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**DID BANKS LEND IN HERDS DURING 2000–2008?**

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## **ABSTRACT**

Systemic risk was one of the greatest concerns during the financial crisis of 2007/2008. But why did financial institutions choose asset portfolios that were highly correlated with their peers'? We seek to identify the degree to which financial institutions intentionally followed the actions of their competitors. Based on a matched bank-firm panel we construct three time varying measures of bank "herding" within the Austrian business loan market for the period 2000-2008. These measures indicate sizable degrees to which banks were copying their peers' actions throughout the 2000s, particularly during the episode of low policy interest rates during 2003-2005.

# Did Banks Lend in Herds During 2000–2008?

September 9, 2013

**Abstract** Systemic risk was one of the greatest concerns during the financial crisis of 2007/2008. But why did financial institutions choose asset portfolios that were highly correlated with their peers'? We seek to identify the degree to which financial institutions *intentionally* followed the actions of their competitors. Based on a matched bank-firm panel we construct three time varying measures of bank "herding" within the Austrian business loan market for the period 2000-2008. These measures indicate sizable degrees to which banks were copying their peers' actions throughout the 2000s, particularly during the episode of low policy interest rates during 2003-2005.

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# 1 Introduction

One of the biggest concerns during the financial crisis of 2007-08 was the significant cross-sectional correlation of financial institutions' exposure to risk (Brunnermeier 2009). A popular explanation for this high degree of correlation is the recent surge in the use of off-balance-sheet derivatives, for which the correlation patterns of the underlying assets were not correctly internalized (Coval et al. 2009). Thus, due to this phenomenon, the high degree of correlation in pre-crisis default risk may in large part be considered an artifact of flawed financial engineering rather than an explicit choice of the institutions trading these structured products.

In this paper, we seek to quantify the degree to which banks were *knowingly* and *intentionally* taking correlated risks within the period 2000-2008, above and beyond the unintentional component through off-balance-sheet derivative markets. Rajan (1994) spells out a formal argument for why such behavior may arise. His theory predicts that rational bank managers with a short term objective have a strong incentive to follow their competitors' lending policies.

The analysis in Gaggli & Valderrama (2013) reveals that Austrian banks were allowing a significant amount of additional expected default risk in their business loan portfolios during the mid 2000s. Was this additional risk also likely to be highly correlated across banks? Our analysis in this paper sheds some light on this question.

Using the same sample of banks as in Gaggli & Valderrama (2013), we show that lending patterns by Austrian banks were significantly cross-sectionally correlated. In particular, our analysis reveals that the average bank increased lending to a particular borrower by about EUR 116 if average lending by other banks to this borrower increased by EUR 1000 in the previous month. This effect is statistically significant after controlling for borrower characteristics (including demand factors), bank characteristics, and aggregate events.

One way to interpret these results is that, on average, a given bank matches 11.6% of its competitors' lending to a given borrower, independent of fundamentals. This suggests that, to some extent, banks are lending in herds. Through this behavior they contribute to systemic risk, even in completely transparent markets, such as that for traditional business lending.

Furthermore, we analyze whether this type of herd behavior also exists if we group borrowers into industries as well as risk-rating classes. Our analysis reveals significant degrees of bank-herding both into industries and risk-rating classes. Moreover, we find that banks' tendency to act in herds at the risk-rating level increased significantly during the low policy-interest-rate period 2003q3-2005q3. This is precisely the period during which a significant amount of additional expected default risk was allowed in these banks' loan portfolios (see Gaggi & Valderrama 2013). Thus, our results suggest that not only did banks take additional expected default risk throughout the period 2003q3-2005q3, but this risk was also unusually strongly correlated across banks. Moreover, since the additional cross-sectional correlation of risk exposure was due to imitation, this uncovers an *intentional* component to the buildup of systemic risk within lending markets throughout 2000-2008.

Our analysis makes several contributions to the literature on herd behavior in lending markets. We are the first to analyze herding in business lending within the period 2000-2008. Our baseline approach adapts methods that have been applied in earlier studies on bank herding and we find qualitatively and quantitatively consistent results (Sias 2004, Uchida & Nakagawa 2007). Beyond that, we conduct detailed firm-bank-month level analyses which allow us to account for two potentially important shortcomings in the baseline estimates: First, the firm-bank-month analysis enables us to control for both borrower and lender characteristics. Second, we not only consider the extensive margin (i.e. the decision to lend or not) but also account for the intensive margin of lending (i.e.

the quantity of lending).

The firm-bank-month level analysis is inspired by the so-called “linear-in-means” model, which is regularly employed in the literature on identifying social interaction and peer-effects in areas such as education or crime. Most studies in this literature do not have access to detailed panel variation, which makes the identification of peer-effects inherently difficult (Manski 2000). However, our dataset allows us to directly identify the conditional cross-sectional correlation of banks’ actions and those of other lenders in the recent past. This eliminates the simultaneity problem inherent in the classic “linear-in-means” model, in which an individual’s *current* actions are related to *current* (i.e. simultaneous) actions of its peers.

Finally, as briefly discussed above, we are the first to analyze herding into risk-rating classes. This is an important extension as the correlation of risk exposure across financial institutions was a major concern in the financial crisis of 2007-08.

The remainder of this paper is organized as follows: Section 2 reviews the related literature, Sections 3 and 4 outline the methodology, Section 5 briefly describes the dataset, Section 6 reports the empirical results, and Section 7 concludes.

## 2 Related Literature

The analysis in this paper is related to several distinct strands of literature. First, there is an old but relatively small empirical literature on herd behavior within various aspects of banking markets (Jain & Gupta 1987, Chang et al. 1997, Barron & Valev 2000, Buch & Lipponer 2006, de Juan 2003, Nakagawa & Uchida 2011). The contribution most closely related to our analysis is by Uchida & Nakagawa (2007), who inquire whether Japanese banks’ herd behavior in lending markets was a major cause for the non-performing loan problem and the resulting Japanese banking crisis in the 1990s. Their main analysis is based on Lakonishok et al.’s (1992) test for investor herding within a sample of banks be-

tween 1975 through 2000. Our baseline analysis also draws on the same test and we are therefore able to directly compare their results to the ones obtained within our sample of Austrian banks and firms throughout the period 2000-2008. While the baseline methodology is similar to theirs, Uchida & Nakagawa's (2007) main objective differs substantially from ours. They are first and foremost interested in disentangling rational from irrational herding. This focus is based on the hypothesis that, if banks' herd behavior is irrational, then banks are to blame for the Japanese non-performing loan problem, while they are not if it was rational for banks to herd.

We take a different point of view and argue that rationality of herding per se is not the key question for understanding banks' share in the blame for market distortions (and a potential banking crisis). For instance, bank managers' incentives may be such that herd behavior is perfectly rational. Rajan (1994) shows that if bank managers are rational but have short-term concerns, then they have an incentive to follow their competitors' lending policies. In a simple model in which managers are periodically evaluated by a market—say the labor market for bank managers—he characterizes conditions in which it is always preferable (and perfectly rational) for a manager to follow other banks into the same industry rather than entering a new “niche” market, regardless of the observable information about these industries. In particular, he shows that a critical condition for this proposition is a sufficiently low expected (monetary and hence reputational) cost to non-performing loans. Thus, Rajan's (1994) model is a nice example showing that it is not necessarily bank management's irrationality that is causing herd behavior. Yet it is the herd behavior (rational or irrational) that causes market distortions.

Accordingly, we don't focus on separating rational from irrational herd behavior, but instead, a key goal of this paper is to disentangle “correlated effects”, due to common signals across borrowers, from “complementarity/peer effects” strictly due to (rational or irrational) imitation of other banks' actions. This identification problem has a long

history in the literature on social interactions and peer effects (Manski 2000, Brock & Durlauf 2001, Sacerdote 2011). The outcome variables studied within different types of “peer groups” range from earnings, academic achievement, substance abuse, criminal behavior, to technology adoption. The dominant identification strategy in the investor/institutional/bank herding literature is based on the excess variability of mean outcomes within groups of investors/institutions/banks (Lakonishok et al. 1992, Sias 2004, Uchida & Nakagawa 2007, Choi & Sias 2009). This approach has also been adopted and gradually refined within the broader literature on social interactions (Glaeser et al. 1996, Glaeser & Scheinkman 2001, 2003, Glaeser et al. 2003, Graham 2008). For our baseline estimates we adopt Lakonishok et al.’s (1992) as well as Sias’ (2004) versions of this strategy.

In addition, we implement a variant of the “linear in means” model (at the lender-borrower-month level) which is the most common econometric specification studied in the literature on social interactions (e.g., Sacerdote 2011, and references therein). A common difficulty in the study of peer effects within fields like economic education is the lack of longitudinal data. Usually actions and/or outcomes within a cross-section of individuals are observed only a few times and not necessarily in regular time intervals. Thus, studying dynamic effects is difficult and peer effects are usually inferred from cross-sectional variation within a time period. The nature of our detailed (long) panel of borrowers and lenders allows us to (a) explicitly treat lending behavior (banks’ actions) as sequential decisions and (b) study the dynamics of herd-behavior over time.

The ability to study the dynamics of herd behavior allows us to test the recently posed hypothesis that extended periods of low and stable policy interest rates may increase the incentive for lenders to herd. For instance, Rajan (2006) argues that bank managers’ compensation contracts encourage herding in their investments. The core of this argument can easily be seen within Rajan’s (1994) model of banks’ lending policies. As already



discussed above, he shows that, if the expected monetary and reputational cost of non-performing loans is sufficiently low, then bank managers have an incentive to herd. An announcement of stable and low interest rates for an “extended period of time” are an implicit insurance that overcoming future expected (or unexpected) cash-flow shortfalls are less expensive. In a similar vein Farhi & Tirole (2012) show that the expectation of a future bailout fosters collective moral hazard and thus collective over-investment. This incentive triggers (individually rational) herd behavior along the intensive margin of investment.

To test this hypothesis we follow Sias (2004) and employ a two stage procedure: First, we leverage cross-sectional variation (across banks and firms) in order to identify time varying degrees of herd behavior. In a second stage we exploit time series variation in the estimated degree of herd-behavior, in order to characterize the dynamics of herd behavior. This allows us to test whether bank herding was significantly more pronounced during the period of low policy interest rates in the mid 2000s.

### 3 Measuring Herd Behavior

We employ three alternative methods to measure the degree to which banks lend “in herds”. The first exploits the variance in mean outcomes across groups of banks lending to the same borrower. Glaeser et al. (1996) show theoretically (in the context of crime rates within U.S. cities) that imitation within groups generates more variation across group means than would be expected if individuals were making independent decisions. This is precisely the rationale behind Lakonishok et al.’s (1992) test to identify herd behavior in institutional investors’ portfolio choices. Thus, we adapt their test to the context of business lending throughout 2000-2008.

The second approach is based on Sias (2004) and Choi & Sias (2009), who also analyze institutional investor herding. For each borrower we explore the cross-sectional

correlation between the current period's fraction of lenders and last period's fraction of lenders. If there is positive correlation then this indicates that lenders follow each other (or themselves) in the decision to extend loans to a given borrower. We then decompose this correlation into the portion that is due to autocorrelation and the portion that is due to other lenders' actions during the last period. The latter portion of this correlation is an indicator for herd behavior.

The first two approaches both exploit the variation in aggregate statistics within groups of lenders for a given borrower (e.g. the fraction of lenders who advance new loans). We pursue a third approach, in which we move away from the group level analysis and directly relate individual banks' actions to those of other banks' actions in the recent past. Our analysis is based on the popular "linear in means" model which is extensively used in applied microeconomic research on social interactions and peer effects (Manski 2000, Sacerdote 2011). Within the traditional "linear in means" model, separating actual "peer effects" from "correlated effects" is inherently difficult (Brock & Durlauf 2001). This is to a large extent due to the types of datasets that are usually available to researchers in fields like economic education. Usually, individuals' actions and/or outcomes are neither available on a high frequency nor in a longitudinal manner. Thus, time variation can usually not be explored and peer effects have to be inferred from the cross-sectional variation within groups of individuals at a single point in time. The nature of our detailed firm-bank-month level dataset allows us to directly analyze the effect of other banks' past actions on the current actions of a given bank. Since current actions of a given bank are unlikely to cause the average of other banks' past actions, this allows us to overcome the inherent simultaneity problem present in the traditional "linear in means" model. Furthermore, the time variation in the longitudinal dataset allows us to filter out common observed and unobserved borrower-level variation in order to separate "correlated effects", due to common shocks/signals, from actual "peer effects". Sections 3.1 through

3.3 illustrate these three approaches in detail.

### 3.1 Excess Variability in Mean Actions

This section describes our adaption of Lakonishok et al.’s (1992, henceforth LSV) measure of investor herding. We apply their measure as follows: First, we count the number of banks who extend credit to a firm (or group of firms),  $L_{i,t}$ , within a given period  $t$ . Second, we express this number as a fraction of all banks “actively interacting” with that firm (or group of firms) in the same period,  $N_{i,t}$ .<sup>1</sup> Third, we compare this fraction to the average proportion of banks extending new credit to a given firm (or group of firms). The average is taken across all firms/groups,  $\mathcal{I}_t$ , actively operating at time  $t$ .<sup>2</sup> Formally, the measure

$$H_{i,t} = \left| \frac{L_{i,t}}{N_{i,t}} - \frac{1}{N_{\mathcal{I}_t}} \sum_{i \in \mathcal{I}_t} \frac{L_{i,t}}{N_{i,t}} \right| = \left| \frac{L_{i,t}}{N_{i,t}} - p_t \right|, \quad (1)$$

captures the concentration of lending to a specific borrower,  $i$ , relative to the average across all borrowers in a given period,  $t$ . The average of this expression captures the variability in the fraction of lenders to borrower  $i$ .

LSV’s simple statistical test is based on the idea that, if there is no systematic herding and lenders independently choose who to lend to,  $L_{i,t}$  is drawn from a binomial distribution with probability of success  $p_t$ . Therefore, under the null hypothesis of “no herding”, the following test statistic has a mean of zero and a binomial distribution:

$$LSV_{i,t} = \left| \frac{L_{i,t}}{N_{i,t}} - p_t \right| - E \left\{ \left| \frac{L_{i,t}}{N_{i,t}} - p_t \right| \right\}, \quad (2)$$

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<sup>1</sup>We consider a bank as “actively interacting” with a firm if there is an outstanding debt balance between the two parties. Thus, for each borrower, this group of lenders includes banks that extend new loans, ones that receive a net repayment of debt, and ones that have an unchanged balance.

<sup>2</sup>We conduct all analyses on the firm/borrower, industry, and risk-class level. Thus, for the sake of brevity, and except for the section presenting the empirical results, we will use the terms “firms”, “borrowers”, and “groups (of borrowers/firms)” interchangeably throughout the rest of the paper.

where the second term is the theoretical expectation under the assumption that  $L_{i,t} \sim B(N_{i,t}, p_t)$ . In order to compute the theoretical expectation, notice that for  $n$  draws of a random variable,  $L$ , following a binomial distribution with probability of success  $p$ , the first absolute central moment can be computed as follows (Johnson 1957):

$$\begin{aligned}
E \{|L - E \{L\}|\} &= E \{|L - np|\} \\
&= 2 \sum_{k=np+\gamma}^n \binom{n}{k} p^k (1-p)^{n-k} (k - np) \\
&= 2(np + \gamma) \binom{n}{np + \gamma} p^{(np+\gamma)} (1-p)^{(1-p)n-\gamma+1}, \tag{3}
\end{aligned}$$

where  $np + \gamma$  is the smallest integer greater than  $np$ . Therefore, we compute the expectation in equation (2) using the formula

$$E \left\{ \left| \frac{L_{i,t}}{N_{i,t}} - p_t \right| \right\} = \frac{2 [p_t N_{i,t} + \gamma]}{N_{i,t}} \binom{N_{i,t}}{p_t N_{i,t} + \gamma} p_t^{(N_{i,t} p_t + \gamma)} (1 - p_t)^{((1-p_t)N_{i,t} - \gamma + 1)}. \tag{4}$$

Under the null hypothesis of no herding and if the number of firms in  $\mathcal{I}_t$  is large, the sample average  $\overline{LSV}_t = \frac{1}{N_{\mathcal{I}_t}} \sum_{f \in \mathcal{F}_t} LSV_{i,t}$  approximately follows a normal distribution with mean zero. We then apply a standard Wald test on the difference between  $\overline{LSV}_t$  and 0 in order to test for statistical significance of perceived herding.

### 3.2 Temporal Correlation in the Fraction of Lenders

To adapt the approach developed by Sias (2004) we define

$$p_{i,t} \equiv \frac{\frac{L_{i,t}}{N_{i,t}} - p_t}{\sigma\left(\frac{L_{i,t}}{N_{i,t}}\right)}, \tag{5}$$

where  $\sigma(x_{i,t})$  is the cross-sectional standard deviation of  $x_{i,t}$  in period  $t$ . Thus, the regression models

$$p_{i,t} = \beta_{0,t}p_{i,t-1} + \beta_{1,t}\tilde{X}_{i,t-1} + \varepsilon_{i,t} \quad (6)$$

allow us to estimate the conditional cross-sectional correlation

$$\rho(p_{i,t}, p_{i,t-1} | \tilde{X}_{i,t-1}) = \beta_{0,t}$$

for each period  $t$ , where  $\tilde{X}_{i,t}$  is a vector of standardized borrower level control variables. This is a direct measure of the temporal correlation in the concentration of banks' lending activity. Thus, if a large fraction of banks is lending to firm  $i$  because a large fraction of banks has been lending to borrower  $i$  in the previous period, then we would expect  $\rho(p_{i,t}, p_{i,t-1} | \tilde{X}_{i,t-1})$  to be positive. Following Sias (2004) we then compute time series averages of the coefficients  $\hat{\beta}_{0,t}$  to test for statistical significance of herding in different time periods.

Sias (2004) further shows that, for the special case of  $\beta_{1,t} = 0$ , one can decompose these estimated correlations into the portion due to autocorrelation (i.e. following ones own lending in  $t - 1$ ) and a portion due to temporal correlation with past lending of other banks. In particular,

$$\begin{aligned} \rho(p_{i,t}, p_{i,t-1}) &= \beta_{0,t} \\ &= \Lambda_t \cdot \sum_{i=1}^{\mathcal{I}_t} \left[ \sum_{j=1}^{N_{i,t}} \frac{(D_{i,j,t} - p_t)(D_{i,j,t-1} - p_{t-1})}{N_{i,t}N_{i,t-1}} \right] \\ &\quad + \Lambda_t \cdot \sum_{i=1}^{\mathcal{I}_t} \left[ \sum_{j=1}^{N_{i,t}} \sum_{\substack{k=1 \\ k \neq j}}^{N_{i,t-1}} \frac{(D_{i,j,t} - p_t)(D_{i,k,t-1} - p_{t-1})}{N_{i,t}N_{i,t-1}} \right], \end{aligned} \quad (7)$$

where  $\Lambda_t = \frac{1}{(\mathcal{I}_t - 1)\sigma(L_{i,t}/N_{i,t})\sigma(L_{i,t-1}/N_{i,t-1})}$ , and  $D_{i,j,t}$  is an indicator variable that takes the value of one if bank  $j$  is lending to borrower  $i$  at time  $t$  and zero otherwise. The second term in equation (7) captures the portion of the correlation in lending concentration that is due to other banks' lending in  $t - 1$ . Again, we compute time series averages of these two separate portions to test for the existence of herding over different time periods.

### 3.3 Lender-Borrower Level Regressions

While the methods proposed by Sias (2004) improve upon LSV's original analysis by accounting for borrower heterogeneity, his approach does not account for observed and unobserved heterogeneity among lenders. Furthermore, the tests described in sections 3.1 and 3.2 only consider the extensive margin of lending and do not take into account the actual quantities of credit being extended to borrowers. To address these shortcomings we directly exploit variation in the amounts of new credit extended across borrowers as well as lenders. To do so we specify a version of the "linear in means" model used in the literature on social interactions and peer effects (Manski 2000). In particular, we specify the following lender-borrower-time level regression:

$$\ell_{b,i,t} = \gamma_{0,t}\bar{\ell}_{b^-,i,t-1} + \gamma_{1,t}X_{i,t} + \gamma_{2,t}Y_{b,t} + \alpha_t + \epsilon_{b,i,t} \quad (8)$$

where  $\ell_{b,i,t}$  represents the amount of new lending (i.e. loans) from bank  $b$  to borrower  $i$  at time  $t$ . The term  $\bar{\ell}_{b^-,i,t-1}$  measures the average amounts of new lending from "other banks",  $b^- \equiv \{\tilde{b} \mid \tilde{b} \neq b\}$ , to borrower  $i$  in period  $t - 1$ . The three dimensions in this model (borrowers, lenders, and time) allow us to control for heterogeneity in both borrowers' and lenders' characteristics. In particular, we control for a vector of borrower specific characteristics (potentially including borrower fixed effects),  $X_{i,t}$ , as well bank specific characteristics (potentially including bank fixed effects),  $Y_{b,t}$ . The matrix  $(\{\gamma_{0,t}, \gamma'_{1,t}, \gamma'_{2,t}\}_{t=0}^T) \in$

$\mathbb{R}^{T \times (1+K+J)}$  records regression coefficients, where  $T$  is the number of time periods, and  $K$  and  $J$  refer to the dimensions of the vectors of bank and borrower specific characteristics, respectively. Finally,  $\alpha_t$  is a time  $t$  specific constant and  $\epsilon_{b,i,t}$  is a random variable with  $E[\epsilon_{b,i,t}] = 0$ .

To estimate this model, we run individual regressions for each  $t$  and exploit the variation across banks and firms, in order to identify the relationship between current lending activity of a given bank and past average lending activity by other banks at each point in time,  $\gamma_{0,t}$ . Like in Section 3.2, we then use time variation in the estimates  $\hat{\gamma}_{0,t}$  to compute the average degree of herding in different subsamples.

Notice that the models in Sections 3.1 and 3.2 measure bank interactions indirectly through the concentration in lending to a given borrower. Model (8) is designed to directly identify the effect of peers' or competitors' past actions on banks' current actions. One important identifying assumption is that banks' past actions are not correlated with unobserved shocks to borrower  $i$  which influences firm  $i$ 's lenders today. Thus, it is crucial to accurately control for both firm and bank heterogeneity, in order to identify the true peer effect rather than a mixture of a peer effect and a correlated effect.

## 4 Bank Herding and Monetary Policy

Besides identifying herd behavior in business lending markets per se, another key goal of this paper is to empirically investigate a potential relationship between the stance of monetary policy during the mid 2000s, the degree of bank herding, and in turn systemic risk. In Gaggl & Valderrama (2013) we show that the stance of monetary policy during 2003q3 – 2005q3 induced banks to take on extra expected default risk in business lending, which they would have otherwise not allowed on their balance sheet. Thus, an important follow-up question is whether the degree to which banks lend in herds has changed as well during the period 2003q3 – 2005q3, relative to the remaining periods

within 2000-2008. If so, then this suggests that traditional monetary policy, through its effect on lending volume and risk-taking, combined with banks tendency to lend in herds, has the potential to influence the degree of systemic risk in the economy. Using the measures outlined in Sections 3.1 through 3.3, this can easily be accomplished by running the following regressions:

$$HM_{i,t} = \mu_0 P_{\text{before}} + \mu_1 P_{\text{low}} + \mu_2 P_{\text{after}} + \mu_3 Z_t + \varepsilon_{i,t}, \quad (9)$$

where  $HM_{i,t} \in \{L\hat{S}V_{i,t}, \hat{\rho}(p_{i,t}, p_{i,t-1}), \hat{\gamma}_{0,t}\}$  is the chosen measure of herding,  $P_\tau$ , with  $\tau \in \{\text{before, low, after}\}$ , are binary variables indicating the time periods before, during, and after the low policy interest rate period in the mid 2000s, respectively, and  $\mu_k$ , with  $k \in \{0, 1, 2, 3\}$  are the corresponding regression coefficients.<sup>3</sup> This analysis also allows us to control for aggregate effects, other than monetary policy, which are collected in the vector  $Z_t$ . Finally,  $\varepsilon_{i,t}$  is a random variable with  $E[\varepsilon_{i,t}] = 0$  and, consequently,  $E[HM_{i,t}|\tau = \text{before}, Z_t] = \mu_0$ ,  $E[HM_{i,t}|\tau = \text{low}, Z_t] = \mu_1$ , and  $E[HM_{i,t}|\tau = \text{after}, Z_t] = \mu_2$ . Within this framework it is straight forward to test the null hypotheses  $H_0^{\text{bef}} : \mu_0 = \mu_1$  as well as  $H_0^{\text{aft}} : \mu_1 = \mu_2$  against the alternatives of non-equality. Thus, the failure to reject these hypotheses would indicate that there was a significantly higher degree of bank herding during the low interest period in the mid 2000s.

## 5 Data

Our empirical analysis draws on four main data sources. Most details about these data sources are described and discussed extensively in the data section of Gaggli & Valderama (2013). We will only briefly summarize the main features of the dataset here.

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<sup>3</sup>Note that regression model (9) will only be individual specific for the dependent variable  $HM_{i,t} = L\hat{S}V_{i,t}$  while for the cases of  $HM_{i,t} \in \{\hat{\rho}(p_{i,t}, p_{i,t-1}), \hat{\gamma}_{0,t}\}$  the model collapses to a pure time series regression. For the sake of brevity we wrote model (9) in the general form only.



First, to capture heterogeneity across borrowers, we draw on annual balance sheets and income statements from an unbalanced panel of 8,653 Austrian firms over the years 1993 to 2009. This data is collected by the Austrian National Bank (OeNB) in the course of its refinancing activities and is stored in a balance sheet register (BILA). On top of usual balance sheet items, the dataset also records various auxiliary characteristics, such as the firms' age, legal form, industry classification, and the number of employees. The sample consists of relatively large business whose total assets range from 5 million to 20 billion Euros. About 72% of the firms in the sample are limited liability companies (GmbH) and 36% operate in the manufacturing sector. On average, firms' liabilities amount to 66% of total assets while bank-liabilities make up 26% of total assets.

In addition to annual firm specific information, the OeNB collects monthly data on individual loans between Austrian firms and banks in its central credit register (GKE).<sup>4</sup> The sample includes the stocks of credit by Austrian banks to Austrian firms whose total liabilities to Austrian banks exceed EUR 350,000, recorded at monthly frequency. We have access to a matched BILA-GKE sample for the years 2000 through 2009 which covers 316 Austrian banks and 6,815 firms whose detailed characteristics are also recorded in BILA. Detailed summary statistics for this matched sample are reported and discussed in the data section of Gaggl & Valderrama (2013).

Furthermore, EMU member states are required to collect detailed balance sheet information on their monetary and financial institutions (MONSTAT).<sup>5</sup> Unfortunately, due to Austrian data confidentiality restrictions, we were not allowed to match this detailed bank-level information at the bank level to our sample of matched firm-bank pairs. How-

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<sup>4</sup>Details on the data collection criteria can be found in the official standards for reporting to the central credit register (Großkreditevidenz), which are publicly available at <http://www.oenb.at/>. The individual data on both firms and banks are strictly confidential. Access to the anonymized individual data, as employed in this study, is granted by the OeNB's credit department on a case-by-case basis. Contact information can be found at [www.oenb.at/](http://www.oenb.at/).

<sup>5</sup>For details see [http://europa.eu/legislation\\_summaries/economic\\_and\\_monetary\\_affairs/institutional\\_and\\_economic\\_framework/125044\\_en.htm](http://europa.eu/legislation_summaries/economic_and_monetary_affairs/institutional_and_economic_framework/125044_en.htm).

ever, we were allowed to merge discrete categories of key bank-level characteristics (e.g., size, capitalization, etc.) that vary on an annual frequency. Summary statistics of these bank characteristics are reported in the data section of Gagli & Valderrama (2013).

Finally, all aggregate data are drawn from the ECB's statistical data warehouse.<sup>6</sup>

## 6 Empirical Results

This section summarizes the empirical results based on the methodology described in Sections 3 and 4.

### 6.1 Excess Variability in Mean Actions

As a first step we perform LSV's original test for the period 2000m2 – 2008m8. Columns (1), (3), and (5) in Panel A of Table 1 illustrate that the degree of bank-herding during this period as a whole was small but significant at the firm, industry, and risk-rating level. This baseline analysis suggests that the degree of cross sectional variation in the concentration of lending activity was on average 1% higher than expected under the null hypothesis of no herding. This result is qualitatively and quantitatively in line with the existing literature on both investor as well as bank herding (e.g., Lakonishok et al. 1992, Sias 2004, Uchida & Nakagawa 2007, Choi & Sias 2009).

Moreover, Figure 1 illustrates that the degree of herding varies substantially over time. The figure plots time series of quarterly averages and the corresponding 95% confidence intervals (based on cross-sectional variation at each point in time). Generally, the graphs illustrate that there is significant variation in the degree of bank herding over time. In particular the variance on the firm-level is smallest while it is largest when looking at risk classes.

Notice further that these plots suggest a significant temporary upswing in the degree

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<sup>6</sup>See <http://sdw.ecb.europa.eu/>.

of herding for all three categories (firms, industries, risk classes) between the years 2003 and 2005. To formally test whether the degree of bank herding was higher during the low policy interest rate period of 2003q3 – 2005q3 we analyze regression model (9). Columns (2), (4), and (6) in Panel A of Table 1 report the coefficient estimates  $(\hat{\mu}_0, \hat{\mu}_1, \hat{\mu}_2)$  and the associated standard errors under the restriction that  $\mu_3 = 0$ . The horizontal lines in Figure 1 plot these coefficient estimates. Thus, the analysis illustrates that the degree of herding was significant for all three sub-periods  $\tau \in \{\text{before, low, after}\}$  and that the average degree of herding was highest during the period 2003q3 – 2005q3 for all categories (firms, industries, and risk classes). However, these sub-period averages were only statistically significantly different from each other for the case of herding into firms and risk classes but not for herding into industries.

The original LSV test neither allows us to directly control for borrower specific effects nor bank specific effects. This is a serious shortcoming as it is quite likely that excess correlation in lending concentration may stem from correlated signals both on the firm as well as on the bank level. One way to partially address this concern is to split banks into different groups according to some bank characteristic. Panels B and C of Table 1 report the estimated degrees of herding when splitting banks into a group of small and large banks.<sup>7</sup> While the magnitude of the estimates changes slightly, the general patterns are broadly consistent across these two groups of banks. Nevertheless, one particular result is worth noting. It turns out that the degree of herding into risk classes is most pronounced among the group of large banks. This seems plausible as more of the large banks are publicly listed and thus their assets split by risk class are readily available from quarterly financial statements. In general the results for the classic LSV test are broadly consistent with both the literature on institutional investor herding (Lakonishok et al. 1992) as well as that on herding in bank lending (Uchida & Nakagawa 2007). However,

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<sup>7</sup>We define “large” as size class 3 and “small” as size classes 1-2. Summary statistics for these size classes are reported in the data section of Gaggli & Valderrama (2013).

the apparent sensitivity of the results with respect to bank characteristics suggests that accurately controlling for both bank and firm heterogeneity is an important extension.

## 6.2 Temporal Correlation in the Fraction of Lenders

In order to separate correlated from social/strategic interaction effects in a more direct manner we next analyze regression model (6), based on Sias (2004). Like the original LSV test, this model still uses the degree of lending concentration aggregated to the borrower level as the main dependent variable. However, we now directly analyze the temporal correlation in this variable across borrowers and can thus condition on borrower specific effects. Furthermore, this approach also allows us to decompose this correlation into the correlation due to banks following their own lending activity and the portion due to following other banks. As this decomposition is based on the unconditional correlation only, we start with this exercise and then move on to the estimates conditional on borrower specific characteristics.

The first column of Figure 2 plots the estimates for the unconditional correlation  $\rho(p_{i,t}, p_{i,t-1})$  as well as averages based on the time series variation in these estimates. Column 2 of Figure 2 decomposes this correlation into the component due to banks following their own lending activity and the portion due to following other banks. One can see that there is generally a significant degree of positive correlation with past lending of other banks. Thus, like the original LSV test, this alternative test also suggests a significant degree of herd behavior in business lending markets. Furthermore, this test also agrees with the original LSV test in that it suggests a higher degree of herd behavior into industries and risk-classes than into individual borrowers. The second column of Figure 2 also reveals an interesting pattern regarding the relative importance of herding versus relationship banking. If a bank is in a close relationship with its borrowers then it is likely that past lending/borrowing between them will be an important predictor for fu-

ture lending/borrowing. We see that the autocorrelation component makes up the bulk of the overall correlation at the firm level. Once we move to bigger groupings of borrowers, namely industries and risk-classes, we see that the herding component becomes more and more important. Interestingly, when considering risk-classes, herding (as opposed to autocorrelation) makes up the bulk of the action, especially in the period between 2003q3-2005q3.

Like the original LSV test, the analysis in this section thus far did not take into account heterogeneity at the borrower level. We follow Sias (2004) and additionally estimate  $\beta_{0,t}$  in model (6) conditional on both the past returns from borrower  $i$  (proxied by the borrowers' average real interest rate paid on debt) as well as the borrowers expected probability of default.<sup>8</sup> Table 3 reports time series averages of the resulting estimates. Like Sias (2004) within the context of investor herding, we find that controlling for these two borrower characteristics does not significantly change the results. This gives more confidence to the conclusion that the temporal correlation in lender concentration is indeed measuring herd behavior as opposed to correlated effects due to fundamentals (like past yield or borrowers' default risk).

Nevertheless, the analysis following Sias (2004) does not control for lender heterogeneity. The analysis reported in the next section attempts to accommodate this concern.

### 6.3 Lender-Borrower Level Regressions

To rule out correlated effects (as opposed to peer effects), due to observed or unobserved heterogeneity/shocks on the borrower and lender level, we analyze the borrower-lender-time level model given in equation (8). This model is a variant of the well known "linear in means" model and directly measures the correlation between lenders current actions and other lenders' actions in the recent past. We modify the classic "linear in

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<sup>8</sup>The measures employed for these two borrower characteristics are described in detail in Gaggi & Valderrama (2013).

means” analysis (Manski 2000) in two ways: First, since we have access to longitudinal data we can directly capture the sequential nature of banks’ actions and estimate the effect of banks’ current actions on other banks’ average actions in the recent past. Second, we have access to a “long” panel, i.e. the number of time periods is sufficiently large to conduct asymptotic inference on the dynamics of the cross-sectional correlations based on time series variation. Thus, to analyze this long panel we will use an approach similar to the one applied in Section 3.2. We will first estimate  $\hat{\gamma}_{t,0}$  using cross-sectional variation and will then exploit the time series variation in these estimates to conduct inference on the average peer effect within business lending. This approach also allows us to analyze whether banks were lending in herds to a larger extent during 2003q3-2005q3.

The vector of observable firm characteristics,  $X_{i,t}$ , includes measures such as firm’s average real interest rate, the ratio of accounts payable to sales, the ratio of profits to expenditure on labor, ordinary business income as a fraction of total assets, and annual sales growth.<sup>9</sup> Observable bank characteristics,  $Y_{b,t}$ , are the bank’s market share in business lending, the bank’s capitalization, and the bank’s cash as a fraction of total assets. In principle either of these vectors could include fixed effects. However, since our first stage regression only exploits cross-sectional variation we cannot have both firm and bank fixed effects at the same time. Since we have access to a rich set of firm characteristics (see Gaggl & Valderrama (2013)) but our bank characteristics are only very crude, and since the sample consists of many more firms than banks, we choose to include bank fixed-effects and control for observable firm characteristics only. Furthermore, since the goal is to estimate banks’ actions that are independent from observable borrower information, this is a reasonable specification. It turns out that both a specification with and without bank fixed-effects produces a virtually identical time series for  $\hat{\gamma}_{t,0}$ .

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<sup>9</sup>The complete list of firm-level characteristics is described in detail in Gaggl & Valderrama (2013). We employ the same characteristics as we use to estimate each borrower’s ex-ante expected default rate in Gaggl & Valderrama (2013).

In the second stage, we then conduct inference based on the time series model (9). Figure 3 plots this time series of the estimated cross-sectional degrees of herding,  $\hat{\gamma}_{t,0}$ , at the firm, industry, as well as risk-class level. Again, as reported in Table 4, even after controlling for both lender and borrower level heterogeneity, we detect a significant degree of herding throughout the period 2000-2008. In particular, we find that the average bank increased lending to a particular borrower by about EUR 116 if average lending by other banks to this borrower increased by EUR 1000 in the past month. This suggests that, on average, a given bank matches 11.6% of its competitors' lending to a given borrower, independent of fundamentals.

Finally, Table 4 reveals that, while herding appears to be significant throughout 2000-2008 for all categories we only detect a significant increase in herding throughout 2003q3-2005q3 for the analysis at the risk-rating level. This confirms the general patterns apparent from the analysis using LSV's and Sias's (2004) tests but suggests that the apparent upswings during 2003q3-2005q3 at the firm and industry level seem to be driven by cross-sectional heterogeneity and are not due to aggregate effects such as the stance of monetary policy. The most likely explanation for this result are demand effects at the firm level. Including firm characteristics such as sales growth and interest rates paid controls for credit demand and thus the remaining variation in observed lending is likely to reflect supply side decisions. This suggests that a more pronounced tendency to lend in herds throughout 2003q3-2005q3 only existed with respect to risk classes.

## 7 Concluding Remarks

Understanding strategic interactions among lenders is an important component in the quest to detect the root causes of systemic risk within lending markets. If banks systematically imitate each others' actions, this creates externalities which are multiplied in the aggregate. Within the general context of social interactions Glaeser et al. (2003) call this

phenomenon the “social multiplier”. They identify significant social multipliers in the context of the impact of education on wages, the impact of demographics on crime, and group memberships among Dartmouth roommates. The same phenomenon is likely to be present among groups of lenders and the aggregate effect of their individual lending decisions.

Thus, when studying the effects of systemic risk (an aggregate phenomenon) based on individuals’ decisions, under the assumption that individuals act independently, one may seriously underestimate the aggregate effect. This concern is of particular importance within this specific context as systemic risk per definition is a measure of the inherent correlation of individuals’ risk exposure.

Our work in this paper contributes to this question. In a first step, we attempt to quantify the extent to which banks’ direct interactions (through imitation) drive their lending decisions. We find a significant degree to which Austrian banks lent in herds throughout 2000-2008. Thus, a slight deviation in lending policies by one bank may trigger a large aggregate deviation in lending policies (and other aggregate outcomes like the cross-sectional correlation of risk exposure) if other banks follow the bank who initially changed its lending behavior. While we are the first to detect this behavior in the context of business lending throughout 2000-2008, similar results have been found in Japanese lending markets throughout the 1990s (Uchida & Nakagawa 2007, Nakagawa & Uchida 2011). Moreover, Sias (2004) finds that, among various groups of institutional investors (banks, insurance companies, mutual funds, independent advisors), banks have the highest tendency to invest in herds (both within the group of banks and other groups of institutional investors). Moreover, his analysis reveals that the degree to which banks follow investment decisions within the group of their own peers (i.e. other banks) is the most pronounced compared to other investor types. It is thus not surprising that banks not only herd in terms of their stock picks (e.g. Lakonishok et al. 1992, Sias 2004) but also in



business lending.

Moreover, our analysis also addresses the question as to whether the degree to which banks move in herds may have changed over time throughout the period 2000-2008. We find evidence that banks' tendency to herd into particular risk classes significantly increased within the period 2003q3-2005q3, relative to the remaining periods throughout 2000-2008. This change precisely coincides with the period during which we find a significant increase in risk-taking by the average bank, within the same sample, that was triggered by the particular low interest rate policy conducted during this time (see Gaggi & Valderrama 2013). This finding is consistent with the hypothesis that a low expected cost of future non-performing loans (either through cheap refinancing, or an expected bailout) may increase the strategic complementarities between banks' actions and in turn boost an individually rational incentive to act collectively (Rajan 1994, Farhi & Tirole 2012).

The analysis in this paper raises several interesting questions to be addressed in future research. First, if the individual level peer effects identified in our analysis lead to a "social multiplier" effect (Glaeser et al. 2003) within the context of business lending, how big is this multiplier? Second, the full lender-borrower-time level analysis in this paper is based on a very particular "linear in means" econometric specification. However, the available longitudinal data should allow for richer specifications of the dynamic interactions between lenders. In particular, panel VAR, cointegration, and dynamic clustering techniques could be useful tools in this context. We leave the development of such models to future research.

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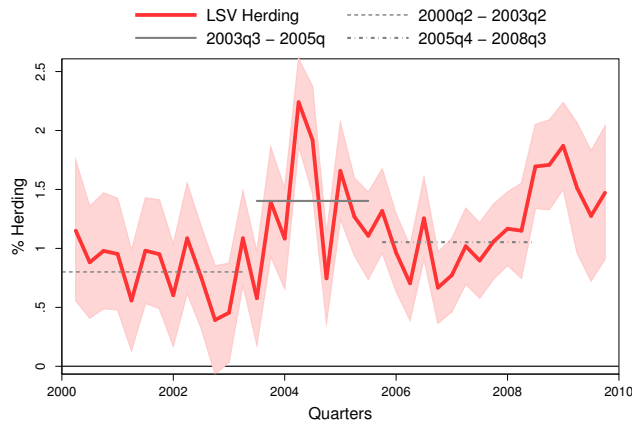
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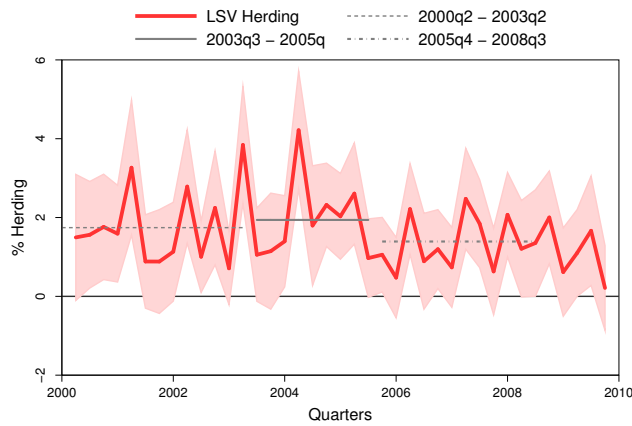
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Figure 1: The LSV measure for Austrian Business Lending: 2000-2010

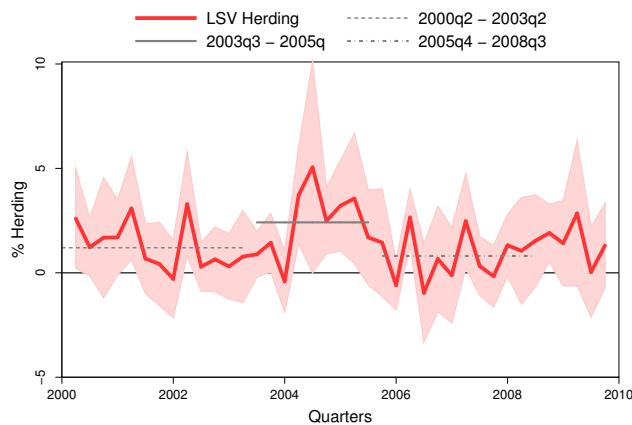
(A) Firm



(B) Industry



(C) Risk Rating



Notes: Confidence bands are based on t-tests for the statistical difference between the sample mean  $\overline{LSV}_t = \frac{1}{T_t} \sum_{i=1}^{T_t} LSV_{i,t}$  and the theoretic mean of 0 under the null hypothesis of no herding, where  $LSV_{i,t}$  is defined in equation (2). The standard errors used to construct the confidence bands are clustered on categories (firm, industry, risk class). We restrict inference to the period 2000m2–2008m8 and explicitly exclude the period after Lehman Brothers' bankruptcy.

Table 1: The LSV measure for Austrian Business Lending: 2000 - 2008

	Firm		Industry		Risk Rating	
Dependent Variable: $LSV_{i,t}$	(1)	(2)	(3)	(4)	(5)	(6)
<b>Panel A: All Banks</b>						
2000q2 - 2008q3	0.0108*** (0.000665)		0.0166*** (0.00219)		0.0136*** (0.00274)	
$P_{\text{before}}$ : 2000q2 - 2003q2		0.00801*** (0.00105)		0.0174*** (0.00313)		0.0120** (0.00474)
$P_{\text{low}}$ : 2003q3 - 2005q3		0.0140*** (0.00106)		0.0194*** (0.00316)		0.0241*** (0.00474)
$P_{\text{after}}$ : 2005q4 - 2008q3		0.0105*** (0.000791)		0.0139*** (0.00259)		0.00809** (0.00314)
F-test p-values						
$H_0$ : P1=P2		0.0000***		0.5983		0.0394**
$H_0$ : P2=P3		0.0011***		0.0728*		0.0162**
$H_0$ : P1=P3		0.0404**		0.3195		0.4814
Obs.	169874	169874	7015	7015	2037	2037
Clusters	4248	4248	78	78	21	21
F Stat.	263.9	91.44	57.47	19.38	24.77	12.77
<b>Panel B: Small Banks</b>						
2000q2 - 2008q3	0.0265*** (0.00175)		0.0169*** (0.00300)		0.0155*** (0.00259)	
$P_{\text{before}}$ : 2000q2 - 2003q2		0.0193*** (0.00253)		0.0171*** (0.00459)		0.0136*** (0.00449)
$P_{\text{low}}$ : 2003q3 - 2005q3		0.0281*** (0.00263)		0.0195*** (0.00423)		0.0203*** (0.00543)
$P_{\text{after}}$ : 2005q4 - 2008q3		0.0303*** (0.00221)		0.0148*** (0.00332)		0.0144*** (0.00359)
F-test p-values						
$H_0$ : P1=P2		0.0053***		0.6375		0.3847
$H_0$ : P2=P3		0.3931		0.2324		0.3104
$H_0$ : P1=P3		0.0004***		0.6514		0.8970
Obs.	40316	40316	5654	5654	1797	1797
Clusters	1227	1227	70	70	21	21
F Stat.	229.4	80.02	31.62	10.75	35.88	12.45
<b>Panel C: Large Banks</b>						
2000q2 - 2008q3	0.00522*** (0.000734)		0.0194*** (0.00270)		0.0242*** (0.00536)	
$P_{\text{before}}$ : 2000q2 - 2003q2		0.00333*** (0.00120)		0.0173*** (0.00360)		0.0151** (0.00603)
$P_{\text{low}}$ : 2003q3 - 2005q3		0.00838*** (0.00118)		0.0219*** (0.00388)		0.0316*** (0.00681)
$P_{\text{after}}$ : 2005q4 - 2008q3		0.00447*** (0.000848)		0.0195*** (0.00335)		0.0293*** (0.00621)
F-test p-values						
$H_0$ : P1=P2		0.0003***		0.3282		0.0073***
$H_0$ : P2=P3		0.0012***		0.5211		0.7165
$H_0$ : P1=P3		0.4047		0.5727		0.0137**
Obs.	127367	127367	6826	6826	2009	2009
Clusters	3210	3210	76	76	21	21
F Stat.	50.56	20.01	51.54	17.32	20.36	10.84

Notes: The table reports sample averages based on regression model (9) with  $HM_{i,t} = LSV_{i,t}$  and  $\mu_3 = 0$ . Standard errors are clustered on categories (firm, industry, risk class) and reported in parentheses underneath the coefficients. Significance levels are indicated by \* for  $p < 0.1$ , \*\* for  $p < 0.05$ , and \*\*\* for  $p < 0.01$ . We restrict inference to the period 2000m2–2008m8 and explicitly exclude the period after Lehman Brothers' bankruptcy.

Table 2: Temporal Correlation in Lending Concentration: 2000 - 2008

Panel A: Firms	$\rho(p_{i,t}, p_{i,t-1})$		Decomposition			
			Own		Other	
2000q2 - 2008q3	0.158*** (0.00821)		0.115*** (0.00595)		0.0392*** (0.00295)	
P <sub>before</sub> : 2000q2 - 2003q2	0.153*** (0.0118)		0.116*** (0.00909)		0.0349*** (0.00385)	
P <sub>low</sub> : 2003q3 - 2005q3	0.187*** (0.0189)		0.130*** (0.0133)		0.0520*** (0.00695)	
P <sub>after</sub> : 2005q4 - 2008q3	0.143*** (0.00835)		0.104*** (0.00752)		0.0342*** (0.00238)	
F-test p-values						
$H_0 : P_{\text{before}} = P_{\text{low}}$	0.1217		0.3968		0.0319**	
$H_0 : P_{\text{low}} = P_{\text{after}}$	0.0340**		0.0943*		0.0169**	
$H_0 : P_{\text{low}} = P_{\text{after}}$	0.4968		0.3032		0.8744	
Obs.	102	102	102	102	102	102
F Stat.	371.9	182.3	376.0	148.1	176.4	112.1
Panel B: Industry						
2000q2 - 2008q3	0.241*** (0.0194)		0.131*** (0.0131)		0.122*** (0.0114)	
P <sub>before</sub> : 2000q2 - 2003q2	0.268*** (0.0330)		0.155*** (0.0251)		0.125*** (0.0188)	
P <sub>low</sub> : 2003q3 - 2005q3	0.273*** (0.0340)		0.138*** (0.0179)		0.144*** (0.0205)	
P <sub>after</sub> : 2005q4 - 2008q3	0.184*** (0.0250)		0.0987*** (0.0184)		0.101*** (0.0173)	
F-test p-values						
$H_0 : P_{\text{before}} = P_{\text{low}}$	0.9088		0.5745		0.5160	
$H_0 : P_{\text{low}} = P_{\text{after}}$	0.0330**		0.1360		0.1093	
$H_0 : P_{\text{low}} = P_{\text{after}}$	0.0462**		0.0715*		0.3355	
Obs.	102	102	102	102	102	102
F Stat.	154.6	60.23	100.5	43.75	114.4	41.54
Panel C: Risk Class						
2000q2 - 2008q3	0.254*** (0.0342)		0.126*** (0.0301)		0.158*** (0.0375)	
P <sub>before</sub> : 2000q2 - 2003q2	0.280*** (0.0340)		0.117*** (0.0247)		0.203*** (0.0318)	
P <sub>low</sub> : 2003q3 - 2005q3	0.302*** (0.0664)		0.0626 (0.0501)		0.275*** (0.0514)	
P <sub>after</sub> : 2005q4 - 2008q3	0.188*** (0.0717)		0.184*** (0.0692)		0.0164 (0.0707)	
F-test p-values						
$H_0 : P_{\text{before}} = P_{\text{low}}$	0.7690		0.3305		0.2387	
$H_0 : P_{\text{low}} = P_{\text{after}}$	0.2471		0.1586		0.0036***	
$H_0 : P_{\text{low}} = P_{\text{after}}$	0.2533		0.3681		0.0179**	
Obs.	102	102	102	102	102	102
F Stat.	55.11	32.48	17.50	10.49	17.81	23.41

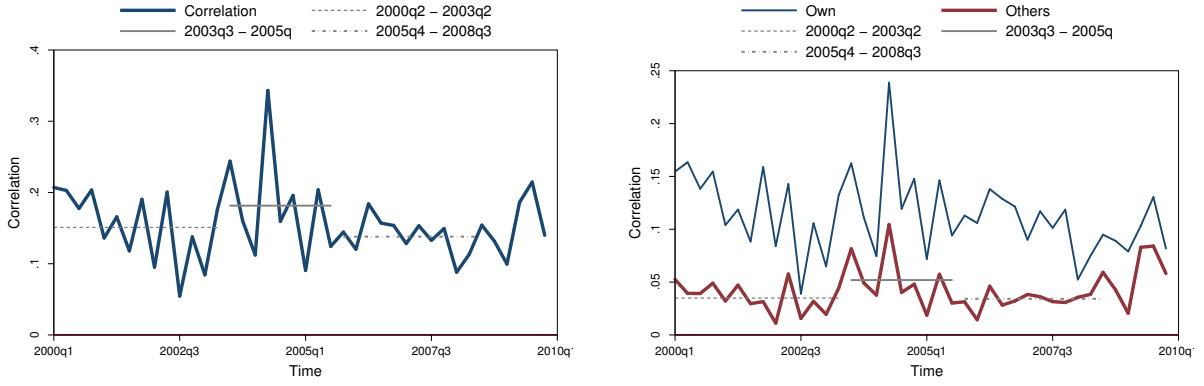
Notes: The first two columns display time series (sub-)sample averages (based on regression model (9) with  $HM_{i,t} = \hat{\rho}(p_{i,t}, p_{i,t-1})$  and  $\mu_3 = 0$ ) of the coefficient estimates  $\hat{\beta}_{0,t} = \hat{\rho}(p_{i,t}, p_{i,t-1})$  based on regression model (6) with  $\beta_{1,t} = 0$ . Columns 3-4 report (sub-)sample averages for the two separate components (due to following ones "own" lending and due to following the lending activity of "other" banks) derived in equation (7). Newey & West (1987) standard errors based on time series variation in  $\hat{\rho}(p_{i,t}, p_{i,t-1})$  are reported in parentheses underneath the coefficients. Significance levels are indicated by \* for  $p < 0.1$ , \*\* for  $p < 0.05$ , and \*\*\* for  $p < 0.01$ . We restrict inference to the period 2000m2-2008m8 and explicitly exclude the period after Lehman Brothers' bankruptcy.

Table 3: Conditional Temporal Correlation in Lending Concentration: 2000 - 2008

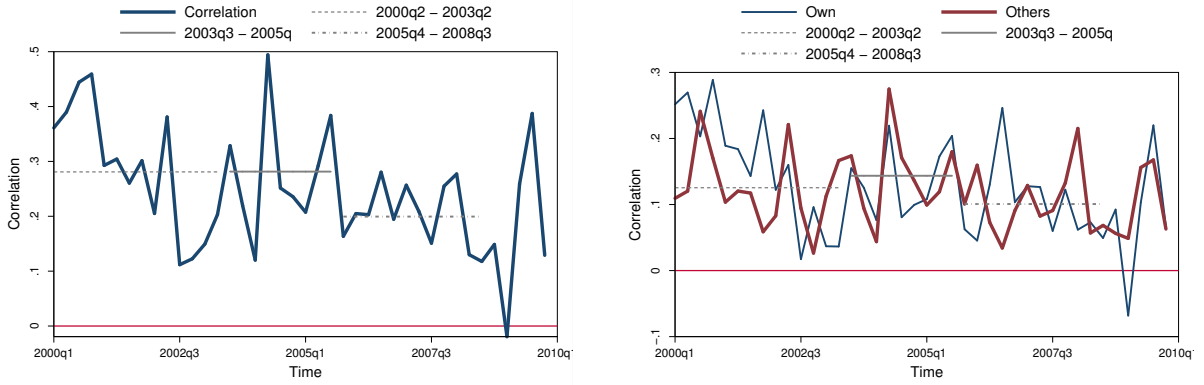
	Firm		Industry		Risk Rating	
Dependent Variable: $\rho(p_{i,t}, p_{i,t-1}   \bar{X}_{i,t})$						
Panel A: Conditional on Past Return	(1)	(2)	(3)	(4)	(5)	(6)
2000q2 - 2008q3	0.156*** (0.00819)		0.229*** (0.0190)		0.237*** (0.0328)	
$P_{\text{before}}$ : 2000q2 - 2003q2		0.146*** (0.0113)		0.241*** (0.0344)		0.248*** (0.0356)
$P_{\text{low}}$ : 2003q3 - 2005q3		0.190*** (0.0185)		0.256*** (0.0309)		0.279*** (0.0654)
$P_{\text{after}}$ : 2005q4 - 2008q3		0.141*** (0.00872)		0.194*** (0.0267)		0.193*** (0.0673)
F-test p-values						
$H_0$ : $P_{\text{before}} = P_{\text{low}}$		0.0471**		0.7501		0.6877
$H_0$ : $P_{\text{low}} = P_{\text{after}}$		0.0194**		0.1261		0.3512
$H_0$ : $P_{\text{low}} = P_{\text{after}}$		0.7360		0.2825		0.4653
Obs.	102	102	102	102	102	102
F Stat.	362.3	175.5	145.3	55.38	52.40	25.04
Panel B: Conditional on Past Return and PD						
2000q2 - 2008q3	0.152*** (0.00798)		0.256*** (0.0197)		0.225*** (0.0336)	
$P_{\text{before}}$ : 2000q2 - 2003q2		0.141*** (0.0118)		0.263*** (0.0364)		0.232*** (0.0397)
$P_{\text{low}}$ : 2003q3 - 2005q3		0.182*** (0.0169)		0.285*** (0.0358)		0.233*** (0.0840)
$P_{\text{after}}$ : 2005q4 - 2008q3		0.143*** (0.00994)		0.226*** (0.0269)		0.212*** (0.0572)
F-test p-values						
$H_0$ : $P_{\text{before}} = P_{\text{low}}$		0.0533*		0.6729		0.9950
$H_0$ : $P_{\text{low}} = P_{\text{after}}$		0.0505*		0.1865		0.8349
$H_0$ : $P_{\text{low}} = P_{\text{after}}$		0.9373		0.4169		0.7706
Obs.	102	102	102	102	102	102
F Stat.	364.8	155.9	168.6	60.85	44.97	18.41

Notes: The table reports time series (sub-)sample averages (based on regression model (9) with  $HM_{i,t} = \hat{\rho}(p_{i,t}, p_{i,t-1} | \bar{X}_{i,t-1})$ ) of the coefficient estimates  $\hat{\beta}_{0,t} = \hat{\rho}(p_{i,t}, p_{i,t-1} | \bar{X}_{i,t-1})$  based on regression model (6). Newey & West (1987) standard errors based on time series variation in  $\hat{\rho}(p_{i,t}, p_{i,t-1})$  are reported in parentheses underneath the coefficients. Significance levels are indicated by \* for  $p < 0.1$ , \*\* for  $p < 0.05$ , and \*\*\* for  $p < 0.01$ . We restrict inference to the period 2000m2–2008m8 and explicitly exclude the period after Lehman Brothers' bankruptcy.

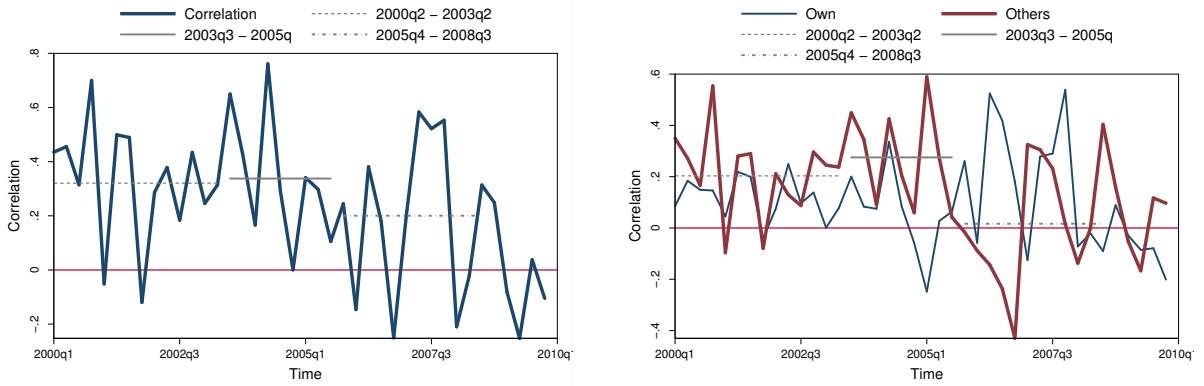
Figure 2: Temporal Correlation in Lending Concentration: 2000-2010  
 (A) Firm



(B) Industry



(B) Risk-Class



Notes: The first column displays time series plots of the coefficient estimates  $\hat{\beta}_{0,t} = \hat{\rho}(p_{i,t}, p_{i,t-1})$  based on regression model (6) with  $\beta_{1,t} = 0$ . The second column plots the time series for the two separate components (due to following ones “own” lending and due to following the lending activity of “other” banks) derived in equation (7). The horizontal lines in the first column plot the unconditional sample averages of  $\hat{\beta}_{0,t} = \hat{\rho}(p_{i,t}, p_{i,t-1})$  while the second column plots the unconditional averages of the contribution due to following “other” banks’ lending as reported in Table 2. We restrict inference to the period 2000m2–2008m8 and explicitly exclude the period after Lehman Brothers’ bankruptcy.



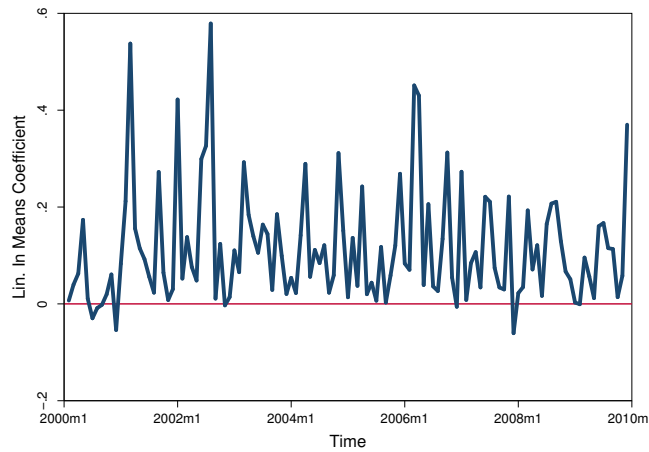
Table 4: Borrower-Lender Level Analysis: 2000 - 2008

	Firm		Industry		Risk Rating	
Dependent Variable: $\hat{\gamma}_{0,t}$						
Panel A: Unconditional Means	(1)	(2)	(3)	(4)	(5)	(6)
2000q2 - 2008q3	0.116*** (0.0122)		0.632*** (0.0860)		0.859*** (0.195)	
$P_{\text{before}}$ : 2000q2 - 2003q2		0.120*** (0.0243)		0.775*** (0.183)		0.312 (0.194)
$P_{\text{low}}$ : 2003q3 - 2005q3		0.0995*** (0.0113)		0.457*** (0.0840)		1.551*** (0.450)
$P_{\text{after}}$ : 2005q4 - 2008q3		0.124*** (0.0197)		0.598*** (0.0593)		0.966*** (0.119)
F-test p-values						
$H_0$ : $P_{\text{before}} = P_{\text{low}}$		0.4452		0.1197		0.0128**
$H_0$ : $P_{\text{low}} = P_{\text{after}}$		0.2776		0.1737		0.2126
$H_0$ : $P_{\text{low}} = P_{\text{after}}$		0.8845		0.3605		0.0049***
Obs.	103	103	103	103	103	103
F Stat.	90.26	47.30	53.92	50.49	19.49	27.13
Panel B: Conditional Means						
2000q2 - 2008q3	0.158*** (0.0309)		0.722*** (0.245)		0.950 (0.744)	
$P_{\text{before}}$ : 2000q2 - 2003q2		0.168*** (0.0321)		0.828*** (0.259)		0.492 (0.451)
$P_{\text{low}}$ : 2003q3 - 2005q3		0.168*** (0.0313)		0.605*** (0.186)		1.734** (0.743)
$P_{\text{after}}$ : 2005q4 - 2008q3		0.218*** (0.0442)		0.819*** (0.228)		1.193** (0.542)
Aggregate Characteristics						
$\Delta$ AT Real GDP Gap	-0.0569** (0.0221)	-0.0780*** (0.0289)	-0.363 (0.253)	-0.339 (0.221)	0.379 (0.374)	-0.0250 (0.347)
AT HICP Inflation	-0.0198* (0.0118)	-0.0327** (0.0135)	-0.0392 (0.0958)	-0.0612 (0.0889)	-0.0508 (0.293)	-0.0967 (0.225)
F-test p-values						
$H_0$ : $P_{\text{before}} = P_{\text{low}}$		0.9801		0.1534		0.0106**
$H_0$ : $P_{\text{low}} = P_{\text{after}}$		0.0359**		0.0888*		0.2042
$H_0$ : $P_{\text{low}} = P_{\text{after}}$		0.1331		0.9336		0.0031***
Obs.	103	103	103	103	103	103
F Stat.	42.07	40.27	43.73	51.30	13.83	18.41

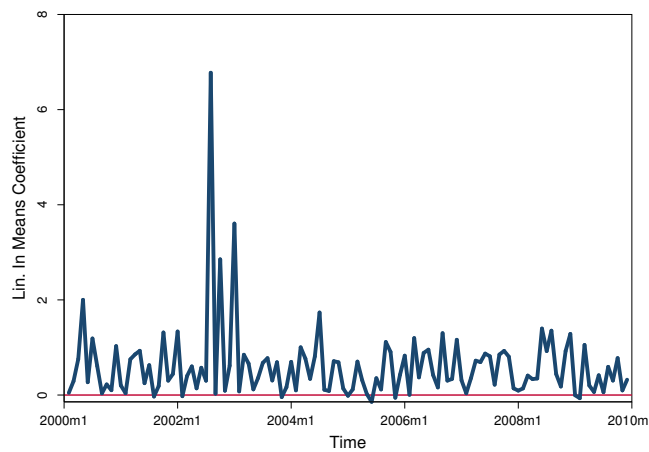
Notes: The table reports coefficient estimates based on regression model (9) with  $HM_{i,t} = \hat{\gamma}_{0,t}$ . Panel A reports the estimates with  $\mu_3 = 0$  while panel B reports estimates conditional on aggregate characteristics  $Z_t$ . Newey & West (1987) standard errors are reported in parentheses underneath the coefficients. Significance levels are indicated by \* for  $p < 0.1$ , \*\* for  $p < 0.05$ , and \*\*\* for  $p < 0.01$ . We restrict inference to the period 2000m2–2008m8 and explicitly exclude the period after Lehman Brothers' bankruptcy.

Figure 3: Borrower-Lender Level Analysis: 2000 - 2010

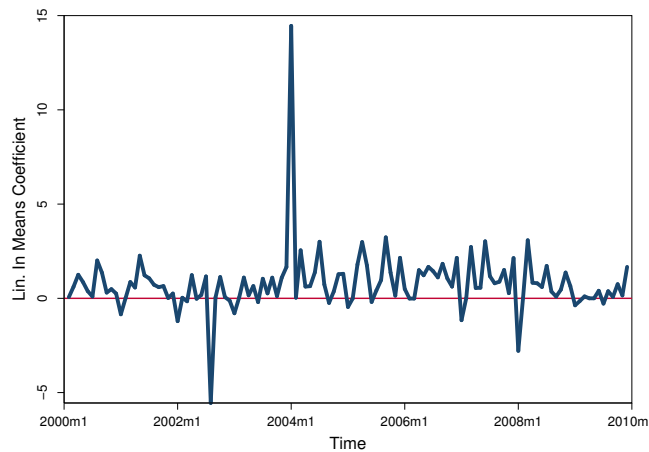
(A) Firm



(B) Industry



(C) Risk Rating



Notes: The solid lines plot quarterly averages of the time series of  $\hat{\gamma}_{0,t}$  based on regression model (8). The horizontal lines correspond to the unconditional sub-period averages (based on monthly estimates of  $\hat{\gamma}_{0,t}$ ) reported in Table 4. We restrict inference to the period 2000m2–2008m8 and explicitly exclude the period after Lehman Brothers' bankruptcy.