispersion of the volumes of trades of the institutions in percentage terms over the trading day. Again, the highest amounts are on average traded at the beginning (about 7%) and at the end of the day (about 10% of the institutional trading volumes at the day).

[3] For each stock, there are usually about two institutions formally mandated as market maker. The institutions are not completely dropped from the sample (unless they are already dropped due to purely engaging in market maker business), but only for those stocks for which they act as designated sponsors. The particular designated sponsors for each stock are published at www.deutsche-boerse.com.

[4] The stocks were selected according to the index compositions at the end of the observation period on March 31, 2009.

Table 4.1: Intra-Day Half-Hour Intervals

Interval Number	Time Period	Average Number of Traders	Average Share of Trading Volume
1	09:00 - 09:30	25.33	6.73
2	09:30 - 10:00	21.05	5.34
3	10:00 - 10:30	15.75	2.57
4	10:30 - 11:00	22.88	6.73
5	11:00 - 11:30	19.58	4.51
6	11:30 - 12:00	18.72	4.15
7	12:00 - 12:30	17.96	3.77
8	12:30 - 01:00	17.08	3.39
9	01:00 - 01:30	17.36	4.31
10	01:30 - 02:00	16.57	3.28
11	02:00 - 02:30	17.85	3.96
12	02:30 - 03:00	18.90	4.63
13	03:00 - 03:30	18.32	4.42
14	03:30 - 04:00	20.42	6.43
15	04:00 - 04:30	20.70	6.98
16	04:30 - 05:00	20.74	7.64
17	05:00 - 05:30	22.50	10.13
18	05:30 - 08:00	18.20	10.91

Notes: This table shows the division of the trading day in 18 half-hour intervals. The opening period for the German stock exchanges at the floor is from 9 a.m. until 8 p.m. CET. On the trading platform Xetra®, on which the great majority of trades and volumes occur, trading takes place from 9 a.m. till 5.30 p.m. CET. The interval number 18 is therefore enlarged. The third column of the table reports the average of the number of traders active in each interval over the whole observation period and over all stock. The fourth column of the table reports the mean allocation of the trading volume of traders over the time intervals in percentage terms. The values are calculated as fraction of institutions trading volume in one interval according to institutions trading volume at the complete trading day and then averaged over all days and all stocks.

For robustness tests, we also divide the trading day into 9 one-hour intervals, see Table 4.5 in the Appendix. Our results are displayed in the Appendix and will not change qualitatively due to this one-hour based division.

4.4 The Methodology

The dynamic herding measure proposed by Sias (2004)[5] explores whether investors follow each others' trades by examining the correlation between the traders buyers tendency over time. The starting point of the Sias measure is the number of buyers as a fraction of all traders. Consider a number of N_{it} institutions trading in stock i at time t. Out of these N_{it} transactions, a number of b_{it} are buy transactions. The buyer ratio br_{it} is then defined as $br_{it} = \frac{b_{it}}{N_{it}}$. According to Sias (2004), the ratio is standardized to have zero mean and unit variance:

$$\Delta_{it} = \frac{br_{it} - \bar{br}_t}{\sigma(br_{it})}, \tag{4.1}$$

where $\sigma(br_{it})$ is the cross sectional standard deviation of buyer ratios across I stocks at time t. The Sias herding measure is defined as the correlation between the standardized buyer ratios in consecutive periods:

$$\Delta_{it} = \beta_t \Delta_{i,t-1} + \epsilon_{it}. \tag{4.2}$$

The cross-sectional regression is estimated for each time t and then the time-series average of the coefficients is calculated: $\hat{\beta} = \frac{\sum_{t=2}^{T} \beta_t}{T-1}$.

The Sias methodology further differentiates between investors who follow the trades of others (i.e., *true herding* according to Sias (2004)) and those who follow their own trades. For this purpose, the correlation is decomposed into two components:

[5] The Sias measure is already set out in Chapter 2, Section 2.4.2 of this thesis. The description is included in this chapter additionally for the sake of completeness. Note the extension at the end of this section.

$$\beta = \rho(\Delta_{it}, \Delta_{i,t-1}) = \left[\frac{1}{(I-1)\sigma(br_{it})\sigma(br_{i,t-1})}\right] \sum_{i=1}^{I} \left[\sum_{n=1}^{N_{it}} \frac{(D_{nit} - \bar{br}_t)(D_{ni,t-1} - \bar{br}_{t-1})}{N_{it}N_{i,t-1}}\right]$$
$$+ \left[\frac{1}{(I-1)\sigma(br_{it})\sigma(br_{i,t-1})}\right] \sum_{i=1}^{I} \left[\sum_{n=1}^{N_{it}} \sum_{m=1, m\neq n}^{N_{i,t-1}} \frac{(D_{nit} - \bar{br}_t)(D_{mi,t-1} - \bar{br}_{t-1})}{N_{it}N_{i,t-1}}\right], \quad (4.3)$$

where N_{it} is the number of institutions trading stock i at time t and I is the number of stocks traded. D_{nit} is a dummy variable that equals one if institution n is a buyer in i at time t and zero otherwise. $D_{mi,t-1}$ is a dummy variable that equals one if trader m (who is different from trader n) is a buyer at time $t-1$. Therefore, the first part of the measure represents the component of the cross-sectional inter-temporal correlation that results from institutions following their own strategies when buying or selling the same stocks over adjacent time intervals. The second part indicates the portion of correlation resulting from institutions following the trades of others over adjacent time intervals. According to Sias (2004), a positive correlation that results from institutions following other institutions, i.e., the latter part of the decomposed correlation, can be regarded as first evidence for informational cascades.

According to Choi and Sias (2009), Equation (4.3) can be further decomposed to distinguish between the correlations associated with "buy herding" and "sell herding". Hence, stocks are classified by whether institutions bought in $t-1$ ($br_{i,t-1} > 0.5$) or sold in $t-1$ ($br_{i,t-1} < 0.5$).

4.5 Correlated Trading by Institutions: Empirical Results

4.5.1 Correlations of Trades

The methodology of Sias (2004) explores whether the buying tendency of traders persists over time. The motivation for adopting this approach is to identify informational cascades. To this end, the Sias measure directly indicates whether institutional investors follow each others' trades by examining the correlation between institutional trades in one time interval and the next interval. In contrast to approaches using anonymous transaction data, see, e.g. Patterson and Sharma (2010), applying this measure to investor-level data directly enables us to explore the extent to which traders follow indeed others and not themselves.

Table 4.2 displays the results obtained from the Sias herding measure for institutional traders. Consider first only the rows for the "whole sample". The estimated correlation at intra-day frequency over the complete period and over all stocks in the datasample is 31.12% (coefficient $\beta = 0.3112$), which is significantly higher than the results obtained by Sias (2004) and Choi and Sias (2009) at quarterly, Puckett and Yan (2008) for weekly and Kremer and Nautz (2010) at daily frequency.[6]

After the decomposition of the coefficient into the two different sources of the correlation, results reveal that the institutions follow their own strategies as well as those of others (i.e., herd) into and out of stocks. The higher part of the correlation, about 66% (=0.2055/0.3126), results from institutions that follow their own trading strategies. Hence, this result supports methods taking into account investor-level data and indicates that correlations on anonymous data must be interpreted with caution. The role of split trades of single institutions becomes even more relevant in case of higher frequency data. With the length of the period under investigation, the part of the correlation dedicated to "follow on trades" behavior shrinks.[7]

Nevertheless, results displayed in column 3 of Table 4.2 reveal a correlation of 10.57% for institutions following the trades of others. This finding may suggest the building up of informational cascades during a trading day. However, the

[6] The coefficients were estimated considering only intraday correlations and not the correlation between interval 18 and 1 at the next day. Including those correlation, the Sias measure slightly decreases to 28.62%. For brevity, these results are not presented, but are available on request.

[7] Results for one-hour intervals reveal similarly a 31.26 % correlation. In that case 53% of the correlation is dedicated to institutions following themselves. The results are displayed in Table 4.6 in the Appendix. Kremer and Nautz (2010) show lower proportions considering monthly and quarterly data.

Table 4.2: Correlations of Trades - Overall, Before and During the Crisis

	Average Correlation	Partitioned Correlation	
		Follow Own Trades	Follow Trades of Others
Whole sample	31.12 (0.01)	20.55 (0.10)	10.57 (0.11)
<08/09/07	33.24 (0.01)	23.74 (0.11)	9.50 (0.14)
≥08/09/07	29.59 (0.01)	18.73 (0.11)	10.86 (0.13)
Buy Herding			
Whole sample	14.08 (0.23)	9.29 (0.14)	4.79 (0.11)
<08/09/07	14.37 (0.37)	10.27 (0.13)	4.10 (0.10)
≥08/09/07	13.87 (0.35)	8.78 (0.19)	5.09 (0.11)
Sell Herding			
Whole sample	17.02 (0.14)	11.24 (0.10)	5.78 (0.10)
<08/09/07	18.87 (0.23)	13.46 (0.11)	5.41 (0.09)
≥08/09/07	15.65 (0.25)	9.91 (0.12)	5.74 (0.08)

Notes: This table reports results of the Sias measure calculated based on half-hour intervals. The correlations are displayed in percentage terms. The correlations were first estimated with a cross-sectional regression for each time interval t and stocks i. The reported correlations display the time-series average of the regression coefficients in percentage terms. The second and third column report the partitioned correlations that result from institutions following their own trades and institutions following the trades of others, see Equation (4.3). In the lower parts of the table the correlation is partitioned into those stocks institutions purchased in the previous time interval (buy herding) and those institutions sold (sell herding). Standard errors are given in parentheses.

correlation may also stem from institutions trading sequentially on correlated information.

4.5.2 The Role of the Crisis

H1: Informational cascades will be observed in times of market turbulence.

According to the models of Bikhchandani et al. (1992) and Avery and Zemsky (1998), informational cascades occur in times of market turbulence as those are associated with increased uncertainly and investor anxiety, see Patterson and Sharma (2010) and Choi and Sias (2009). The main intuition is that if agents have a weak information signal and a lot of uncertainty about the value of an asset but observe a lot of trading in the asset, they are more likely to ignore their own signals and follow the crowd. To examine this issue, we divide our sample into crisis and non-crisis periods, i.e., before and after August 9, 2007 as this date is widely considered as starting point of the financial crisis.

However, results displayed in the second and third row of Table 4.2 reveal only weak evidence for higher "following others" behavior during the crisis period, contradicting the implications of the information cascade model.[8] Also, differentiating between correlations resulting from buy and sell trades does not show notifiable differences. However, overall there seems to be a slightly higher herding tendency on the sell side.

4.5.3 The Availability of Information

H2: Informational cascades will be observed in times with fewer public information in the market.

Table 4.3 breaks down the correlations into the intra-day intervals. The third column again shows the correlation resulting from institutions following other institutional trades. Those correlations are higher at the beginning of the trading

[8] Results for one-hour intervals will not change this conclusions and are are displayed in Table 4.6 in the Appendix.

Table 4.3: Correlations of Trades - Intra-Day Half-Hour Intervals

	Average Correlation	Partitioned Correlation	
		Follow Own Trades	Follow Trades of Others
1-2	25.92 (0.23)	16.00 (0.31)	9.92 (0.26)
2-3	28.59 (0.22)	21.05 (0.32)	7.54 (0.24)
3-4	30.43 (0.29)	22.58 (0.34)	7.85 (0.23)
4-5	34.30 (0.31)	24.32 (0.38)	9.98 (0.22)
5-6	33.98 (0.29)	25.74 (0.37)	8.24 (0.23)
6-7	33.91 (0.30)	26.08 (0.34)	7.83 (0.24)
7-8	33.81 (0.25)	26.85 (0.32)	6.96 (0.21)
8-9	33.28 (0.24)	25.44 (0.32)	7.84 (0.21)
9-10	34.00 (0.28)	25.44 (0.31)	8.56 (0.21)
10-11	34.74 (0.25)	26.14 (0.31)	8.60 (0.26)
11-12	33.38 (0.24)	25.09 (0.34)	8.29 (0.26)
12-13	34.21 (0.26)	24.90 (0.43)	9.31 (0.26)
13-14	34.19 (0.28)	23.59 (0.35)	10.60 (0.26)
14-15	35.65 (0.28)	22.79 (0.32)	12.86 (0.26)
15-16	34.62 (0.27)	22.72 (0.36)	11.90 (0.26)
16-17	32.94 (0.28)	20.41 (0.41)	12.53 (0.26)
17-18	18.16 (0.21)	11.80 (0.31)	6.36 (0.26)

Notes: This table reports results of the Sias measure calculated based on half-hour intervals and averaged for the specific half-hour intervals. The correlations are displayed in percentage terms. The correlations where first estimated with a cross-sectional regression for each time interval t and stocks i. The reported correlations display the time-series average of the regression coefficients in percentage terms for the respective intervals. The second and third column report the partitioned correlations that result from institutions following their own trades and institutions follow the trades of others, see Equation (4.3). Standard errors are given in parentheses.

day, suggesting that intra-day herding occurs very likely in the opening interval with a correlation of 9.92%. This finding is in line with the evidence provided by Lin et al. (2009) and rather implies unintentional herding which is based on publicly available information. Opening intervals are those with a lot of new information that gets into the market. The model of Back, Cao and Willard (2000) suggests that at the market opening informed investors trade heavily with correlated information. Lin et al. (2009) argue therefore that herding at market opening should not be explained by informational cascades.[9]

However, as market goes further to near close, an information cascade effect might increase. Actually, around the mid-day, correlations are lowest but then rise slightly. The peak of the correlation, i.e. 12.86%, is found for the intervals between 3:30 and 4:30 p.m. CET (intervals 14-15). While Lin et al. (2009) suggest informational cascades are most likely in the close interval, for the German stock market we have to consider a different interpretation: In fact, the U.S. market opens at 3:30 p.m. CET, introducing new information into the German market. Hence, higher correlations in these time zones are again consistent with institutions trading on correlated information and thus again result less likely from informational cascades.

4.5.4 The Dispersion of Opinions

H3: Informational cascades will be observed in times when analysts opinions disperse.

The theory of Avery and Zemsky (1999) predicts that informational cascades occur under the conditions of information asymmetry and uncertainty. Shares included in the DAX 30 are those with highest market capitalization, trading volumes and transparency among the German stock market. Hence, those stocks are attributed with less information asymmetry and uncertainty. Those characteristics lead to the conclusions in Chapter 3 that herding evidence in DAX 30 stocks rather results

[9] They rather relate their finding to the search model of Vaxanos and Wang (2007) and argue that stronger herding is driven by shorter search time and lower transaction costs. Trading concentration occurs where investors with similar costs choose to trade similar assets.

Table 4.4: Correlations of Trades - Dispersion of Opinions

	Average Correlation	Partitioned Correlation	
		Follow Own Trades	Follow Trades of Others
Low Dispersion	29.39 (0.03)	15.86 (0.05)	13.53 (0.21)
Mid Dispersion	30.23 (0.02)	16.94 (0.05)	13.29 (0.24)
High Dispersion	28.49 (0.03)	16.68 (0.05)	11.81 (0.23)

Notes: This table reports results of the Sias measure calculated based on half-hour intervals and averaged for the specific dispersion tertiles. The correlations are displayed in percentage terms. See Table 4.2 for further information.

from correlated information than from the formation of informational cascades. Chapter 3 also shows that volatility as a measure of uncertainty has an asymmetric affect on herding. Volatility does only force herding on the sell side but not on the buy side, thus again suggesting herding more as a result of common reactions on risks rather than cascades due to uncertainty.

To further investigate whether the evidence of correlated trading activity during the day in DAX 30 stocks results from informational cascades, we investigate the impact of dispersion of opinions among investors on herding. Analyst dispersion captures the magnitude of beliefs heterogeneity and is a measure of information uncertainty and asymmetry, see Christoffersen and Tang (2009). If the correlation of institutional trades stems from informational cascades, we would expect higher levels of beliefs' dispersion arising from noisy information leading to higher "following others" behavior. The models of informational cascades would then imply that investors are more likely to herd as they infer information from others.

Dispersion in opinions is measured consistent with Brown et al. (2010) as standard deviation of all outstanding recommendations each day. Analyst recommendations received from Bloomberg indicate "Buy", "Hold" and "Sell" and are assigned to the numerical values 1, 3 and 5. The dispersion variable shows how information is correlated across informed agents. While a low dispersion indicates a general agreement and thus correlated information in the market, a high dispersion indicates noisy information and thus information uncertainty, a condition under which informational cascades build up.

We classify different stocks i at different trading days into three groups on the basis of the standard deviation, i.e. "Low", "Mid" and "High" dispersion. We then investigate intra-day correlations and estimate averages separately for the three different groups. Results are presented in Table 4.4 and reveal that the "following other behavior" is not attributed to higher dispersions in opinions. In fact, the fraction of the correlation resulting from following other traders, as displayed in column three, is lowest for the stocks and days with "Highest" dispersions. Hence, the higher the level of dispersion of opinion among investors the less are trades correlated. The hypothesis is rejected and, therefore, the evidence does not support the models of informational cascades.

4.6 Conclusion

This paper contributes to the existing literature on informational cascades using high-frequent investor-level data that directly identify transactions by each trader. To investigate the formations of informational cascades, we apply the method developed by Sias (2004) to intra-day data. In line with earlier evidence on anonymous transaction data, our results reveal strong correlation of institutional transactions during a day. However, our investor- specific data show that the correlation stems from both sources: Institutions following other institutions and institutions following own trades, as they may split their transactions. The following own trades part becomes even more pronounced using higher frequency data. Hence, our findings emphasize the use of investor-level data to account for institutions that build on sequential own trades.

An important precondition for informational cascades in the stock market is uncertainty about the value of an asset and regarding the accuracy of information. Based on these implications, we test three hypotheses. Yet, our results cannot confirm higher "following others" behavior in times of market turbulence during the crisis. Moreover, we find rather a negative relationship between the Sias measure and analyst dispersions which capture uncertainty regarding the asset values. Furthermore, our estimation results reveal that correlation of trades is significantly higher in the opening intervals and the afternoon session when new information enters into the German market due to the opening of the U.S. market. Overall, our results do not support the popular theory of informational cascades as explanation for correlated trading. Our findings rather suggest that correlated trading activity results unintentionally, through the common reaction on information.

On the one hand, our findings are in line with recent evidence from laboratory experiments, also questioning imitative behavior in the financial market, see, e.g., Drehmann et al. (2005). On the other hand, one could argue that the evidence is based on a statistical method only measuring correlations and not on a full-fledged model for trading behavior. A first step towards a structural estimation framework has been recently suggested by Cipriani and Guarino (2010), as an interesting avenue for future research.

4.7 Appendix

Table 4.5: Intra-Day One-Hour Intervals

Interval Number	Time Period	Average Number of Traders	Average Share of Trading Volume
1	09:00 - 10:00	30.32	12.07
2	10:00 - 11:00	25.72	9.30
3	11:00 - 12:00	24.76	8.66
4	12:00 - 01:00	22.67	7.16
5	01:00 - 02:00	22.07	7.59
6	02:00 - 03:00	23.60	8.58
7	03:00 - 04:00	24.87	10.85
8	04:00 - 05:00	26.20	14.63
9	05:00 - 08:00	28.11	21.24

Notes: This table shows the division of the trading day in 9 intervals. The opening period for the German stock exchanges at the floor is from 9 a.m. until 8 p.m. CET. On the trading platform Xetra®, on which the great majority of trades and volumes occur, trading takes place from 9 a.m. till 5.30 p.m. CET. The interval number 9 is therefore enlarged. See Table 4.1 for further information.

Table 4.6: Correlations of Trades - One-Hour - Overall, Before and During the Crisis

	Average Correlation	Partitioned Correlation	
		Follow Own Trades	Follow Trades of Others
Whole sample	31.26 (0.12)	16.51 (0.21)	14.75 (0.21)
<08/09/07	32.97 (0.04)	18.30 (0.19)	14.67 (0.24)
≥08/09/07	30.08 (0.03)	15.27 (0.14)	14.81 (0.23)
Buy Herding			
Whole sample	14.30 (0.23)	7.55 (0.14)	6.75 (0.15)
<08/09/07	14.56 (0.37)	8.03 (0.13)	6.53 (0.15)
≥08/09/07	14.18 (0.35)	7.21 (0.19)	6.97 (0.15)
Sell Herding			
Whole sample	16.96 (0.24)	8.96 (0.20)	8.01 (0.12)
<08/09/07	18.41 (0.33)	10.27 (0.19)	8.14 (0.12)
≥08/09/07	15.90 (0.35)	8.07 (0.18)	7.83 (0.13)

Notes: This table reports results of the Sias measure calculated based on one-hour intervals. The correlations are displayed in percentage terms. See Table 4.2 for further information.

Table 4.7: Correlations of Trades - Intra-Day One-Hour Intervals

	Average Correlation	Partitioned Correlation	
		Follow Own Trades	Follow Trades of Others
1-2	28.21 (0.28)	14.16 (0.21)	14.05 (0.26)
2-3	33.57 (0.32)	19.38 (0.22)	14.19 (0.24)
3-4	33.65 (0.29)	21.02 (0.24)	12.63 (0.23)
4-5	33.02 (0.31)	21.13 (0.28)	11.89 (0.22)
5-6	33.25 (0.29)	20.41 (0.27)	12.84 (0.23)
6-7	33.50 (0.30)	19.69 (0.24)	13.81 (0.24)
7-8	33.15 (0.25)	17.45 (0.22)	15.70 (0.21)
8-9	21.80 (0.25)	13.50 (0.22)	8.30 (0.21)

Notes: This table reports results of the Sias measure calculated based on one-hour intervals and averaged for the specific intervals. The correlations are displayed in percentage terms. The correlations were first estimated with a cross-sectional regression for each time interval t and stocks i. See Table 4.3 for further information.

Table 4.8: Correlations of Trades - One-Hour - Dispersion of Opinions

	Average Correlation	Partitioned Correlation	
		Follow Own Trades	Follow Trades of Others
Low Dispersion	29.85 (0.03)	13.14 (0.21)	16.71 (0.21)
Mid Dispersion	30.94 (0.04)	14.28 (0.19)	16.66 (0.24)
High Dispersion	29.40 (0.03)	14.93 (0.14)	14.47 (0.23)

Notes: This table reports results of the Sias measure calculated based on one-hour intervals and averaged for the specific dispersion tertiles. The correlations are displayed in percentage terms. See Table 4.2 for further information.

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