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ABSTRACT

Lehman Brothers: What Did Markets Know?*

On September 15, 2008, Lehman Brothers Inc. announced their filing for bankruptcy. The reaction of Lehman's competitors and market participants to this bankruptcy filing announcement provides a unique field experiment of how the insolvency spills over to other financial institutions and how interconnectedness might trigger a financial crisis. Specifically, we analyze transaction prices of major U.S. investment and commercial banks prior to and after the bankruptcy. By decomposing their equity bid-ask spreads, we find evidence that the bankruptcy contributed to increasing adverse selection risk as well as inventory holding risk. Moreover, we find supporting evidence that the degree of competition among market makers did decline. All three components did contribute to a significant rise in transaction costs. Interestingly, the relative contribution of each channel has remained roughly constant. Finally, there is little evidence about insider information within the banking industry just prior to the bankruptcy. In the case of Lehman's stocks the adverse selection component rises in the last days of trading prior to the bankruptcy filing announcement. Moreover, we find no evidence of an increase in the adverse selection component of potential bidders, from which we interpret that the market did not expect a take-over or merger. We explore the robustness of our decomposition by employing volume-synchronized probability of informed trading-measures and impact regressions on prices, quantities, and their respective innovations. In general, we find that information effects are rather short-lived except for the three days prior to the Lehman insolvency.

JEL Classification: D53, G12 and G14
Keywords: adverse selection costs, bid ask spreads, contagion and systemic risk

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1 Introduction

On January 29, 2008, the investment bank Lehman Brothers announced record revenues of approximately \$60 billion and earnings of about \$4 billion. Their share price traded at around \$65.73.

Not even eight months later, on September 15, 2008, Lehman's share price traded at around \$4. On that same day, Lehman Brothers had to announce their filing for bankruptcy. As one might expect, Lehman's competitors in the banking industry reacted strongly to this bankruptcy announcement. Some of the competitors even reacted to Lehman's troubles before the bankruptcy filing announcement. Lehman Brothers itself also already showed strong signs of distress before September 15, 2008. The relative equity bid-ask spreads of Lehman Brothers increased by 40 basis points from the beginning of September 2008 until the day of the bankruptcy filing announcement. Their equity trading volume more than trippled over the course of September 2008. Furthermore, Lehman's stock price decreased from about \$20 in the beginning of September 2008 to \$4 on the day of the bankruptcy announcement. Figures 1 to 5 document this development.

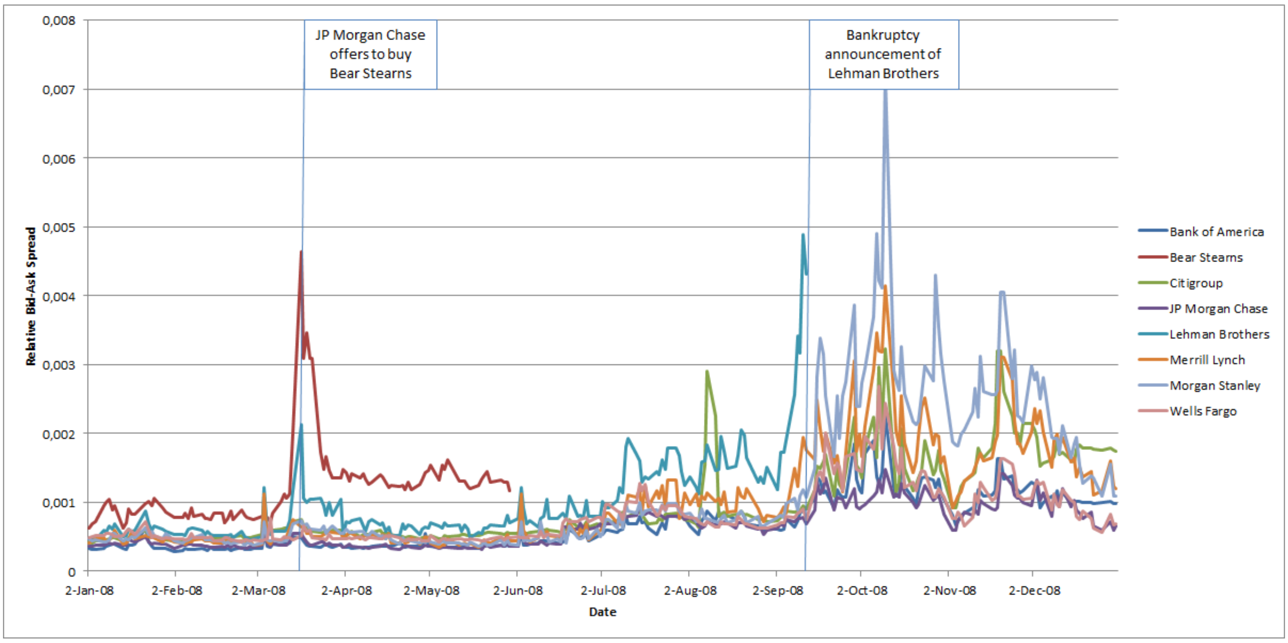

Figure 1: Relative Equity Bid-Ask Spreads, U.S. Banks

If some of the most important measures of liquidity already show strong signs of distress before the actual bankruptcy event, the question is not about whether market participants knew about Lehman's troubles. It is obvious that they did. But the question is, what they had known in the days leading up to the announcement. Did market participants anticipate the bankruptcy or did they trust in the "Too-Big-to-Fail" (TBTF)-

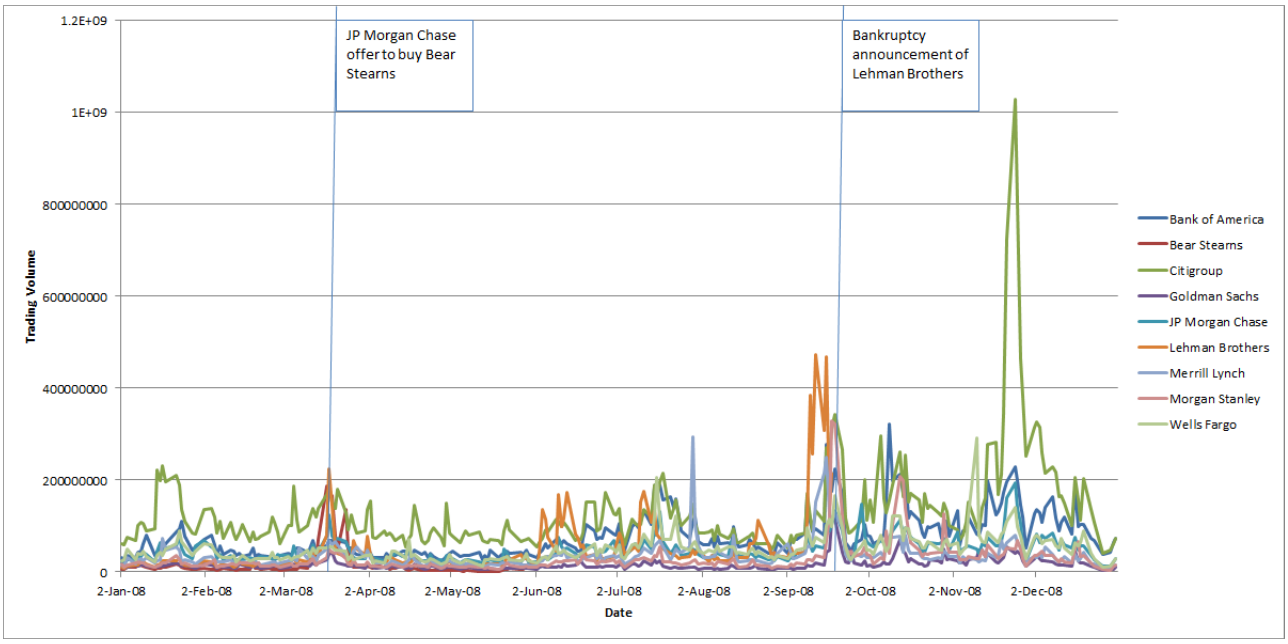

Figure 2: **Volumes, U.S. Banks**: Daily equity trading volume

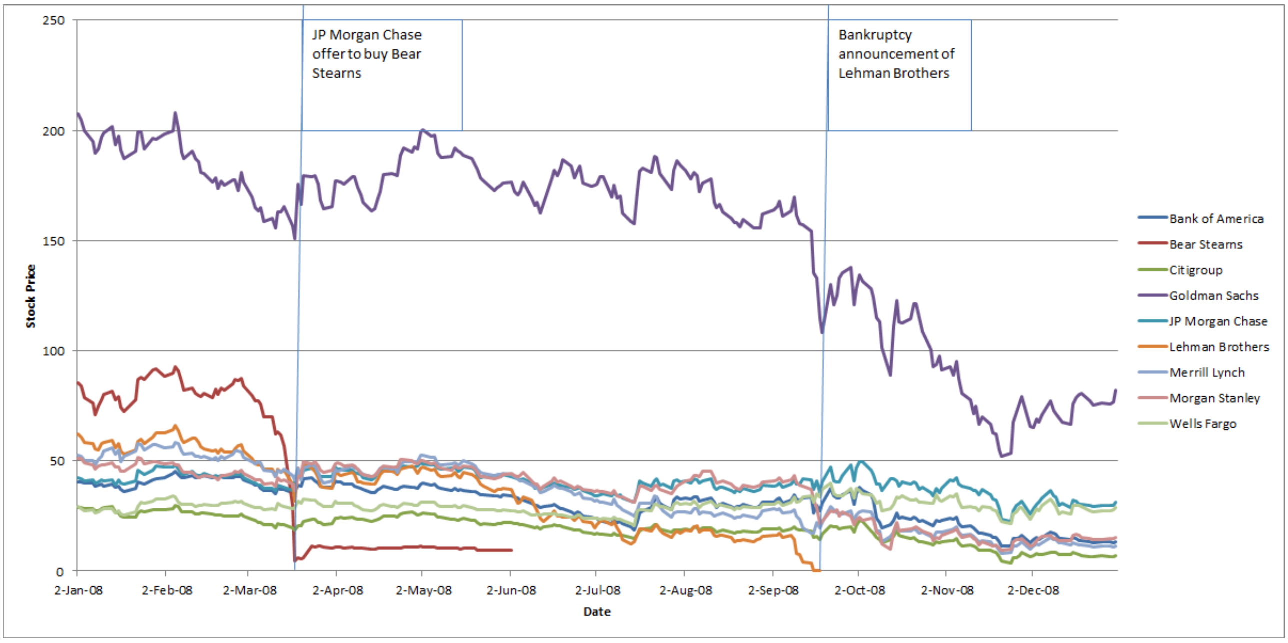

Figure 3: **Stock Prices, U.S. Banks**: Daily stock prices

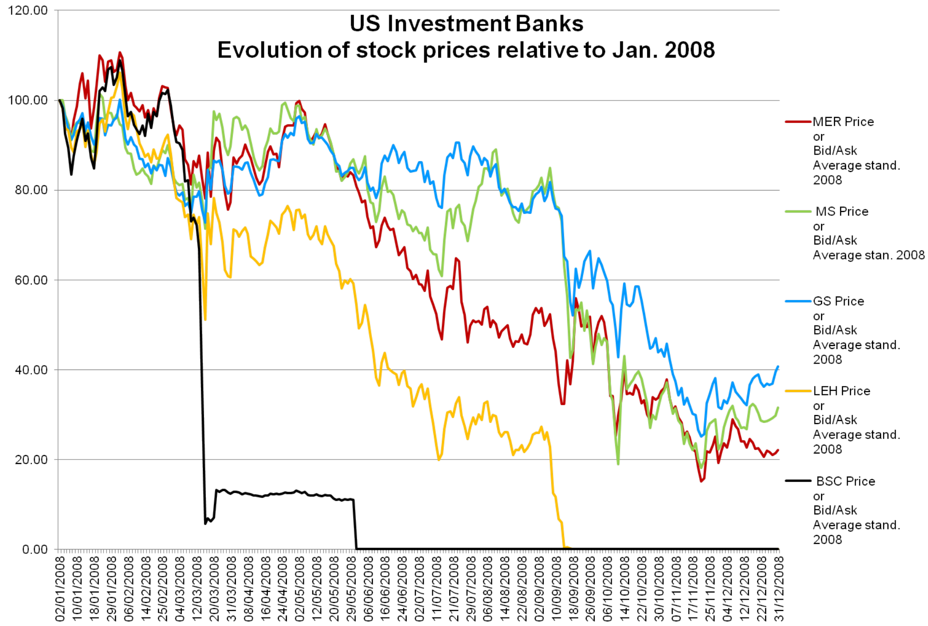

Figure 4: Stock Prices, Investment Banks: Daily stock prices of U.S. investment banks relative to January 1, 2008.

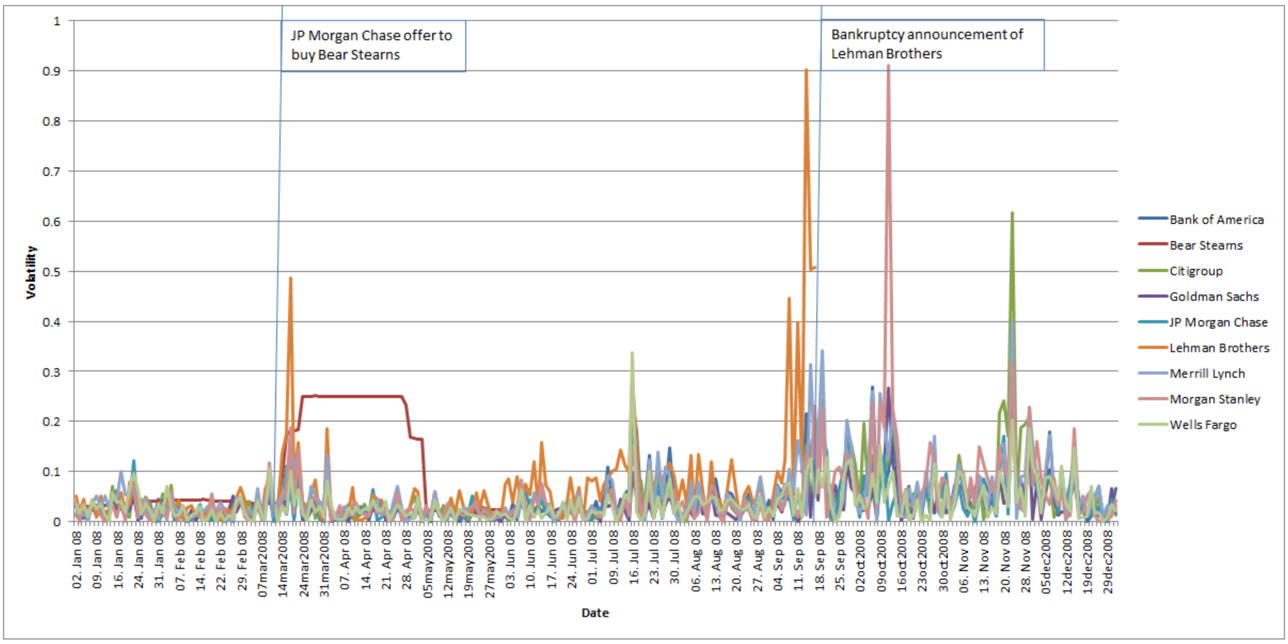

Figure 5: Volatility, U.S. Banks

guarantee of the U.S. governement? Did they expect a merger or take-over as in the case of Bear Stearns in order to save the ailing investment bank? Who could be the bidder? Is there any evidence about market expectations concerning the British bank Barclays PLC as a potential bidder? And was information risk (i.e. adverse selection) or economic risk the driving source behind the dry-up of liquidity at other banks? We try to answer these questions by examining the following overall research question: How did Lehman Brothers bankruptcy announcement impact the price setting behavior of liquidity suppliers? Specifically, we analyze intradaily equity bid-ask spreads of the biggest U.S. banks in 2008 and the British bank Barclays. We expect that if increased informational risk was the driving force behind the dry-up of liquidity, then we should observe a significant shift in the spreads' means. If there had instead existed specific rumors about a possible take-over of Lehman Brothers by another bank, then we should observe a change in the mean of the spreads of that specific bank only. And if it was general economic uncertainty that made market participants withdraw liquidity, then we should observe a mean reversion of spreads in the long run.

In order to figure out what actually happened shortly before and after Lehman's bankruptcy announcement, we use a methodology that decomposes equity bid-ask spreads into so-called adverse selection cost, inventory holding cost, and order processing cost. According to previous research in the field of market microstructure, those three types of costs should predominantly be responsible for the existence of the spread between equity bid and ask prices. The adverse selection cost, thereby, describes how costs attached to adverse selection contribute to price setting (Bagehot (1971), Kyle (1985), and Easley and O'Hara (1987)). Inventory holding costs describe how economic uncertainty contributes to price setting by making liquidity suppliers alert to holding too many toxic securities or too few demanded securities (Ho and Stoll (1981) and Stoll (1978)). The latter, order processing costs, include potential rents to dealers due to market power and general administrative trading costs.

We follow Huang and Stoll (1997), who developed a model of transaction prices and quotes, in order to empirically estimate the three different types of cost. We refine their methodology in order to guarantee positive cost components by applying a logistic transformation to the cost components in the estimation procedure.

Our analysis reveals strong hints for the pending failure only during the last two days before Lehman Brothers filed for bankruptcy. In the case of Lehman Brothers itself, the bid-ask spreads widened in the last weeks of trading and this increase in spreads was largely caused by an increase in adverse selection costs. Regarding a potential takeover of Lehman by a competitor, we find no indication that markets expected other banks to take over the troubled investment bank. Even in the case of Barclays, who entered in merger negotiations the weekend just before the bankruptcy announcement, market prices did not seem to convey any informtation about this.

Ex post, i.e. after the bankruptcy declaration, we see a dramatic increase in transaction costs for all investment and commercial banks (Figure 1). The spreads also do not revert back to their pre-bankruptcy levels even though the U.S. regulators banned short-selling and introduced the so-called "Troubled Asset Relief Program" (TARP). Interestingly, the relative contributions of all three cost components to the spread remained roughly the same throughout the months following Lehman's failure. This suggests that all risk factors, i.e. information and inventory risk, contributed equally to the spillover effects between the different banks.

In the next section we review the circumstances that led to Lehman's bankruptcy announcement, and establish three hypotheses. Section 3 explains the data and methodology with which we try to answer the above posited questions and test our hypotheses. Section 4 presents empirical results, and Section 5 concludes.

2 Historical Framework and Testable Hypotheses

Lehman Brothers was a U.S. investment bank that was deeply involved in the business of securitizing mortgage loans and other collateralized debt obligations during the housing bubble in the run-up to the 2007-2008 financial crisis. Lehman Brothers was particularly aggressive in taking risks on its books. In 2006, "Lehman made the deliberate decision to embark upon an aggressive growth strategy, to take on significantly greater risk, and to substantially increase leverage on its capital. In 2007, as the sub-prime residential mortgage business progressed from problem to crisis, Lehman was slow to recognize the developing storm and its spillover effects upon commercial real estate and other business lines. Rather than pull back, Lehman made the conscious decision to "double down", hoping to profit from a counter-cyclical strategy. As it did so, Lehman significantly and repeatedly exceeded its own internal risk limits and controls." (Report of Anton R. Valukas, Examiner of Chapter 11 Case No. 08-13555 (JMP)). Or, as Lehman's management expressed it at a March 20, 2007, board meeting: "The current distressed environment provided substantial opportunities as in the late 1990s" (Report of Anton R. Valukas, Examiner).

Lehman exceeded its own internal risk limits consequently in the following months. In July 2007, for example, by about $41 billion, in September 2007 by about $608 billion and in January 2008 by about $ 708 billion; just to mention a few of many months in which Lehman exceeded its own risk limits.

As Figure 4 documents, it became obvious that Lehman's strategy had been flawed when Bear Stearns almost collapsed. The markets were in heavy turmoil and, after Bearn Stearns' near collapse, Lehman's stock price lost about half of its value relative to the beginning of 2008. As we now know from the Examiner's report on Lehman Brothers, by June 2008 most components of Lehman's reported liquidity pool had become almost impossible to liquidate. As Anton R. Valukas, the Examiner, reports: "By September 12, two days after [Lehman Brothers] publicly reported a $41 billion liquidity pool, the pool actually contained less than $2 billion of readily monetizable assets."

From Figures 1 to 5 it becomes obvious that Lehman's bid-ask spread, trading volume, and volatility heavily increased from the beginning of September 2008 until its bankruptcy announcement. The failure also triggered a substantial and permanent increase in transaction costs as measured by the relative equity bid-ask spreads at Lehman's competitors. What is the reason behind this increase in trading costs for Lehman Brothers and for other banks after the failure? Is it informational risk due to the fact that insiders were trading on private information about the pending failure, or was it just protection against higher volatility and inventory holding costs?

In order to answer these questions, we try to identify the contribution of each of the following possible drivers of transactions costs: information, inventory holding costs, and order processing costs.

Information:

Privileged information as a source of trading costs may have arisen both prior to Lehman's failure as well as after this event.

Prior to the failure the possibility of informed trading arose in the run-up to the failure, both for Lehman stocks and for stocks of potential bidders for Lehman's assets. If there was speculation about certain bidders, this should be reflected in a larger adverse selection component for those stocks.

The failure itself is informative about the (non-)validity of a potential "Too-Big-to-Fail"-doctrine. The failure of a government bailout exposes the industry to potentially higher risks than originally accounted for. In particular, counter-party risk has risen significantly. Moreover, since banks' balance sheets are exceedingly opaque, it is difficult for outside investors to precisely value the extent of counter-party risk. In this situation one might conjecture that informed trading in financial firms' stocks becomes more profitable, and hence adverse selection costs should increase.

Obviously, since the arguments above are rather specific to the financial sector, these arguments should not be reflected in the trading costs of non-financial stocks.

Inventory Risk:

An increase in counter-party risk also affects inventory risk and should hence be reflected in the inventory holding cost component. This is especially true for financial firms' stocks for which significant interbank liabilities are traded.

Inventory risk should also increase because of the deterioration of general economic conditions, both for financial as well as non-financial companies.

Order Processing Costs:

Lastly, to the extent that investors massively left markets, the exit of market makers or liquidity suppliers and a structural consolidation in the trading sector would tend to reduce the competitive pressure on pricing and allow order processing costs to increase.

Obviously, one would expect that all the hypotheses sketched above would seem to play a role during the financial crisis of 2007-2008. For that reason it is important to assess the relative contribution of each. Would any of the components dominate, and if so, would this be specific to the financial sector or also extend to the non-financial sector?

3 Data and Methodology

In order to analyze the reason behind the increase in equity trading costs, we estimate the costs that liquidity suppliers attach to the above-mentioned information risk, inventory risk, and order processing risk. These costs altogether should make up the total relative bid-ask spread. We call these costs relative adverse selection costs, relative inventory holding costs, and relative order processing costs. In order to compute such costs, we apply the so-called spread decomposition procedure proposed by Roger Huang and Hans R. Stoll in 1997. With the help of this procedure, we are able to estimate the contribution of each cost type to the bid-ask spread.

In the following sub-section, we review the decomposition analysis proposed by Huang and Stoll and describe which transformations we applied to their methodology.

3.1 Methodology

In their work published in 1997 in the Review of Financial Studies, Huang and Stoll developed a model of transaction prices and quotes. We shortly review the model here before we continue with describing the estimation procedure.

In their model, the time frame consists of three separate and sequential events. The stock's value, V_t, is not observeable. The bid and ask quotes are set right after the fundamental stock value has been determined. M_t denotes the quote midpoint and is calculated from the quotes that were posted just before a transaction happened. P_t denotes the price of this transaction. Q_t denotes the so-called trade direction indicator variable. It is 1 if the transaction price P_t exceeds the midpoint M_t, and it is -1 if the transaction price is smaller than the midpoint. It equals zero if the transaction price is equal to the midpoint.

Trade flows are serially correlated as several studies show and as is shown later in the data section. Hence, the conditional expectation of the trade indicator variable Q_t at time *t-1* given Q_{t-2} is shown to be:

$$E(Q_{t-1}|Q_{t-2}) = (1 - 2\pi)Q_{t-2}. \tag{1}$$

Huang and Stoll model the change in the (unobserveable) fundamental stock value as follows, where the parameter π, the probability that the next trade is of opposite sign to the current trade, is allowed to differ from one-half:

$$\Delta V_t = \alpha \frac{S}{2} Q_{t-1} - \alpha \frac{S}{2}(1 - 2\pi)Q_{t-2} + \epsilon_t. \tag{2}$$

Here, S denotes the constant spread and α denotes the percentage of the spread that is associated with adverse selection cost. ϵ_t denotes a public information shock and it is assumed to be serially uncorrelated. Therefore, equation 2 decomposes a stock's value into a private information component, α, and a public information shock component, ϵ_t. The difference between the first and the second term in equation 2 measures the unexpected order flow. Or to put it differently, it measures the surprise in the order flow from what was expected based on the trade before the last trade, and what actually happened in the last trade. This surprise in order flow is solely attached to private information. If there was no (fear of) private information and there were no changes or surprises in order flow, α would be zero and the change in the fundamental value would be completely based on public shocks ϵ_t. So, according to equation 2, a change in the fundamental value of the security can only occur if α and ϵ_t take positive values. A problem with V_t, as already stated above, is that it is not observeable. So, as Huang and Stoll called it, it is a hypothetical construct. The midpoint instead is observeable. Since dealers are assumed to be alert to inventory risk and want to have inventory equilibrium trades (Ho and Stoll (1981) and Stoll (1978)), they set the midpoint relative to V_t. Hence, the midpoint becomes:

$$M_t = V_t + \beta\frac{S}{2}\sum_{i=1}^{t-1} Q_i, \tag{3}$$

where β is the percentage of the spread that is associated with inventory holding cost. $\sum_{i=1}^{t-1} Q_i$ is the cumulated inventory from the market opening until time $t-1$.

Huang and Stoll combine equations 2 and 3 to get:

$$\Delta M_t = (\alpha + \beta)\frac{S}{2}Q_{t-1} - \alpha\frac{S}{2}(1 - 2\pi)Q_{t-2} + \epsilon_t. \tag{4}$$

Note that there is inventory risk only when inventory is acquired and there is no inventory risk when inventory is not acquired. Therefore, quote adjustments due to inventory risk solely depend on actual trades and not trade surprises, in contrast to equation 2. The expected sign of the trade thus does not matter for inventory costs. This differentiation allowed Huang and Stoll to clearly separate the inventory component from the adverse selection component.

As mentioned before, we will not estimate the bid-ask spread but rather infer it directly from the data. Hence, we use a variation of equation 4, as did Huang and Stoll:

$$\Delta M_t = (\alpha + \beta)\frac{S_{t-1}}{2}Q_{t-1} - \alpha\frac{S_{t-2}}{2}(1 - 2\pi)Q_{t-2} + \epsilon_t. \tag{5}$$

With equation 5 we arrived at the equation that we use for our estimation procedure.

3.2 Estimation Procedure

The parameters of equation 5, α, β, and π, are estimated using the generalized method of moments (GMM) procedure outlined in Hansen and Singleton (1982) and Hansen (1982). The optimal weighting matrix is constructed using the method proposed in Wooldridge (2002).

Under this GMM procedure, the parameter estimates have to be chosen such that they minimize:

$$Q_N(\theta) = \left[N^{-1}\sum_{i=1}^{N} g(w_i, \theta)\right]' \widehat{\Lambda}^{-1} \left[N^{-1}\sum_{i=1}^{N} g(w_i, \theta)\right]. \tag{6}$$

Here, following the notation of Wooldridge (2002), θ is the vector of unknown coefficients. For the decomposition, this vector includes the component for adverse selection risk (α), the component for inventory holding risk (β), and the trade direction reversal probability (π). The order processing component is computed by subtracting α and β from one. This is because those three components represent costs, which have to add up to 100% or one. $g(w_i, \theta)$ is an (L x 1) vector of moment functions (or orthogonality conditions). In our case, these functions are non-linear and given by:

1. $g_1 = (Q_{t-1} - (1-2\pi)Q_{t-2})\, Q_{t-2}$
2. $g_2 = (Q_{t-1} - (1-2\pi)Q_{t-2})\, S_{t-1}$
3. $g_3 = (Q_{t-1} - (1-2\pi)Q_{t-2})\, S_{t-2}$
4. $g_4 = \left(\Delta M_t - (\alpha+\beta)\frac{S_{t-1}}{2}Q_{t-1} + \alpha\frac{S_{t-2}}{2}(1-2\pi)Q_{t-2}\right) S_{t-1}$
5. $g_5 = \left(\Delta M_t - (\alpha+\beta)\frac{S_{t-1}}{2}Q_{t-1} + \alpha\frac{S_t t-2}{2}(1-2\pi)Q_{t-2}\right) S_{t-2}$
6. $g_6 = \left(\Delta M_t - (\alpha+\beta)\frac{S_{t-1}}{2}Q_{t-1} + \alpha\frac{S_{t-2}}{2}(1-2\pi)Q_{t-2}\right) (Q_{t-1} - (1-2\pi)Q_{t-2})\,.$

$\widehat{\Lambda}$ is the optimal weithing matrix which is determined following Wooldridge (2002):

$$\widehat{\Lambda} \equiv \frac{1}{N}\sum_{i=1}^{N} [g(w_i, \theta)]\, [g(w_i, \theta)]'\,. \tag{7}$$

In order to estimate θ, several steps are necessary. First, we start with the identity matrix as the weighting matrix to estimate θ. We then use this estimate of θ to estimate the weighting matrix. We can then re-estimate θ using the new weighting matrix. We perform these steps as often as necessary until θ converges.

3.3 Transformations

3.3.1 Nonlinear Transformation & the Computation of Standard Errors

The three different components of the spread represent costs that market makers pass on to traders. Market makers do so because they want to be compensated for the different risks that they are facing, e.g. the risk of sitting on too much or too little inventory and the risk of losing against a better informed market participant. And since the three components of the spread should explain all of the possible cost types that the market maker is passing on to customers, those three components have to add up to one.

To make sure that, when estimating α and β, the resulting estimates lie between zero and one, we impose restrictions on the parameters. When imposing restrictions, we follow Christensen et al. (2008), who propose to "specify the underlying problem in such a way that an unconstrained algorithm will nevertheless choose model parameters that always satisfy the constraint conditions." They suggest to use bijective mapping from the true parameter space into a user-specified unconstrained parameter space. In contrast to adopting the formal constrained optimization procedures, they claim that "the bijective mapping together with the unconstrained optimization still allows for an easy and fast algorithm to estimate the desired parameters."

We follow Christensen et al. (2008) and constrain the parameters to lie in (0,1). The key idea is to transform θ by means of a non-linear mapping, $\theta = g(\theta)$, between the constrained interval (0,1) and the real line. So θ would be the vector of parameters that we get from unconstrained optimization, with $\theta \in \mathbb{R}$. To derive parameter values that lie between zero and one, we use an inverse transform function of the following form:

$$g^{-1}(\theta) = \phi = \frac{1}{1 + e^{-\theta}}. \tag{8}$$

Obviously, altering θ and using ϕ demands that, when computing standard errors, it needs to be taken into account that one is working with scaled variables. Hence, the gradient of the objective function must be provided with respect to ϕ and not θ. Again, following Christensen et al. (2008), the gradient with respect to ϕ is computed by scaling the gradient with respect to θ by the gradient of the mapping with respect to ϕ.

3.4 Data

As can be inferred from equation 5, our data needs to consist of intradaily midprices, bid-ask spreads, and a trade direction indicator variable. Since this kind of data is not readily available, we need to generate it from intradaily trades and quotes data. This data is taken from data files provided by TickData, Inc.

We use intradaily best bid and ask quotes (BBO) to compute bid-ask spreads (ask price minus bid price) and midprices (average between ask and bid price). From this, we compute the trade direction following mainly Lee and Ready (1991). Since Lee and Ready, however, treat trades that happened at the midprice differently than Huang and Stoll, we follow Huang and Stoll for those kinds of trades. Hence, our trade direction variable can take on three possible values:

- $+1$ if the trade price exceeds the midprice
- -1 if the midprice exceeds the trade price
- 0 if the trade price equals the midprice.

Establishing a timing rule to apply the Lee-Ready algorithm is an important step in our data-cleaning process: Lee and Ready (1991) and Huang and Stoll (1997) matched trades with quotes that happened at least five seconds earlier. Since then, however, technology has become much faster and we need to reduce the time distance between matched trades and quotes. In doing so we follow the recent literature (e.g. Henker and Wang (2006)) and match trades with quotes in the same second.

We restrict our analysis to the nine biggest U.S. banks in 2008, including both what one generally considers to be commercial and investment banks. Additionally, we include the British bank Barclays because this bank was in direct acquisition talks with Lehman Brothers. Specifically, we chose the following banks as ”commercial” banks:

1. Bank of America Corporation
2. Barclays PLC
3. Citigroup Inc.
4. JP Morgan Chase & Co.
5. Wells Fargo & Company,

and the following investment banks:

1. Bear Stearns Companies Inc.
2. Goldman Sachs Group, Inc.
3. Lehman Brothers Holding Inc.
4. Merrill Lynch & Co., Inc.
5. Morgan Stanley

We furthermore examine five non-banks for comparison purposes:

1. AIG, Inc.
2. AT&T Inc.
3. General Motors Company
4. Hewlett Packard Company
5. Wal-Mart Stores Inc.

AIG is here of special interest because on the day of Lehman's bankruptcy announcement, three major rating agencies issued investment grade ratings for AIG, despite AIG's exposure to Lehman Brothers. Hence, the government bailout of AIG of about $85 billion, which happenend at 9:00 PM on September 16, 2008, came as a surprise to many investors. Using this line of event, we will examine – on an intradaily basis – when AIG's rescue needs became apparent to market participants and are therefore observeable in the microstructure of transaction costs.

For our analysis we concentrate on data covering the New York Stock Exchange (NYSE) for all eight U.S. banks and the London Stock Exchange (LSE) for Barclays. To ensure the integrity of the dataset, we only use quotes that are coded as regular quotes. Also, a selected stock must meet four criteria to be eligible: (1) it must be a common stock; (2) it must have a primary listing on the LSE or NYSE; (3) it cannot change primary exchange, ticker symbol or its CUSIP code during the sample period; and (4) it must be listed in the Center for Research in Security Prices (CRSP) database. All of the above-listed banks and companies meet these criteria.

We then apply the following screens to the trades and quotes data. Only quotes and trades during normal market hours (9:30 AM and 4:00 PM) are considered. We delete cases in which the bid is greater than or equal to the ask. We furthermore assume that bid (ask) quotes that have a bid (ask) price or bid (ask) size that is set to zero or a missing value have been withdrawn. We drop all withdrawn quotes. We also exclude the first transaction price of the day if it is not preceeded by a quote.

The time period that we use covers March 2008 for Bear Stearns and August 2008 to October 2008 for Lehman Brothers and the rest of the above-listed banks and companies. We specifically look at these months because of the two major bank failures that happened during these months. By including August and October, we get a good understanding of what happened before and after Lehman's bankruptcy filing, or to put it in other words, what made transaction costs increase before and after the bankruptcy filing.

Figures 1 to 5 plot the evolution of relative bid-ask spreads, stock prices, trading volumes, and volatilities for all nine U.S. banks for the months January to December 2008. Figures 32 to 35, in the Appendix, plot these data for Barclays. Since the NYSE deferred the trading of Lehman Brothers after the bankruptcy announcement, we do not have data for Lehman's spread, stock price, trading volume, and volatility after September 15, 2008. The same holds true for Bear Stearns. Bear Stearns stopped being traded in May 2008.

The relative bid-ask spread (r), hereby, is a measure of transactions costs. It is defined as the spread (ask price minus bid price) normalized by the midprice. Hence, the relative bid-ask spread measures the percentage transaction costs relative to the current midprice.

We decompose the spread into its three cost components: adverse selection costs ca, inventory holding costs ci, and order processing costs co, where $ca+ci+co=r$. The relative contributions to the costs are measured by the adverse selection component $sa=ca/r$, the inventory holding component $si=ci/r$, and the order processing component $so=co/r$.

As can be seen from figures 50 to 52 in the Appendix, trades of Lehman Brothers are autocorrelated over many lags. Also, the autocorrelation coefficient ρ increases for Lehman Brothers towards September 12, 2008. This indicates that subsequent trades were of a similar nature: either buys or sells over many lags. This already suggests that market participants traded on information. Otherwise, we would not have such a strong persistence in the trades' signs over time.

4 Results

In this section, we address the central research questions: do market prices reveal any evidence of market speculation about a potential take-over or the pending insolvency just prior to the failure of Lehman Brothers? Is there any evidence about market speculation concerning potential bidders? How did the failure affect transactions prices of related stocks after the insolvency? Is the effect concentrated on financial companies or does it extend to non-financial companies as well? We present our empirical findings in the following sequence.

4.1 Lehman Brothers

Transactions costs for Lehman Brothers' stocks began to increase in July 2008. Relative bid-ask spreads almost doubled from below 0.1% in June to almost 0.2% in August before they jumped to almost 0.5% in the last week prior to the failure (Figure 6). We test that the level of Lehman's spread in August (August 6 to August 22) is significantly different from the time shortly before until the bankruptcy announcement (August 26 to September 12) by performing a so-called t-test (i.e., mean-comparison test). For Lehman Brothers, as well as for all other banks, we find that the means of bid-ask spreads of the time before Lehman's failure are significantly different from the means after this failure (Tables 2 to 10 in the Appendix). Hence, the increase in spreads that we observe is also significant in the longer run (i.e., late October 2008).

Are these increases due to speculation about the possible pending insolvency, or due to different reasons? The decomposition of the relative spreads into their components shows that actually all three components contribute to the rise in transactions costs (Figure 7) until September 10. From September 10 on, relative adverse selection costs jump from about 0.05% to 0.48%. Hence, this type of cost is almost solely responsible for the sharp spread increase during the last two days of Lehman's existence.

Viewed in relative terms, the adverse selection component rises in the last week from about 40% to almost 100%, while the other two components are correspondingly reduced (Figure 8). Therefore, the decomposition reveals that in the last week of trading there

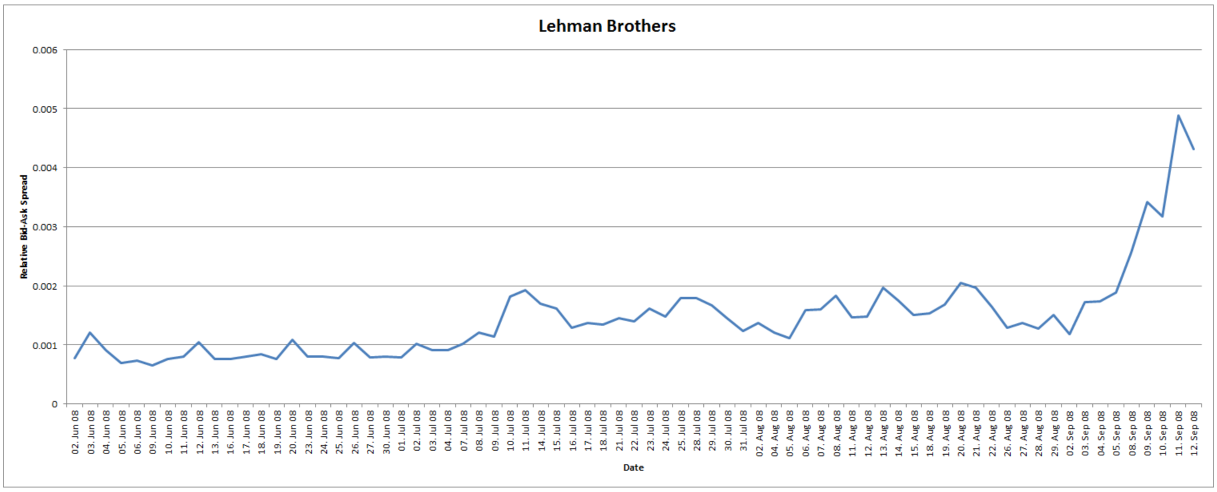

Figure 6: **Relative Bid-Ask Spread: Lehman Brothers**

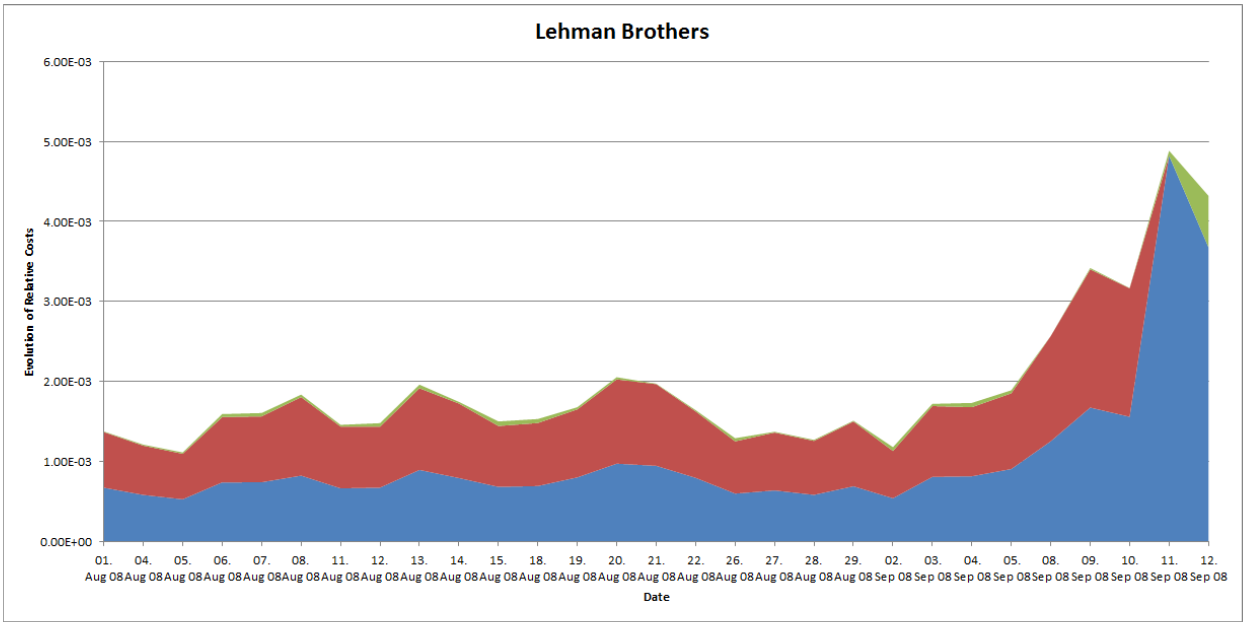

Figure 7: **Evolution of Relative Adverse Selection Costs, Inventory Holding Costs, and Order Processing Costs:** The graph plots the evolution of the three types of costs of Lehman Brothers. The blue area corresponds to adverse selection cost, the red area corresponds to inventory holding costs, and the green area corresponds to order processing costs.

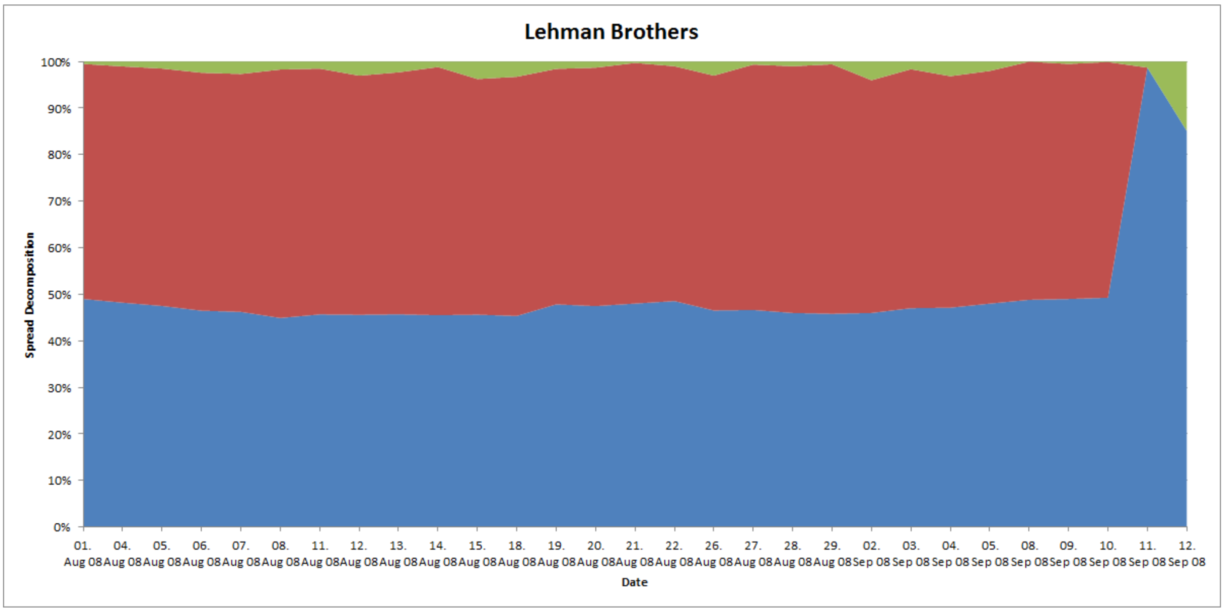

Figure 8: Evolution of the Spread Components of Lehman Brothers: The graph plots the evolution of the relative contribution of the three cost components of Lehman Brothers. The blue area corresponds to the contribution of the adverse selection component to the spread, the red area corresponds to the inventory holding component, and the green area corresponds to the order processing component.

is empirical evidence of heightened information risk in Lehman Brothers stocks. In the period before September 8, however, the relative contribution of the three components seems rather constant across time. Given that there is some evidence of speculation in the market about Lehman Brothers' problems, can we also detect evidence of speculation about potential bidders for Lehman Brothers? We start with a decomposition of the transactions prices of Barclays. Then we continue with a discussion of Bear Stearns' cost evolution before we turn to the other banks in our sample in the next sub-section. The evolution of the relative spread of Barclays seems to suggest an increase only after the failure of Lehman Brothers (Figures 9 and 32). Therefore, there seems to be little evidence of increased risk perception in the market prior to the insolvency. Likewise, the spread decomposition does not reveal any particular role of information; the relative contribution remains relatively stable over time (Figure 10).

4.2 Bear Stearns

This section compares the evolution of the relative importance of the three different components of Lehman Brothers to another bank failure, namely that of Bear Stearns. When examining the evolution of the three different cost types, we see that there does not seem to exist any evidence of increased risk perception in the market prior to Bear

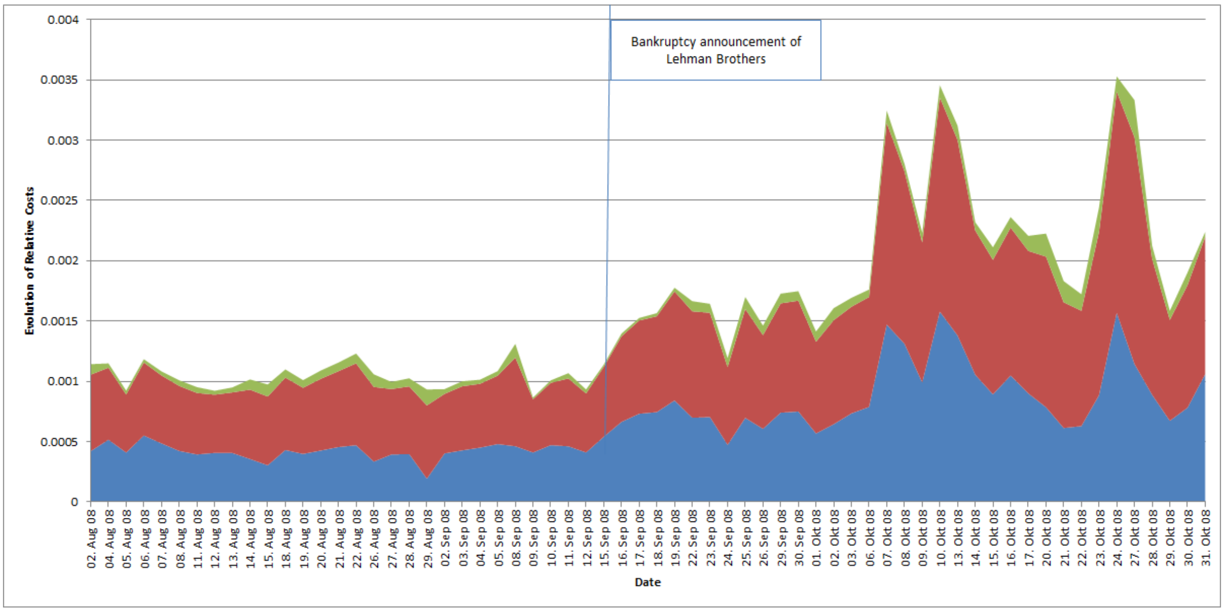

Figure 9: Evolution of Relative Adverse Selection Costs, Inventory Holding Costs, and Order Processing Costs: The graph plots the evolution of the three types of costs of Barclays PLC. The blue area corresponds to adverse selection cost, the red area corresponds to inventory holding costs, and the green area corresponds to order processing costs.

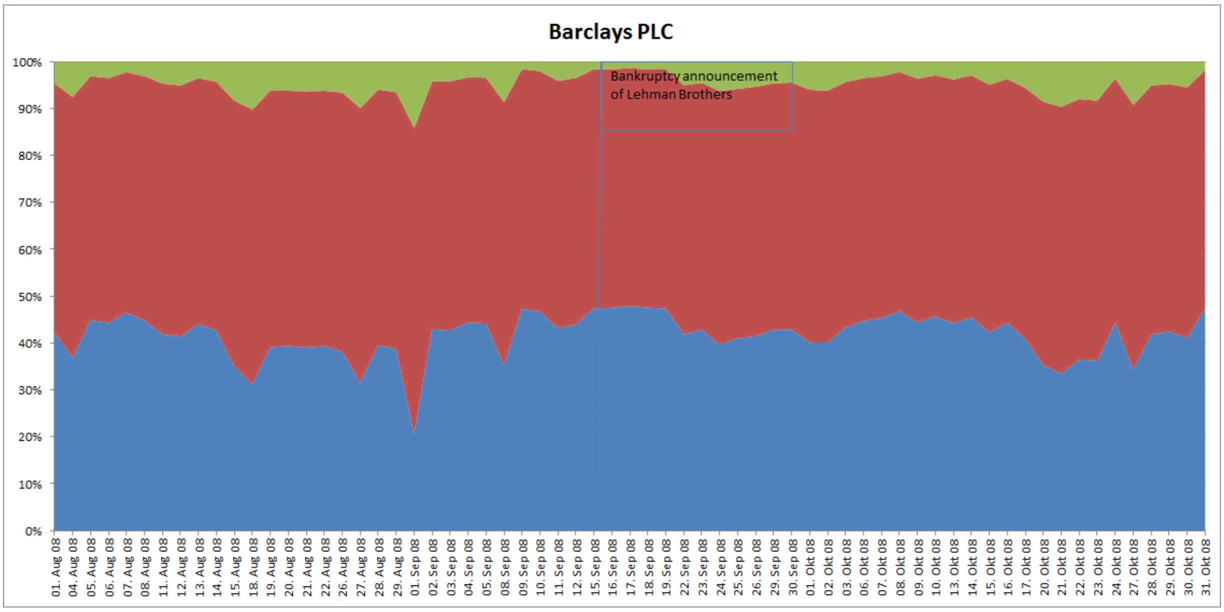

Figure 10: Evolution of the Spread Components of Barclays PLC: The graph plots the evolution of the relative contribution of the three cost components of Barclays PLC. The blue area corresponds to the contribution of the adverse selection component to the spread, the red area corresponds to the inventory holding component, and the green area corresponds to the order processing component.

Stearns' troubles. Likewise, the spread decomposition does not reveal any particular role of information; the relative contribution of information even declines towards the end of April and the relative importance of inventory holding costs rises (Figure 12). This is interesting because it suggests that market participants did not fear informed trading in Bear Stearns' stocks all along. Instead, after a merger deal was signed with JP Morgan Chase, traders steadily assigned more weight to inventory holding costs, probably because it was already clear that Bear Stearns would cease to exist and traders did not want to hold these stocks in their portfolios.

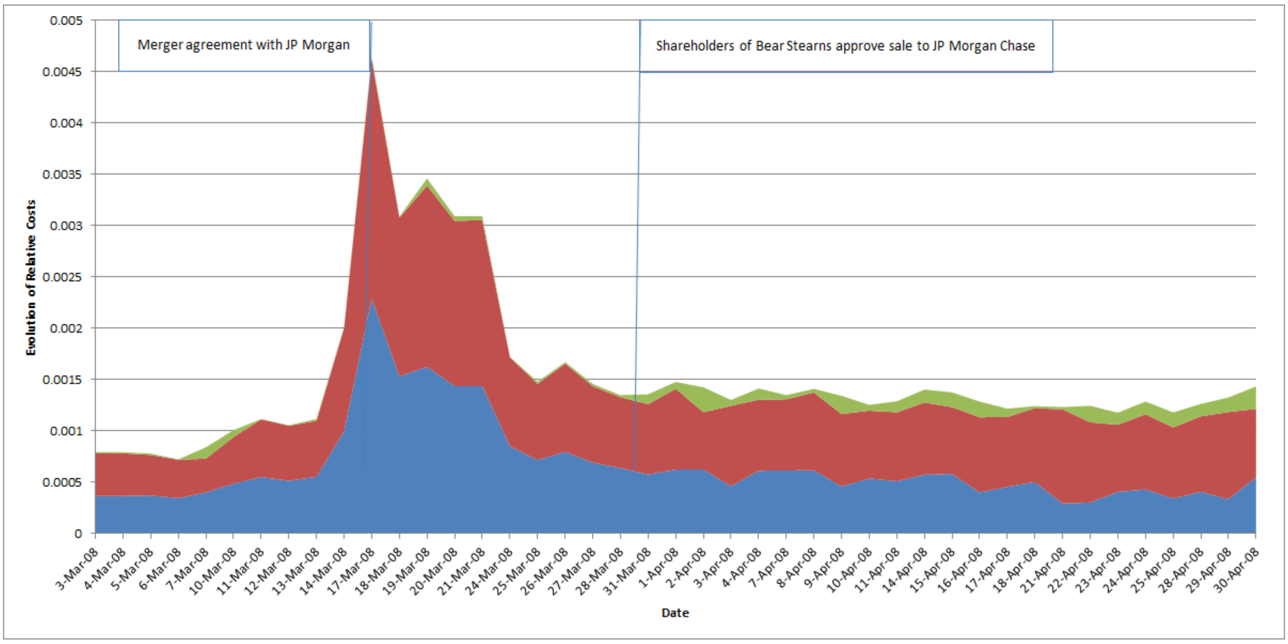

Figure 11: Evolution of Relative Adverse Selection Costs, Inventory Holding Costs, and Order Processing Costs: The graph plots the evolution of the three types of costs of Bear Stearns. The blue area corresponds to adverse selection cost, the red area corresponds to inventory holding costs, and the green area corresponds to order processing costs.

4.3 Banking industry

Can we identify any other potential bidders for Lehman Brothers' stocks prior to its failure? The evolution of relative spreads is similar to the pattern observed for Barclays. Essentially, relative spreads start to increase significantly and permanently after the insolvency but not before (Figure 1). Lehman's bankruptcy announcement, hence, had consequences for the liquidity of the other banks. The spreads increased from 10 to 30 basis points for the investment banks and by 10 basis points for the commercial banks. The spreads also did not revert back to their previous levels in late September

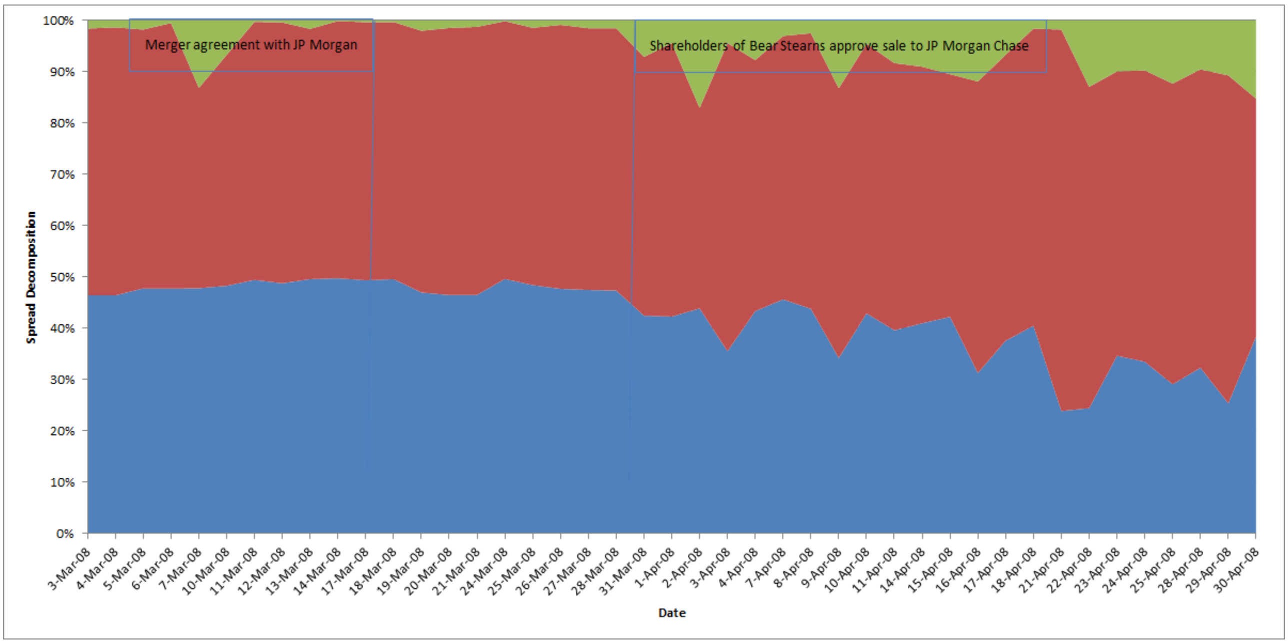

Figure 12: Evolution of the Spread Components of Bear Stearns: The graph plots the evolution of the relative contribution of the three cost components of Bear Stearns. The blue area corresponds to the contribution of the adverse selection component to the spread, the red area corresponds to the inventory holding component, and the green area corresponds to the order processing component.

and throughout October, even though the U.S. government introduced a ban on short-sales for the financial industry (September 19, 2008 to October 8, 2008) as well as TARP (Tables 2 to 10). TARP was designed to strengthen the financial sector through purchases of assets and equity from financial institutions. The effect on liquidity, though, seems to have been only moderate. We test that the level of spreads of all banks in early September (September 02 to September 12), i.e. the time before the bankruptcy filing announcement, is significantly different from the time after the bankruptcy announcement (October 21 to October 31) by performing mean-comparison tests for the bid-ask spreads. For all banks in our sample, we find that the means of bid-ask spreads of the time before Lehman's failure are significantly different from the means after that failure (Tables 2 to 10). However, this is only true for late October. We compare means of bid-ask spreads of the time before the bankruptcy announcement with late December. For late December, the bid-ask spreads of four banks (Goldman Sachs, JP Morgan Chase, Merill Lynch, and Wells Fargo) have reverted back to their pre-bankruptcy levels (Tables 5, 6, 8, and 10).

Decomposing the relative costs demonstrates that information costs immediately and dramatically shoot up after the failure of Lehman Brothers, both for all remaining investment banks (Figure 13) as well as for the commercial banks (Figure 14). We interpret this as clear evidence of informational contagion in the financial sector. The failure of the

TBTF doctrine apparently made investors aware of increasing counter-party risk and the opaqueness of bank balance sheets, which left ample space for informed trading. Accordingly, the market significantly and permanently increased the premium on information risk. The increase in relative adverse selection costs remains stable even after the liquidity support measures of TARP and the short-selling bans were implemented. This suggests that, while supporting demand for stocks of U.S. financial companies, the emergency support measures were not able to affect the underlying trading costs. Instead, trading costs remained at elevated levels. Interestingly, as in the case of Barclays, inventory holding costs and order processing costs also shoot up throughout the industry (Figures 15 and 16). In fact, all components increase by about the same percentage, leaving the relative contribution of each relatively constant (Figures 55 to 61 in the Appendix). Immediately after the failure, for a number of institutions the contribution of inventory holding costs even exceeded the informational costs, reflecting serious counter-party risk after the TBTF policy had become unreliable. Also, these two components remain at significantly elevated levels after the introduction of TARP, suggesting deeper structural implications of the Lehman failure. Overall, this finding suggests that information risk has been an important driver of the increase in transactions costs. But at the same time, inventory risk and the associated inventory holding costs increased dramatically due to the turmoil that followed for the financial industry and subsequently for the real economy. Apparently, consolidation in market making and exit of traders and liquidity providers also contributed to an increase in order processing costs.

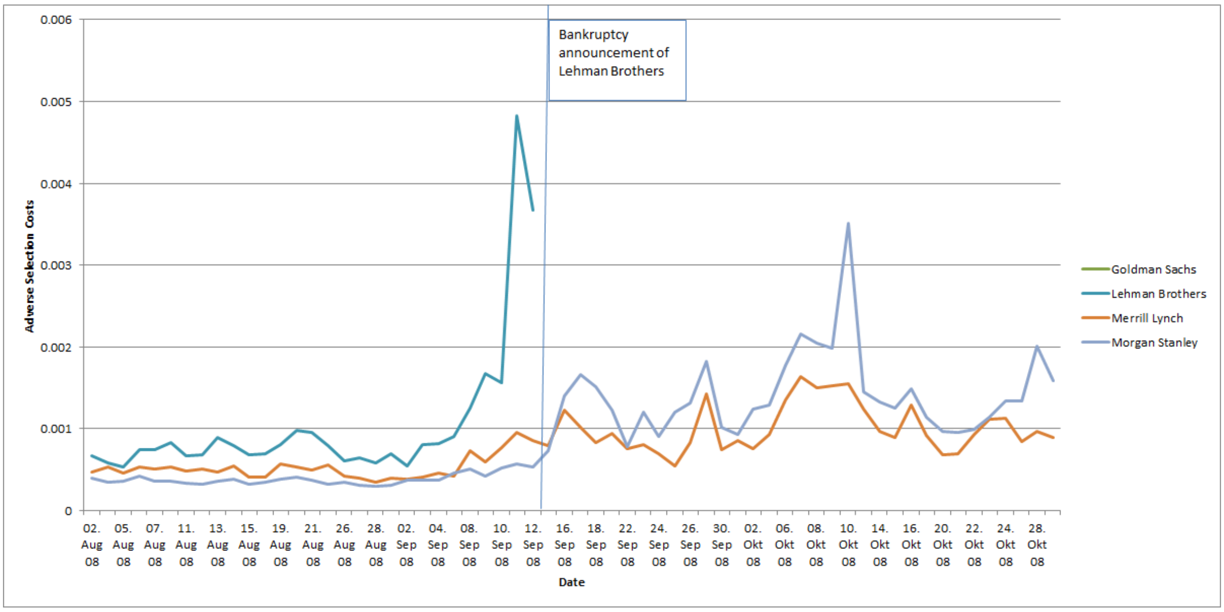

Figure 13: Evolution of Adverse Selection Cost of Investment Banks: The lines plot the evolution of the share that the adverse selection component had in the relative bid-ask spread. This share is computed by multiplying the adverse selection component with the relative bid-ask spread.

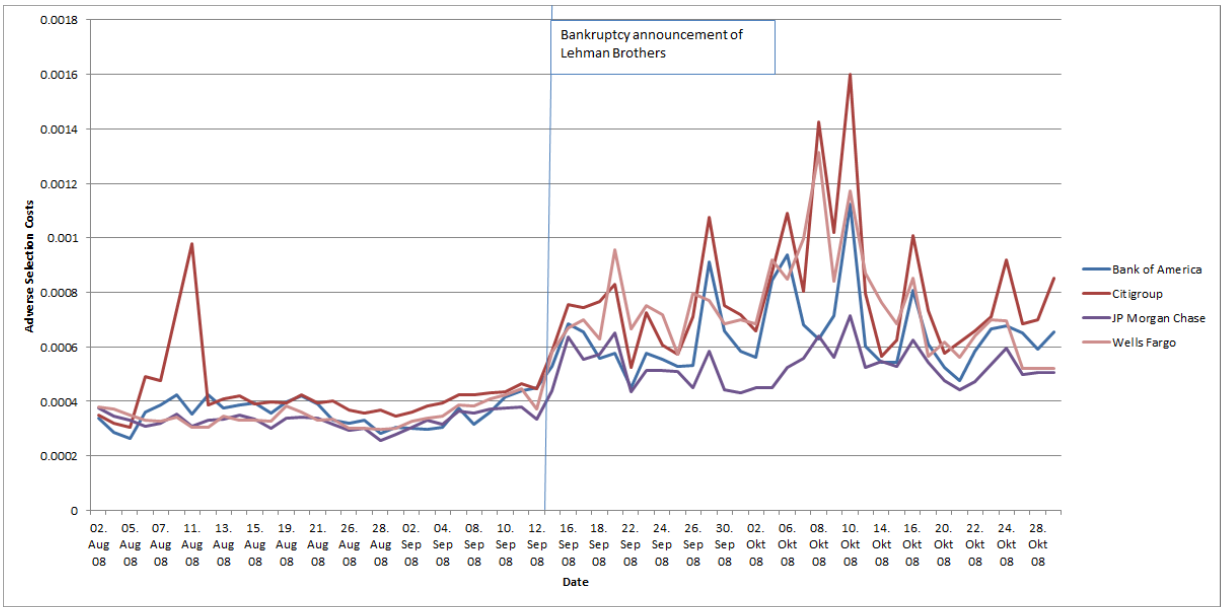

Figure 14: Evolution of Adverse Selection Cost of Commercial Banks: The lines plot the evolution of the share that the adverse selection component had in the relative bid-ask spread. This share is computed by multiplying the adverse selection component with the relative bid-ask spread.

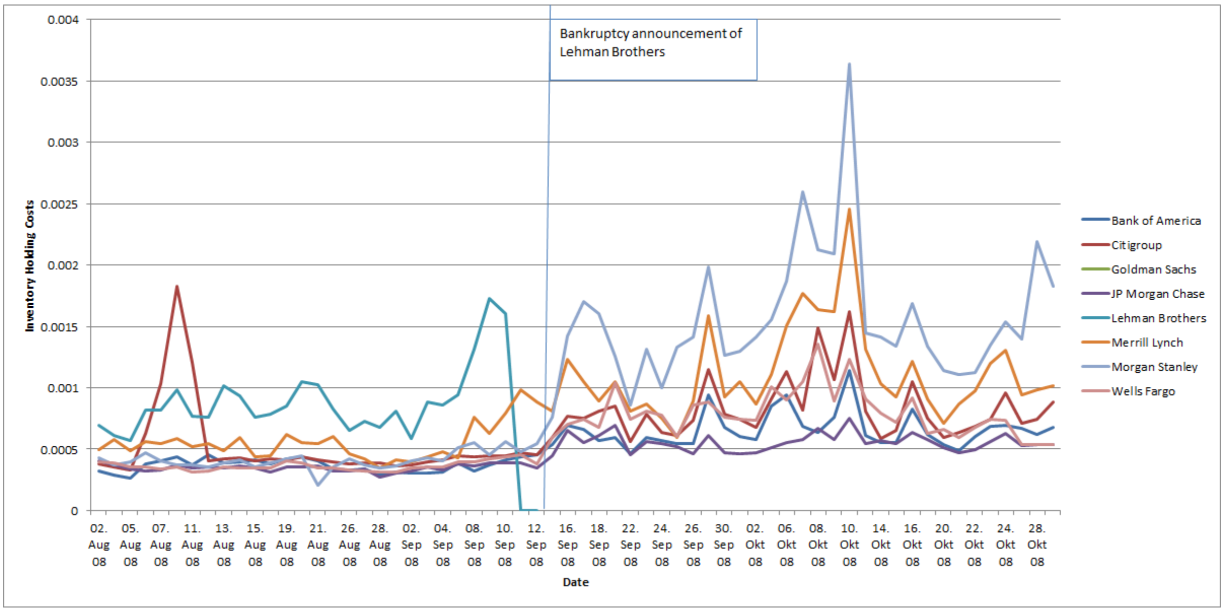

Figure 15: Evolution of Inventory Holding Cost of U.S. Banks: The lines plot the evolution of the share that the inventory holding component had in the relative bid-ask spread. This share is computed by multiplying the inventory holding component with the relative bid-ask spread.

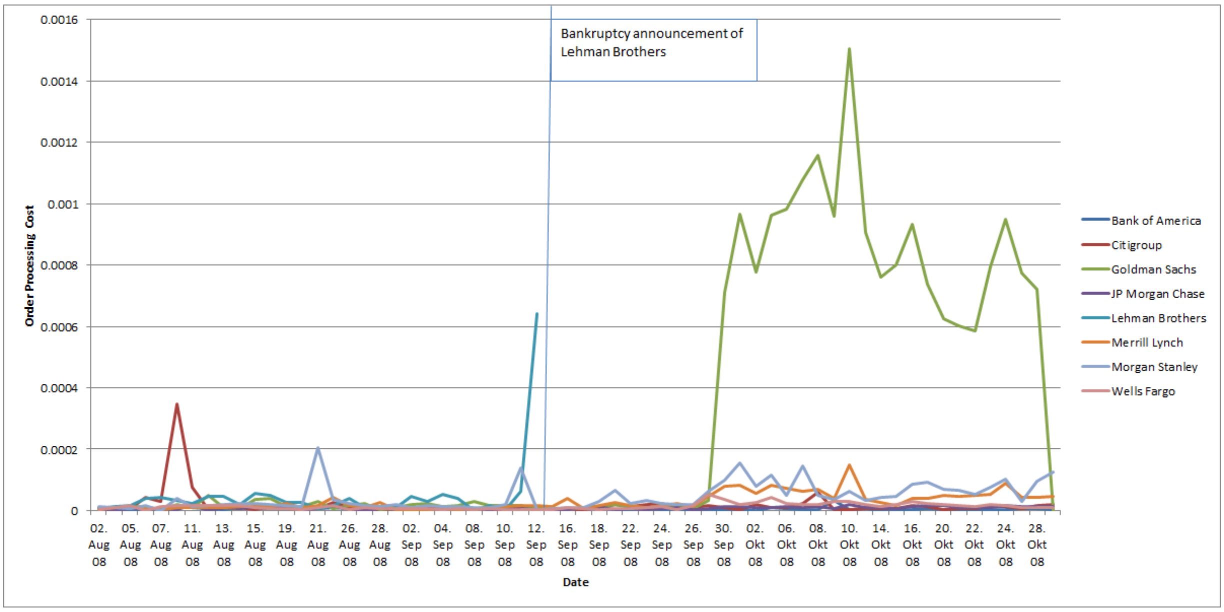

Figure 16: Evolution of Order Processing Cost of U.S. Banks: The lines plot the evolution of the share that the order processing component had in the relative bid-ask spread. This share is computed by multiplying the order processing component with the relative bid-ask spread.

4.4 AIG, Inc.

As mentioned in Section 3, it is especially interesting to analyze the microstructure of transaction costs of AIG because three major rating agencies issued investment grade ratings for AIG despite their exposure to Lehman Brothers on the day of Lehman's bankruptcy announcement. Hence, the government bailout of AIG ($85B), which happened at 9:00 PM on September 16, 2008, came as a surprise to many investors. Now, when decomposing AIG's equity bid-ask spreads into the three different cost types on a daily basis, there does not seem to be any shift in the relative importance of any of the three cost types (see Figures 17 and 18)

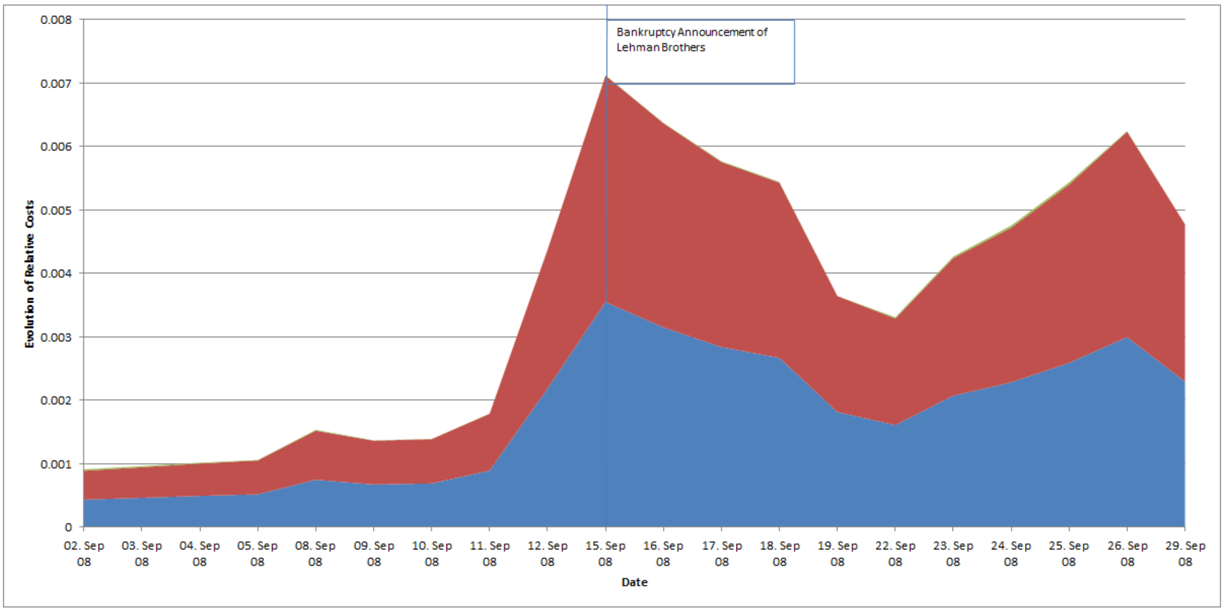

Figure 17: Evolution of Relative Adverse Selection Costs, Inventory Holding Costs, and Order Processing Costs: The graph plots the evolution of the three types of costs of AIG, Inc.. The blue area corresponds to adverse selection cost, the red area corresponds to inventory holding costs, and the green area corresponds to order processing costs.

This picture changes when we decompose the spread of AIG on the days of the ratings and subsequent bailout announcements on an intradaily basis. There is a clear intradaily shift in the relative contribution of the cost types to the overall transaction costs. On September 17, the relative importance of the adverse selection component rises temporarily, as does the order processing component. Similar to Lehman Brothers, the inventory holding component loses its importance.

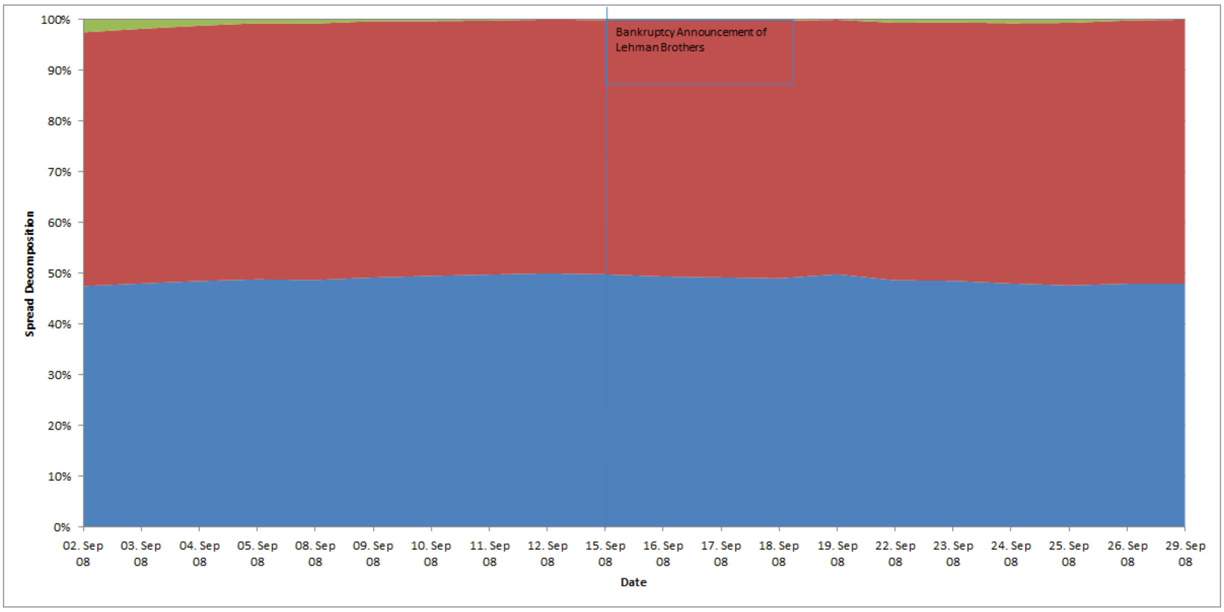

Figure 18: Evolution of the Spread Components of AIG, Inc.: The graph plots the evolution of the relative contribution of the three cost components of AIG, Inc.. The blue area corresponds to the contribution of the adverse selection component to the spread; the red area corresponds to the inventory holding component, and the green area corresponds to the order processing component.

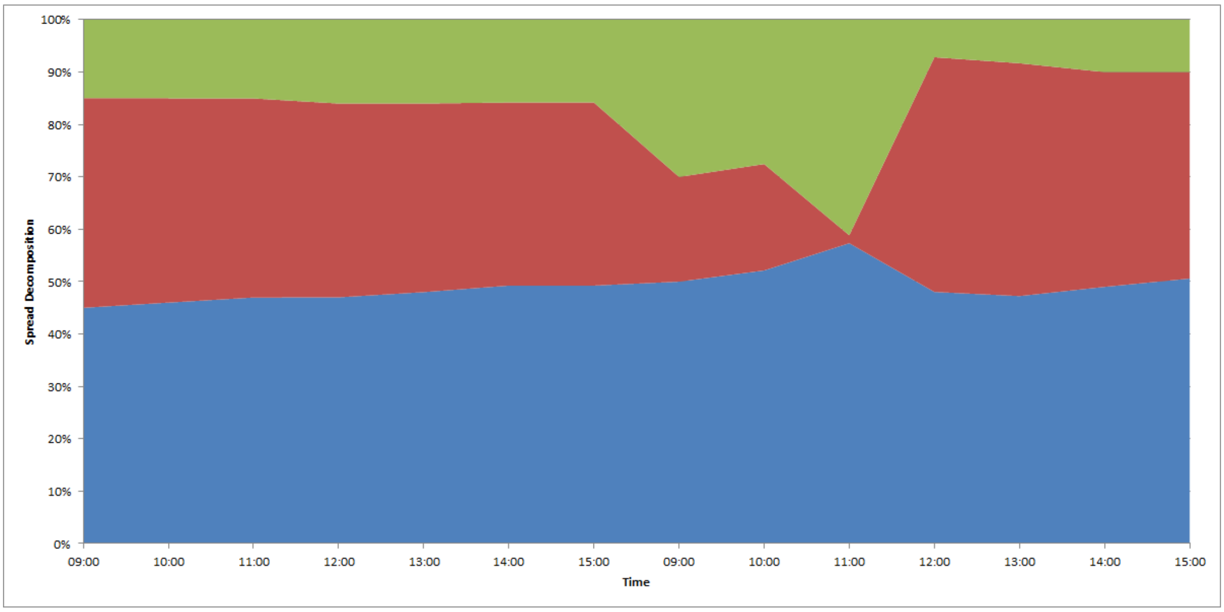

Figure 19: Evolution of the Spread Components of AIG, Inc. on September 16 and 17, 2008: The graph plots the evolution of the relative contribution of the three cost components of AIG, Inc.. The blue area corresponds to the contribution of the adverse selection component to the spread; the red area corresponds to the inventory holding component, and the green area corresponds to the order processing component.

4.5 U.S. Non-Financial Sector

One of the surprising features of our analysis so far is the observation that in the case of U.S. financial companies all three spread components increased with similar growth rates, leaving the relative contribution largely constant. Would we find the same picture for U.S. non-financial companies? Arguably, these stocks may have also suffered from decreased liquidity, heightened economic risk, and exit of market makers. But would information risk be affected in the same way, given that information about TBTF or information about counter-party risk seems less relevant for the real sector? This issue is addressed in this section.

Transactions costs for stocks of non-financial companies began to increase shortly after Lehman Brothers declared bankruptcy. From that day on, relative bid-ask spreads, stock prices, and trading volume became volatile (Figures 36 to 49). We test that the level of non-financial firms' spreads before the bankruptcy announcement is significantly different from the following time period by performing a mean-comparison test as in Section 4.3. We find that the means of relative bid-ask spreads for the time after Lehman's failure are significantly different from the means before. Hence, the increase in spreads that we observe is significant. However, spreads revert back to pre-bankruptcy levels more quickly than what was observed for most financial companies, as they are back to their pre-bankruptcy levels in late December.

For the time period of September 2008, the decomposition of the relative spreads of all non-financial companies into their components shows that, actually, all three components contribute to the rise in transactions costs (Figures 20 to 22).

Interestingly, none of the components changes its contribution to the spread. The overall contribution stays absolutely constant over the entire course of September 2008.

Summarizing these findings, we can say that the decomposition reveals that there is empirical evidence of heightened information risk as well as increased inventory risk in the non-financial stocks. However, none of the three components drove the increase in transaction costs. Here again, just as with the financial stocks, all of the components contributed equally to the increase in relative bid-ask spreads.

4.6 Robustness Checks

It is only for Lehman Brothers that the composition of the three cost types changes significantly shortly before Lehman's bankruptcy filing date. In this section we present results from robustness checks, which we conducted in order to confirm the results of the bid-ask spread decomposition for Lehman Brothers.

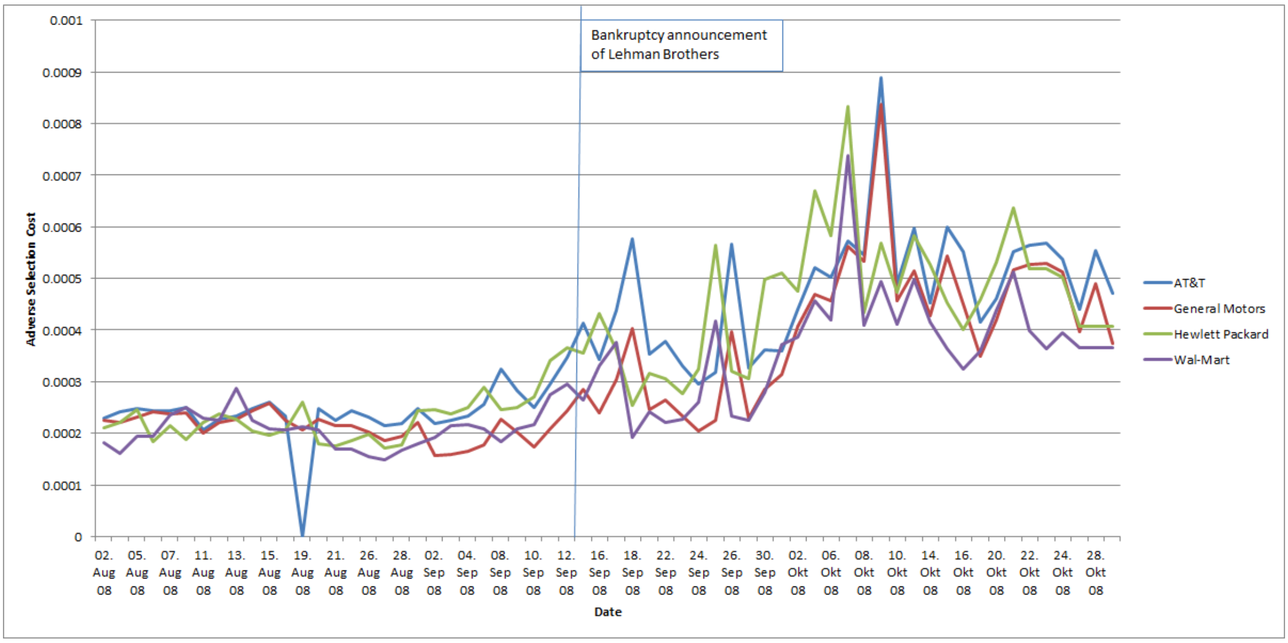

Figure 20: Evolution of Adverse Selection Cost of Non-Financial Companies: The lines plot the evolution of the share that the adverse selection component had in the relative bid-ask spread. This share is computed by multiplying the adverse selection component with the relative bid-ask spread.

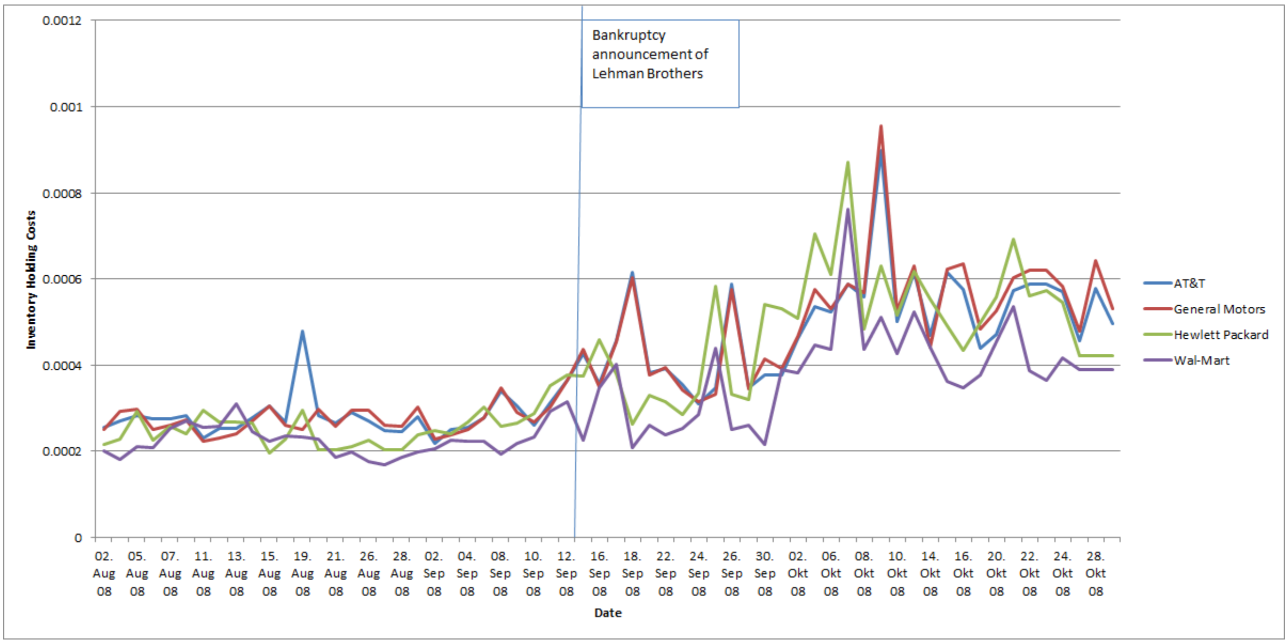

Figure 21: Evolution of Inventory Holding Cost of Non-Financial Companies: The lines plot the evolution of the share that the inventory holding component had in the relative bid-ask spread. This share is computed by multiplying the inventory holding component with the relative bid-ask spread.

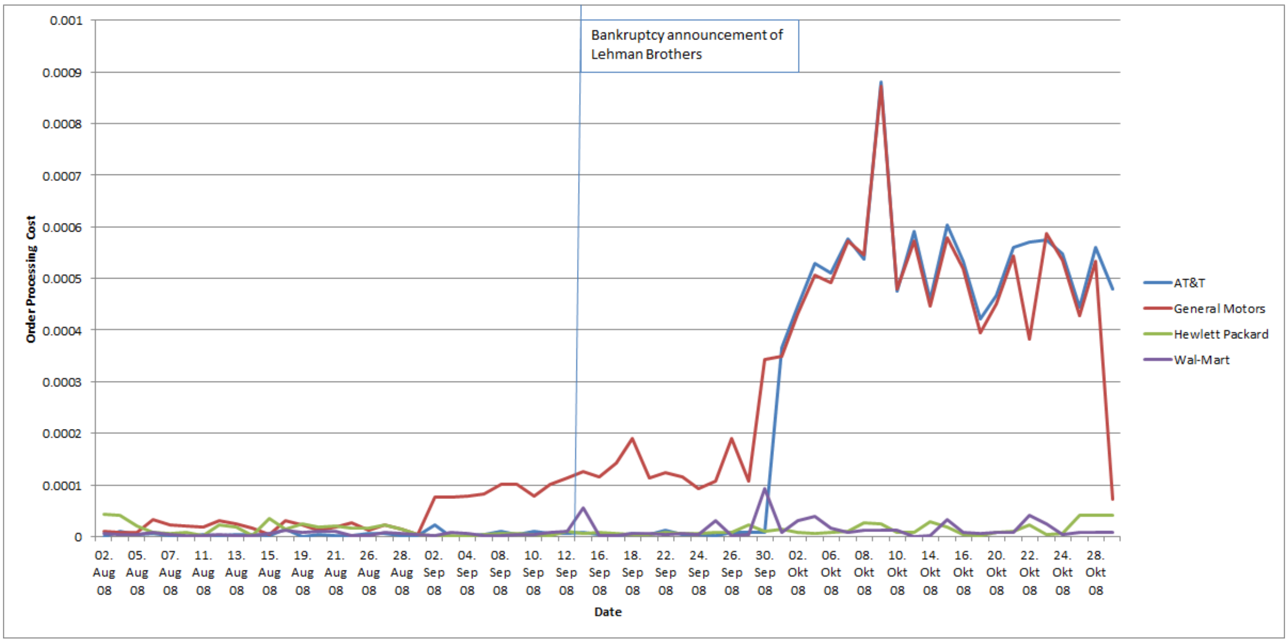

Figure 22: Evolution of Order Processing Cost of Non-Financial Companies: The lines plot the evolution of the share that the order processing component had in the relative bid-ask spread. This share is computed by multiplying the order processing component with the relative bid-ask spread.

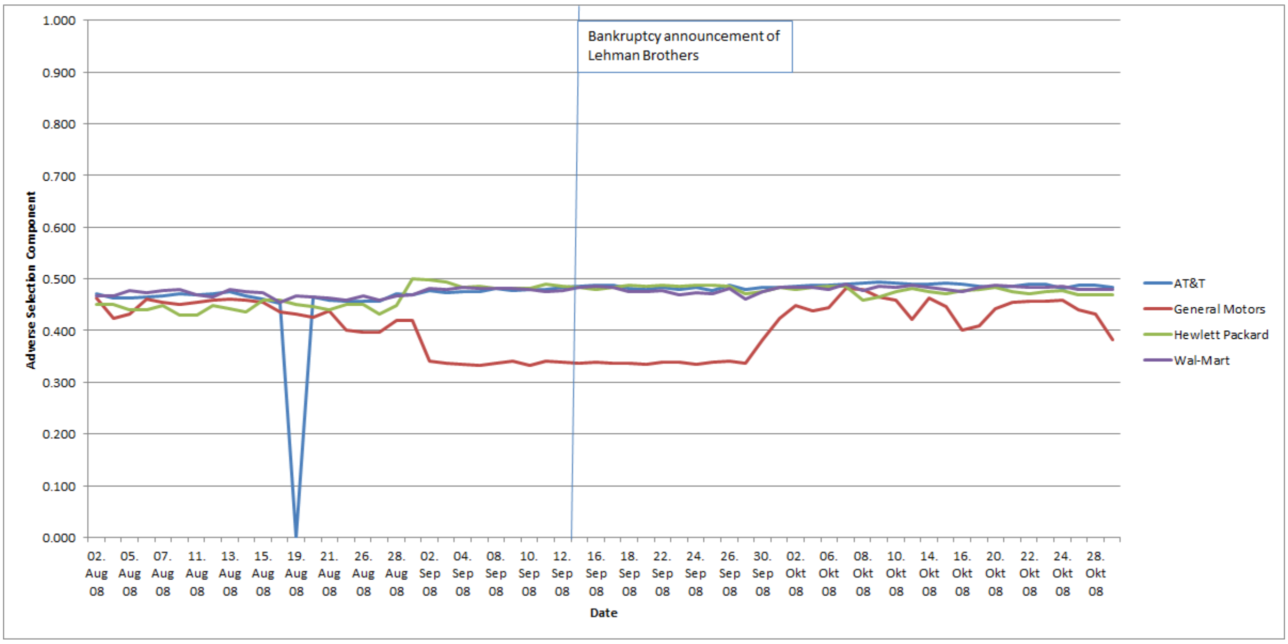

Figure 23: Evolution of the Adverse Selection Component of the Non-Financial Companies: The lines plot the evolution of the adverse selection component *sa* of all non-financial companies in our sample.

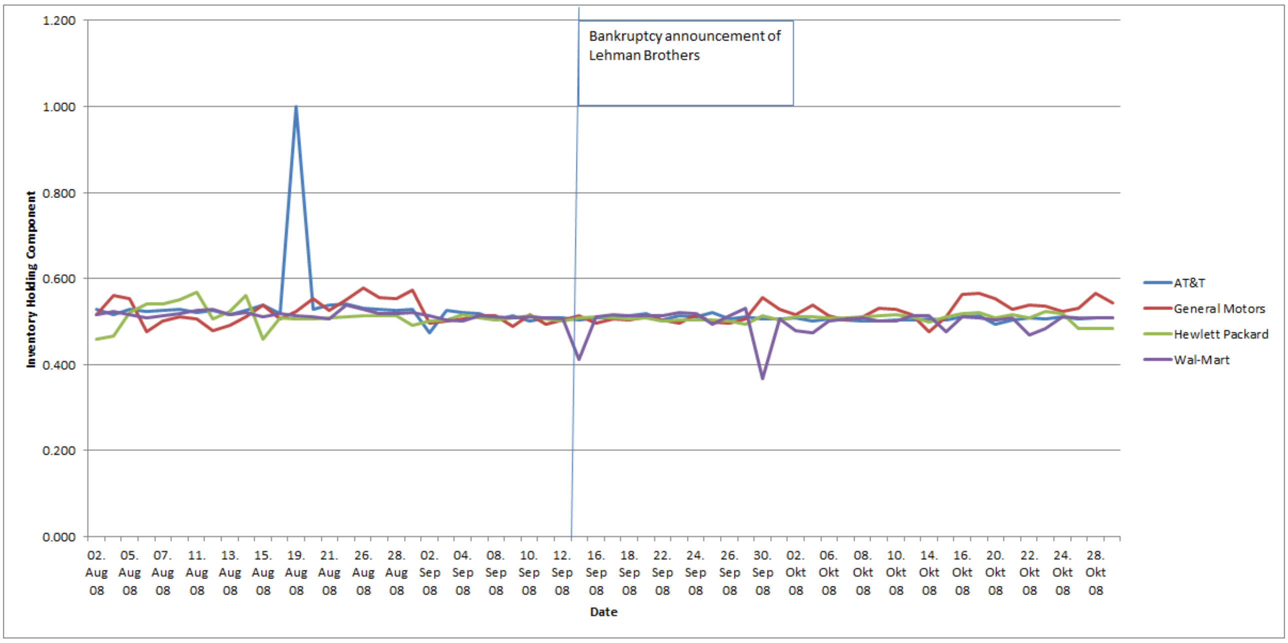

Figure 24: Evolution of the Inventory Holding Component of the Non-Financial Companies: The lines plot the evolution of the inventory holding component *si* of all non-financial companies in our sample.

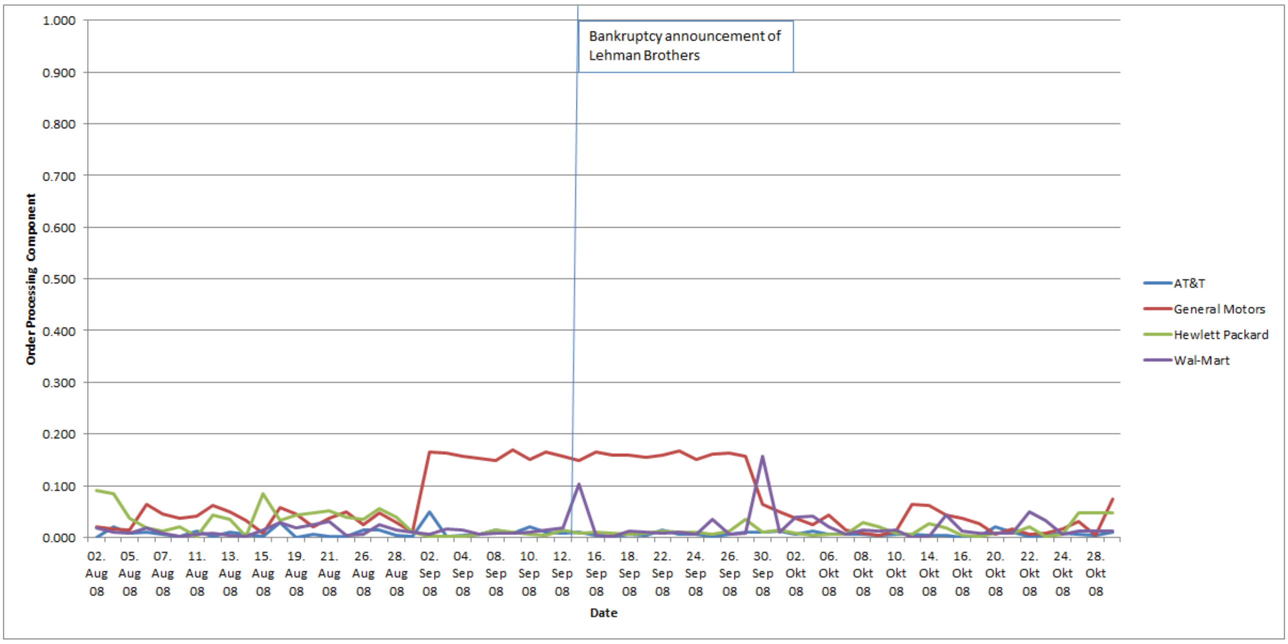

Figure 25: Evolution of the Order Processing Component of the Non-Financial Companies: The lines plot the evolution of the order processing component *so* of all non-financial companies in our sample.

4.6.1 VPIN (Volume-Synchronized Probability of Informed Trading)

As the first robustness check, we calculate the so-called volume-synchronized probability of informed trading (VPIN) (Easley et al. (2012)). According to the authors, order flow may be "toxic" (i.e. disadvantageous) for market makers in cases in which they are unaware that they are providing liquidity at a loss. According to the microstructure literature the order arrival process is informative for both subsequent price movements in general and the "toxicity" of order flow. Easley et al. (2012) present a procedure with which to estimate this so-called order flow informativeness and toxicity, respectively. Their procedure is based on volume imbalance and trade intensity:

$$VPIN = \frac{\sum_{\tau=1}^{n} |V_{\tau}^{S} - V_{\tau}^{B}|}{nV}, \tag{9}$$

where τ is an index of equal volume buckets, V^B denotes the overall buy volume in each bucket, V^S denotes the sell volume in each bucket, V is the total trading volume, and n is the total number of buckets chosen for computing the VPIN metric.

The VPIN toxicity metric is based on the same model as is the original PIN (probability of informed trading) metric. Both approaches have the same theoretical foundation. In contrast to the estimation of the PIN metric, however, the VPIN metric does not require the estimation of unobservable variables and is updated in stochastic time, meaning it is calibrated to have an equal volume of trade in each time interval. According to the authors, this is why the VPIN measure is superior to the PIN measure and this is also why we follow Easley et al. (2012) in applying the VPIN metric as one of our robustness checks.

Figure 26 plots the development of the VPIN metric for Lehman Brothers for the time between August 2008 and Lehman's initial bankruptcy filing date.

In September, the VPIN metric reaches higher values on average than in August. For example, in August the VPIN exceeded the value of 60% 12 times per day. This means that the probability of observing informed trading in Lehman's stocks was higher than 60% for at least twelve times a day in August. In September, this probability reached at least 60% on average 24 times per day. This number increased towards the bankruptcy filing date.

Overall, the VPIN metric of Lehman Brothers becomes more volatile from August to September 2008. This suggests that market makers became insecure about the informativeness of order flow and order flow toxicity. Figure 27 plots the variance of the VPIN metric and shows that information risk has increased towards Lehman's bankruptcy filing date, which supports our initial findings of the bid-ask spread decomposition of Section 4.1.

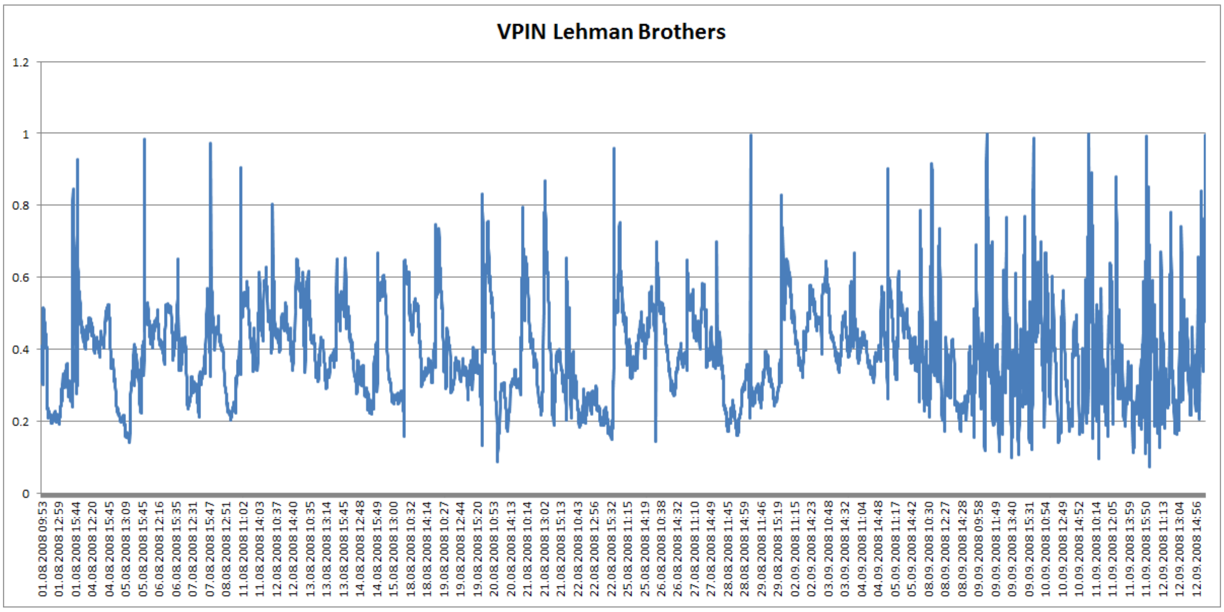

Figure 26: Evolution of the VPIN metric: The graph plots the evolution of the VPIN (volume-synchronized probability of informed trading) metric for Lehman Brothers for August and September 2008.

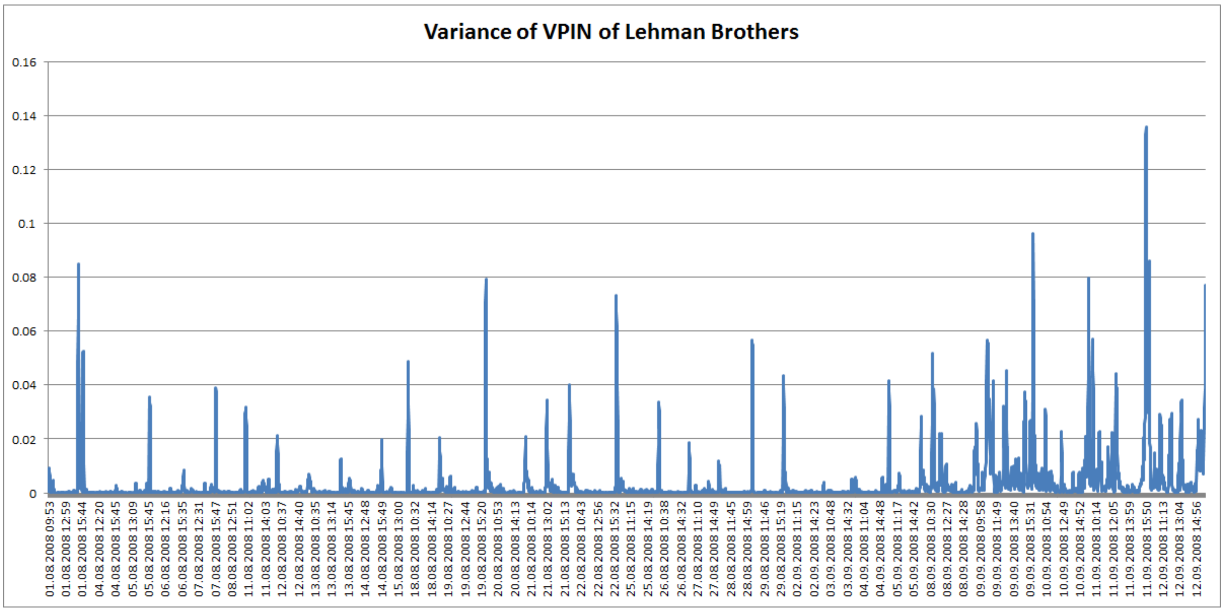

Figure 27: The VPIN metric becomes more volatile towards September, 15: The graph plots the evolution of the variance of the VPIN (volume-synchronized probability of informed trading) metric for Lehman Brothers for August and September 2008.

Figures 28 and 29 plot the development of the VPIN measure and its respective variance for Bear Stearns for March 2008. As is immediately obvious, the announcement of the Federal Reserve Bank of New York on March 14, 2008, of the provision of a \$25 billion loan to Bear Stearns had a smoothing effect on the VPIN metric. It seems that this announcement removed the toxicity and lowered the associated informed trading in Bear Stearns' stocks. This effect lasted until March 16, 2008. On this date, Bear Stearns officially signed a merger agreement with JP Morgan Chase in a stock swap worth \$2 per share which meant a significant loss as Bear Stearns' stock had traded at \$93 a share as late as February 2008. In response to this announcement, the VPIN metric and its respective variance increase.

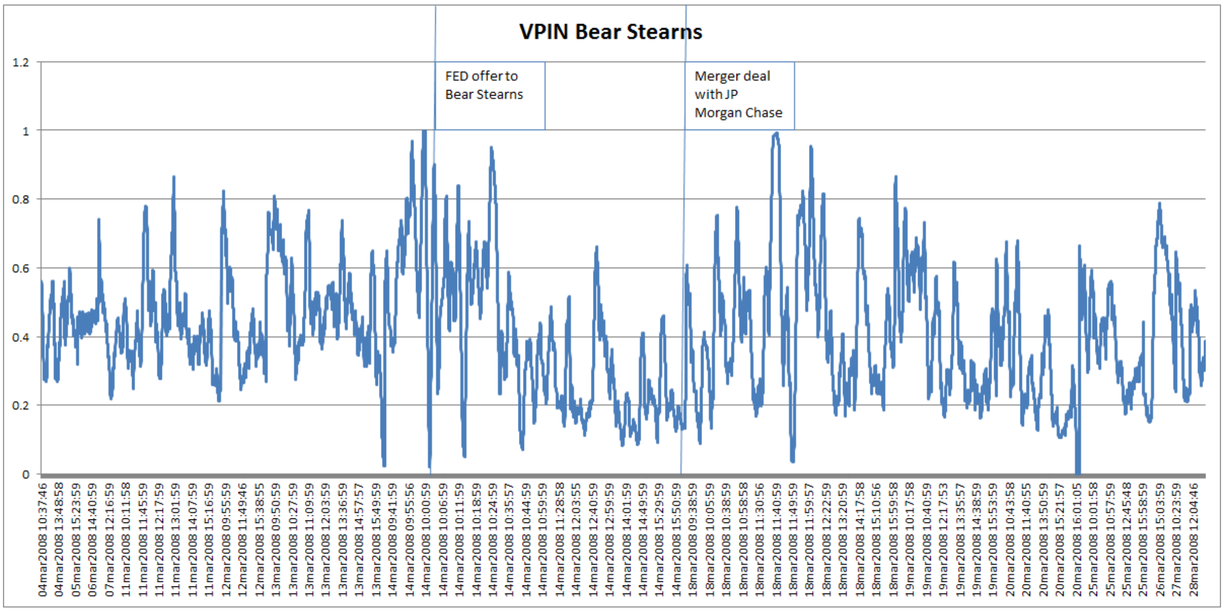

Figure 28: Evolution of the VPIN metric: The graph plots the evolution of the VPIN (volume-synchronized probability of informed trading) metric for Bear Stearns for March 2008.

For AIG, we see a similar smoothing reaction of the VPIN metric in September 2008 when several rating agencies issued investment grade ratings for AIG despite AIG's exposure to Lehman Brothers. However, as the intradaily bid-ask spread decomposition has already shown, this effect did not last long. After these fairly positive credit ratings, the government bailout of AIG (\$85 billion), which happenend at 9:00 PM on September 16, came as a surprise to many investors. The VPIN measure shoots up dramatically on September 16, 2008, indicating that markets were alert to toxicity in trading, which is proxied by the VPIN measure. On September 17 and early on September 18, the VPIN calms down as a reaction to the bailout announcement. However, again, this time of low toxicity does not last long. In the afternoon of September 18, the VPIN is volatile again. The bailout announcement, therefore, did not seem to have a long-lasting smoothing

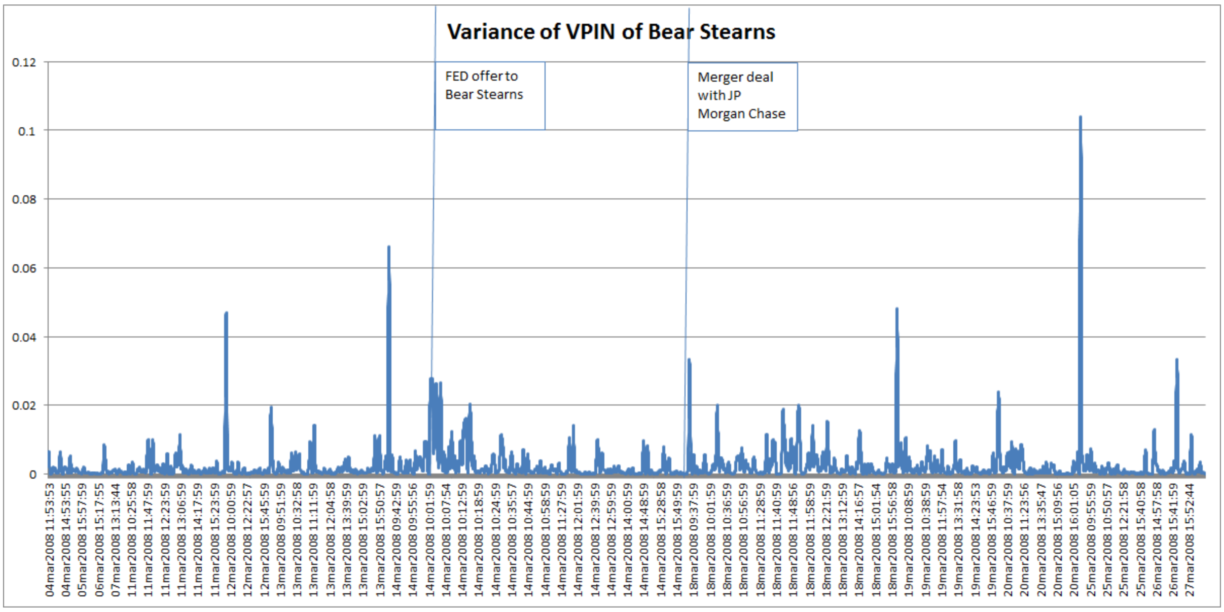

Figure 29: The VPIN metric becomes more volatile around important FED announcements: The graph plots the evolution of the variance of the VPIN (volume-synchronized probability of informed trading) metric for Bear Stearns for March 2008.

effect. Figures 30 and 31 plot this development.

Interestingly, this "smoothing" of the VPIN metric is not observable in our original information measure, the adverse selection component. For both financial companies, AIG and Bear Stearns, there is no smoothing observable in the adverse selection component (see Sections 4.2 and 4.3). The adverse selection component either constantly increases with the spread and with the other two cost types, as in the case of Bear Stearns, or increases abruptly, as in the case of AIG. The relatively positive announcements of the Federal Reserve Bank of New York (Bear Stearns) or rating agencies (AIG) do not seem to play a role in the evolution of the adverse selection component. So why is it that both measures seem to capture the increased adverse selection risk for troubled firms, but only the VPIN does so with more sensitivity and reacts to all major announcements? One explanation could be that volume, the underlying liquidity dimension of the VPIN metric, reacts much more sensitively to announcements, whereas prices, the underlying liquidity dimension of the adverse selection component, are more sticky and only change after the evaluation of fundamental changes. This seems to be confirmed in the volume and spread data. Figure 45 shows that trading volume of AIG starts to increase heavily from the beginning of September 2008 on. The spreads of AIG, on the other hand, react only in the second week of September. However, the overall trading volume of AIG does not decrease in times of positive credit ratings as the VPIN might have suggested. It reaches a peak shortly after the fairly positive ratings and then decreases after the Federal Reserve Bank

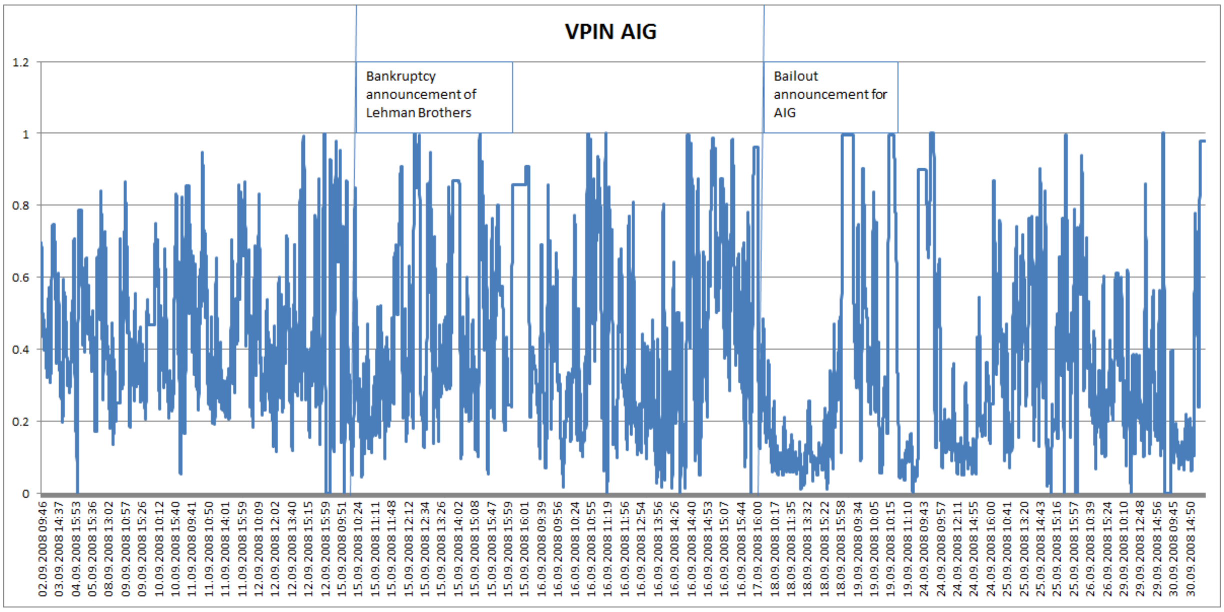

Figure 30: Evolution of the VPIN metric: The graph plots the evolution of the VPIN (volume-synchronized probability of informed trading) metric for AIG for September 2008.

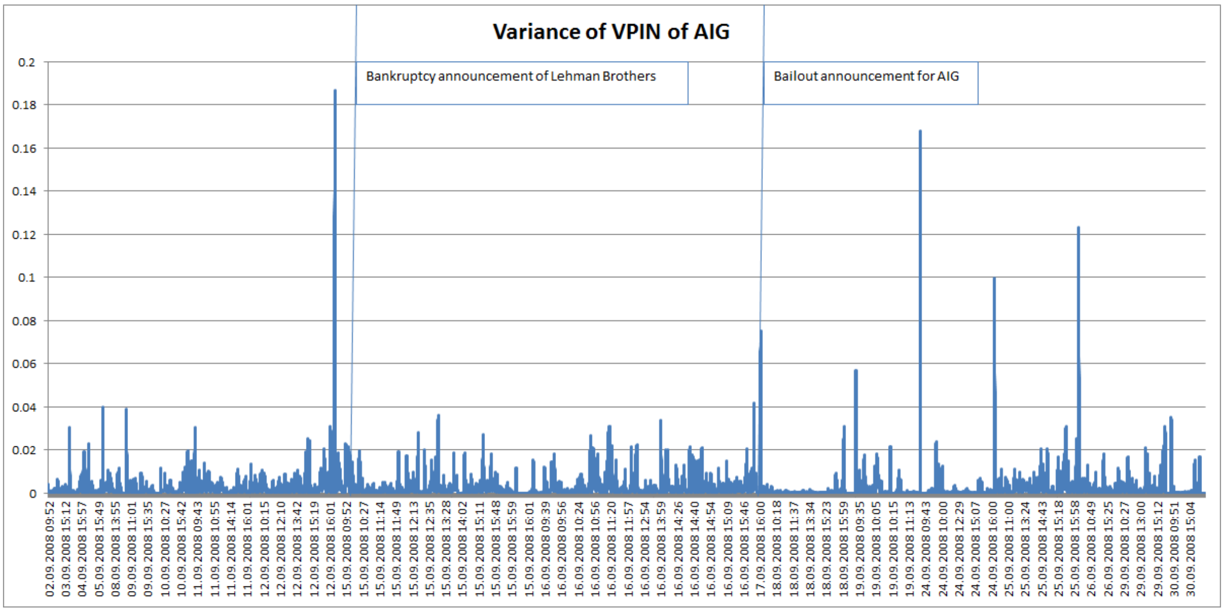

Figure 31: The VPIN metric becomes less volatile after September, 16: The graph plots the evolution of the variance of the VPIN (volume-synchronized probability of informed trading) metric for AIG for September 2008.

of New York bailout on September 16, 2008. Hence, it is not the volume per se that indicates information-sensitive time periods, but rather the signed volume or signed order flow – as captured by the VPIN metric – that reacts most sensitively to news.

4.6.2 Price impact regressions

An alternative way to assess the relative importance of adverse selection costs, inventory holding costs, and order processing costs is to estimate so-called "price impact regressions" (see Foucault et al. (2013)). Underlying these regressions are the assumptions that liquidity suppliers are risk-neutral and that they face the risk of trading with better-informed investors.

We start with a price impact regression that evaluates the effect that the price of a current trade has on subsequent trade prices. There are two major reasons for the persistence of price effects, inventory holding costs and dynamic informed trading. Both suggest that a trade at date t should affect future trades at dates $t+1$, $t+2$, ..., $t+n$. Hence, future prices can be related to a current trade by so-called price impact regressions:

$$p_{t+k} = \lambda_k p_t + \epsilon_t \tag{10}$$

The values, that the coefficient λ takes for Lehman Brothers for September 2 - 12, 2008, over many lags, are plotted in Graphs 62 to 64. While the values themselves are positive, the slope of the evolution of λ is negative for each day for Lehman Brothers. Hence, the effect that the transaction price of a current trade has on subsequent trades diminishes with lags and time. The slope becomes particularly negative on September 10 - 12, 2008.

1000 lags, thereby, comprise on average the following time spans in September 2008:

Table 1: 1000 lags in calender time:

Time	**09/02**	**09/03**	**09/04**	**09/05**	**09/08**	**09/09**	**09/10**	**09/11**	**09/12**
09:00-12:00 am:	11 min	07 min	25 min	25 min	09 min	04 min	05 min	05 min	06 min
12:00-02:00 pm:	48 min	69 min	71 min	31 min	15 min	13 min	22 min	10 min	20 min
02:00-04:00 pm:	20 min	18 min	18 min	20 min	10 min	03 min	05 min	02 min	09 min

Therefore, the slope of the coefficients' evolution is even steeper than what the graphs of September 10, 11, and 12 suggest as 1000 lags cover a shorter time span than what the same number of lags would cover in early September 2008. This indicates that information was incorporated into prices much faster on September 10, 11, and 12, 2008 as compared to early September 2008.

To what extent is the persistence of the price effects due to inventory effects and to what extent is it due to the persistence of information? As established by Kyle (1985), the optimal dynamic strategy of informed traders implies piecemeal revelation of information over time. While the decomposition strategy of Huang and Stoll, used earlier in Section 4.1, identifies inventory holding costs by means of autorcorrelations, in an environment with dynamic informed trading this identification needs to be adjusted to a richer information environment. In order to identify the information effects, we rely on the innovation of a higher-order autoregression of transaction prices. This innovation is the unexpected news to a given observation and we may relate the persistence of this innovation to the persistence of the full price. Accordingly, we estimate impact regressions on price innovations as follows:

$$p_{t+k} = \alpha_k \eta_t + \epsilon_t, \tag{11}$$

where η_t, the surprise or innovation, is given by:

$$p_t = \beta_1 p_{t-1} + ... + \beta_n p_{t-n} + \eta_{t-n}. \tag{12}$$

The values that the coefficient α takes for Lehman Brothers for September 2 - 12, 2008 over many lags, are plotted in Graphs 65 to 67. α takes positive values over all examined lags for each day in September 2008. However, for September 2 - 9, the lower confidence bound is either zero or eventually hits zero which makes the estimates insignificant. Apparently, these results provide some justification for the indentification strategy used in the decomposition of Section 4.1 for the early period from September 2 - 9, 2008.

However, the picture changes completely when we examine the evolution of α on September 10, 11, and 12, 2008. Here, all results are significantly positive. Therefore, in those three days the price innovation has a significant and positive effect on subsequent transaction prices. Since, with the Huang and Stoll approach, we interpreted all intertemporal effects as being caused by inventory holding considerations, it seems that our earlier decomposition underestimated the adverse selection and overestimated the inventory holding component in those three critical days. However, this finding reinforces the role of information prior to the insolvency. Both our main decomposition approach as developed by Huang and Stoll and these price innovation regression measures agree on a significant information component on September 10, 11, and 12.

We can furthermore ask if information might also be incorporated into trades themselves or trading volume. Hence, in order to analyze the role of volume and the informational content therein, we estimate a new set of regressions to assess the effect that signed trading volume has on subsequent prices. In particular, we estimate the following regressions:

$$p_{t+k} = \gamma_k q_t + \epsilon_t, \tag{13}$$

where q_t represents signed trading volume.

The values, that the coefficient γ takes for Lehman Brothers for September 2 - 12, 2008, over many lags, are plotted in Graphs 68 to 70. The slope of the evolution of γ is negative with fairly small values and insignificant for most days in September 2008 for Lehman Brothers. Hence, the effect that the signed volume of a current trade has on subsequent trade prices diminishes and is negligible. There is no signifcant persistence in trades.

As before, we treat innovations in the autoregressions of trading volume as innovations or news and analyze the persistence of this news on subsequent trades:

$$p_{t+k} = \beta_k \kappa_t + \epsilon_t, \tag{14}$$

where κ_t is given by:

$$q_t = \rho_1 q_{t-1} + ... + \rho_n q_{t-n} + \kappa_{t-n}. \tag{15}$$

Interestingly, unlike in the case of price innovations, there is virtually no persistence of innovations in trading volume. The coefficients over the first five to ten lags take positive and large values (see Figures 74 to 73), but this effect is statistically insignificant and vanishes rather quickly after about ten lags. This picture changes when we differentiate trades according to their size in trading volume. While there is no persistence of large trades, interestingly, small trades are persistent (74 to 76). This result seems to suggest that informed traders indeed employ dynamic trading strategies, breaking up an informed trade into many smaller trades and releasing information only gradually. In contrast, large trades seem to be either liquidity-motivated or portfolio rebalancing operations with little informational content (Figures 77 to 79).

Summarizing these findings, it seems that it is the transaction prices and not volumes that carry and process new information revealed by trading. The evolution of the coefficients of equation 10 and especially of equation 11 seem to support our initial finding of

Section 4.1.[1]

5 Conclusion

The empirical decomposition of relative equity bid-ask spreads in the U.S. banking sector reveals that information risk was indeed an important driver of the increase in trading costs. While we identify evidence of market speculation about an imminent failure of Lehman Brothers only in the last week of trading, there is no indication that markets expected other banks to take over the troubled investment bank. Even in the case of Barclays, which entered into merger negotiations the weekend just before the bankruptcy announcement, market prices did not seem to convey any information about this.

Ex post, i.e. after the bankruptcy declaration, we see a drastic increase in transactions costs for all investment and commercial banks even though the U.S. government introduced measures designed to strengthen liquidity such as TARP or bans on short-sales. Unexpectedly, the relative contributions of all three cost components to the spread remained roughly the same throughout the months following Lehman's failure. This indicates that it was information risk as well as economic uncertainty that drove transaction costs to increase.

Methodologically, we find that modified variants of the decomposition of Huang and Stoll (1997) are remarkably robust with respect to the high frequency of trading under normal conditions. Only in the last three days of trading are price innovations persistent. On the other hand, there is some persistence in the impact of small trades on the subsequent sequences of trades also under normal conditions.

[1]The results are also robust to the inclusion of trades and quotes that were originated at exchanges other than the NYSE. Regression specifications that have returns – instead of prices – as their dependent variable turn out to have insignificant estimates.

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6 Appendix

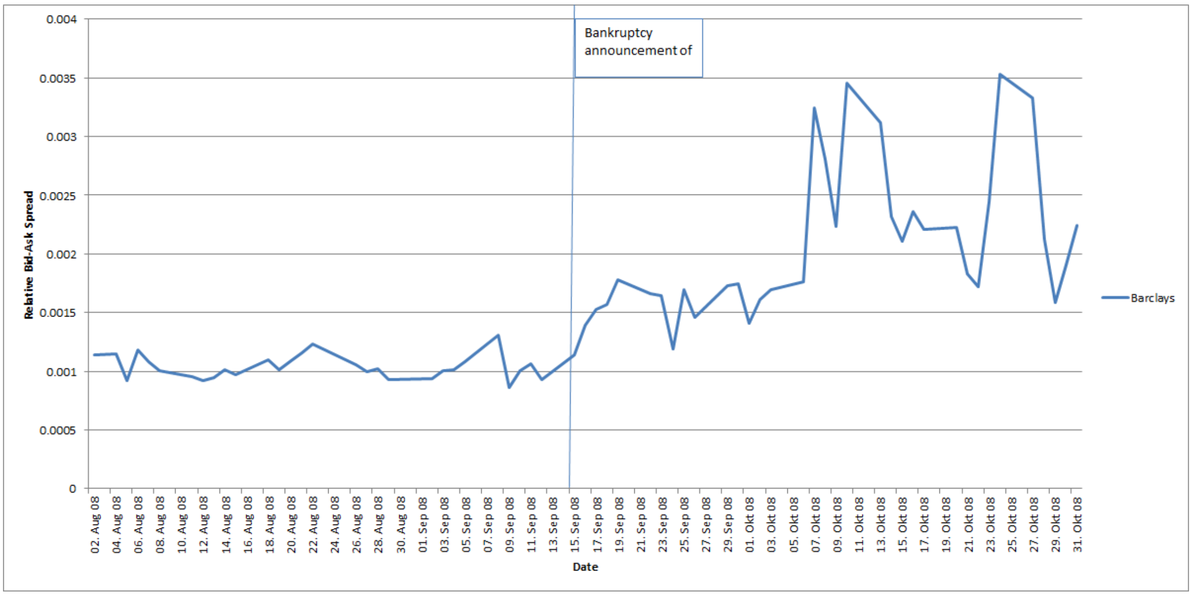

Figure 32: Relative Bid-Ask Spread: Barclays PLC

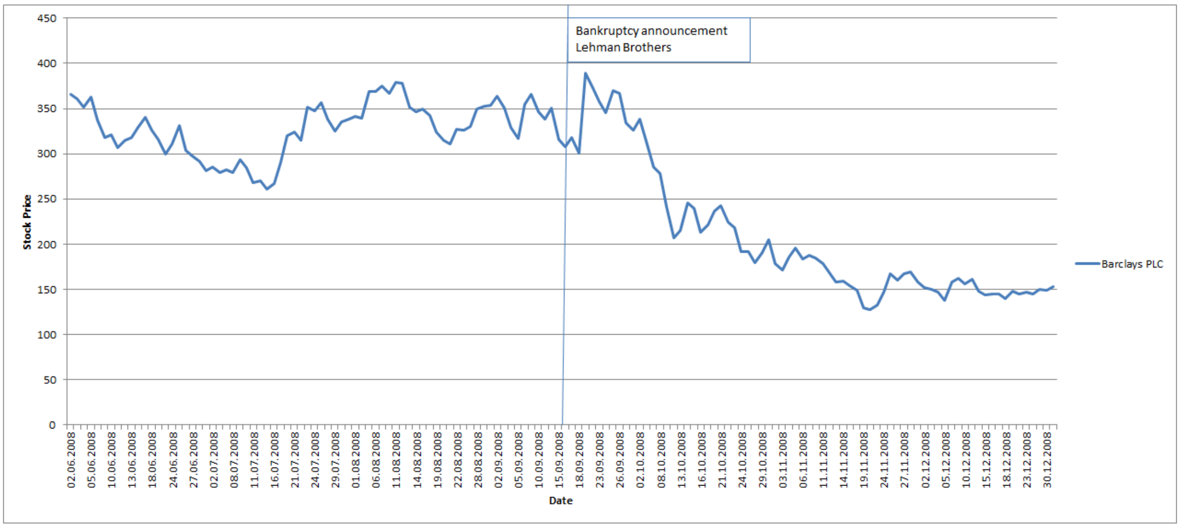

Figure 33: Stock Price: Daily stock price for Barclays PLC

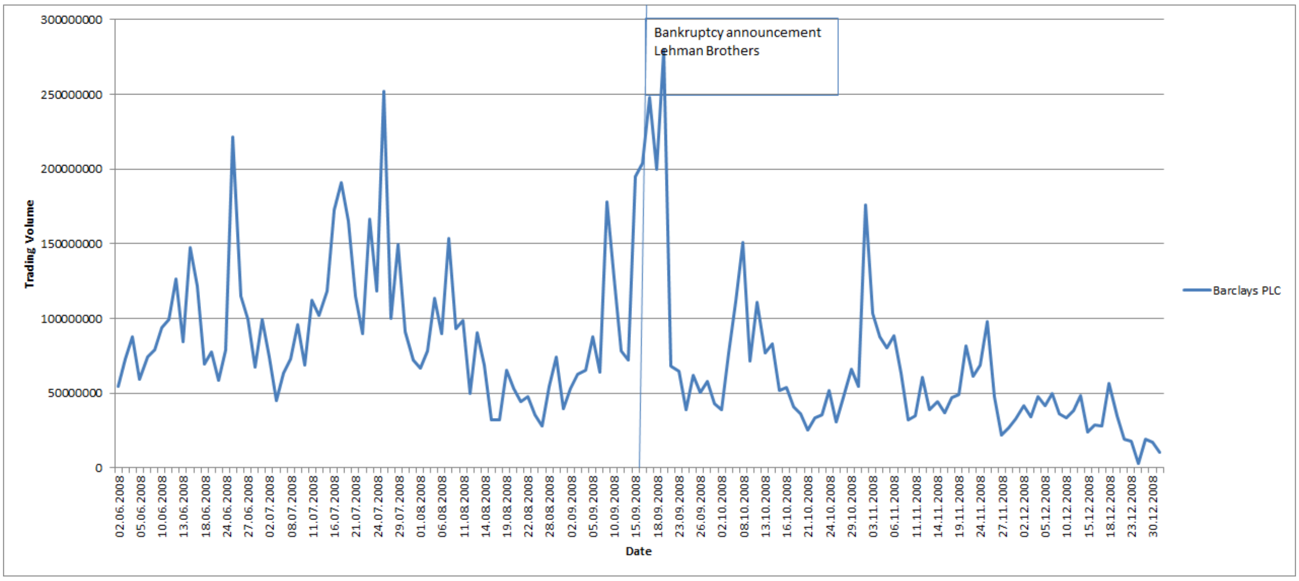

Figure 34: Trading Volume: Daily trading volume for Barclays PLC

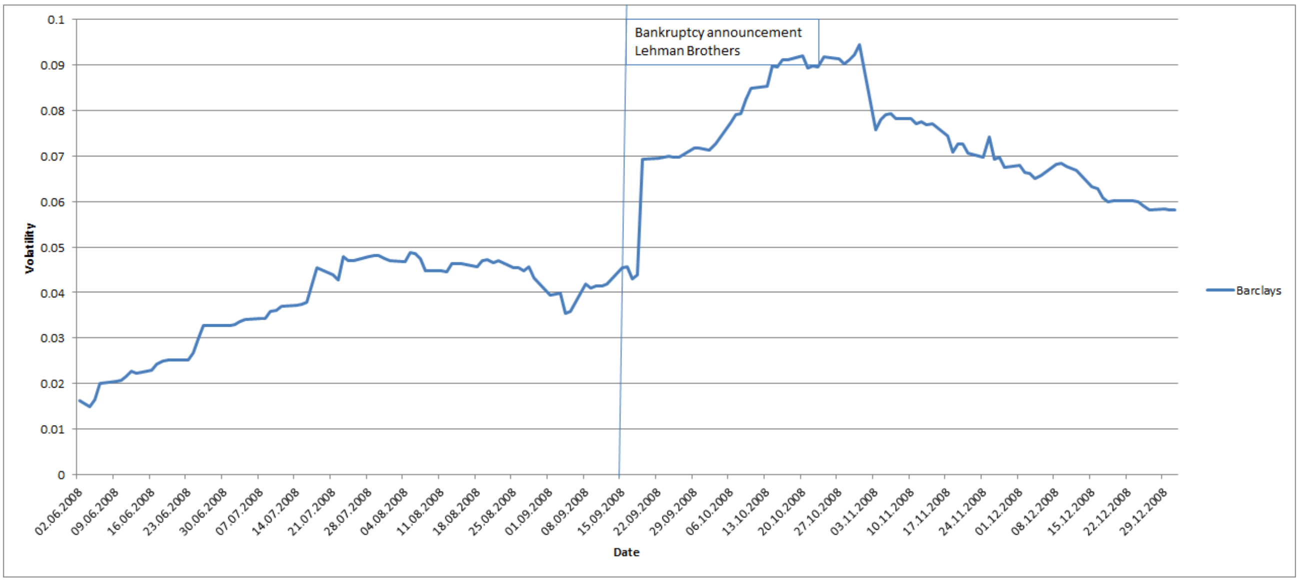

Figure 35: Volatility Barclays PLC

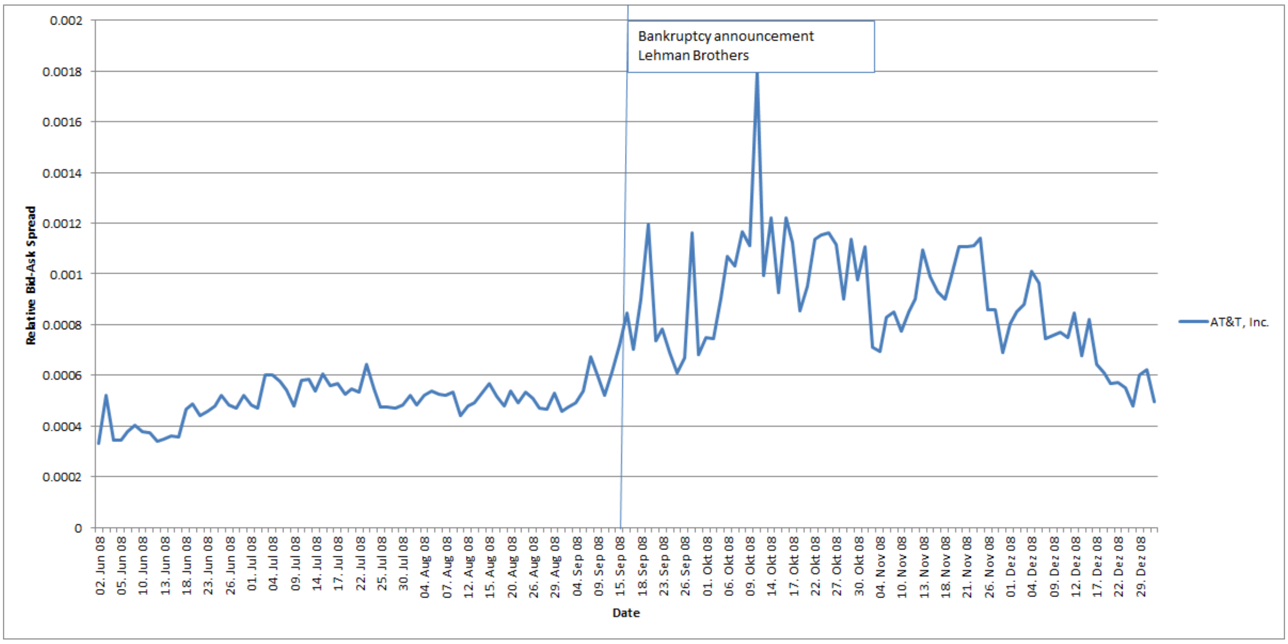

Figure 36: Relative Bid-Ask Spread: AT&T, Inc.

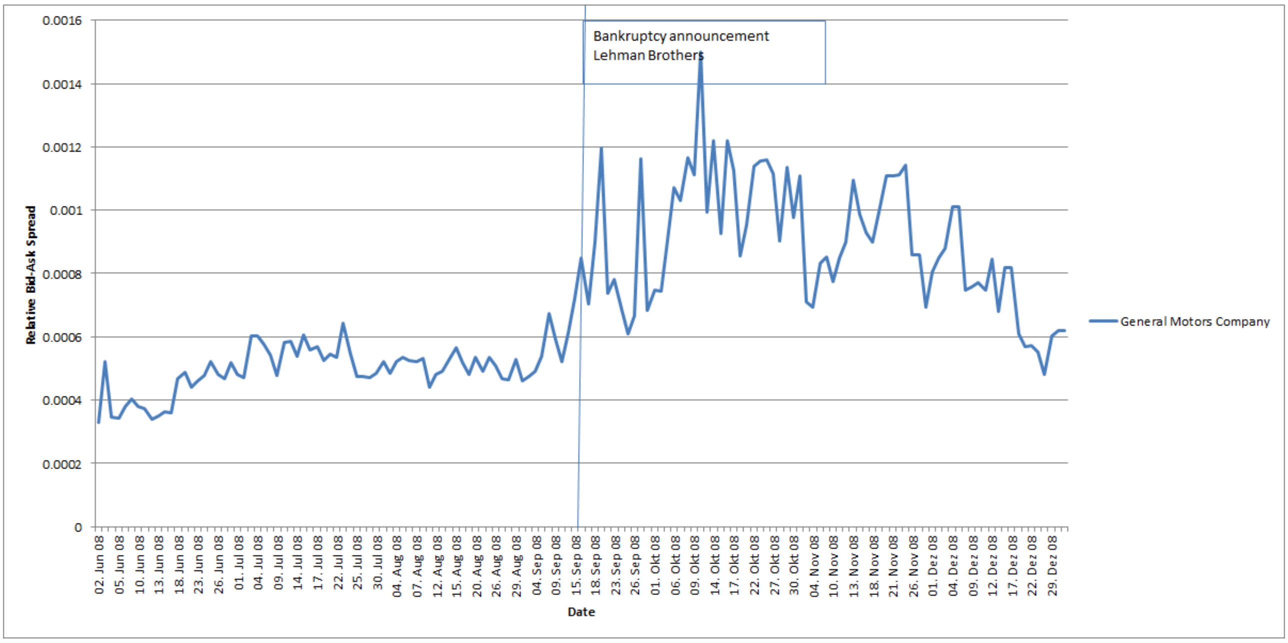

Figure 37: Relative Bid-Ask Spread: General Motors Company

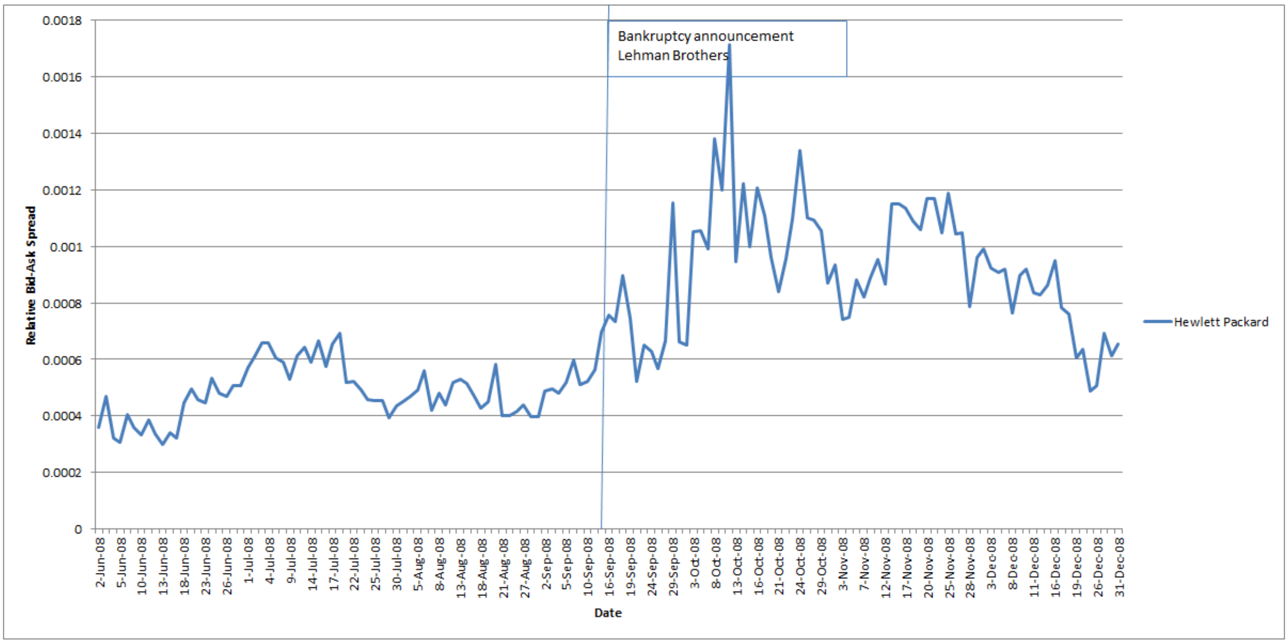

Figure 38: Relative Bid-Ask Spread: Hewlett Packard Company

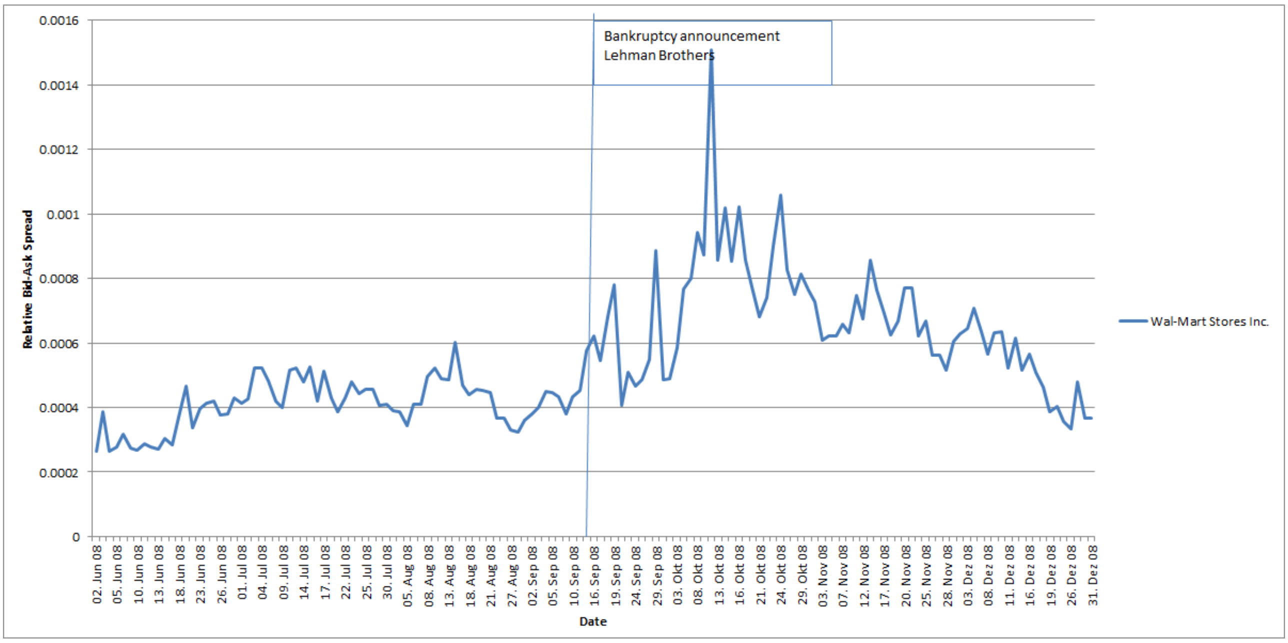

Figure 39: Relative Bid-Ask Spread: Wal-Mart Stores Inc.

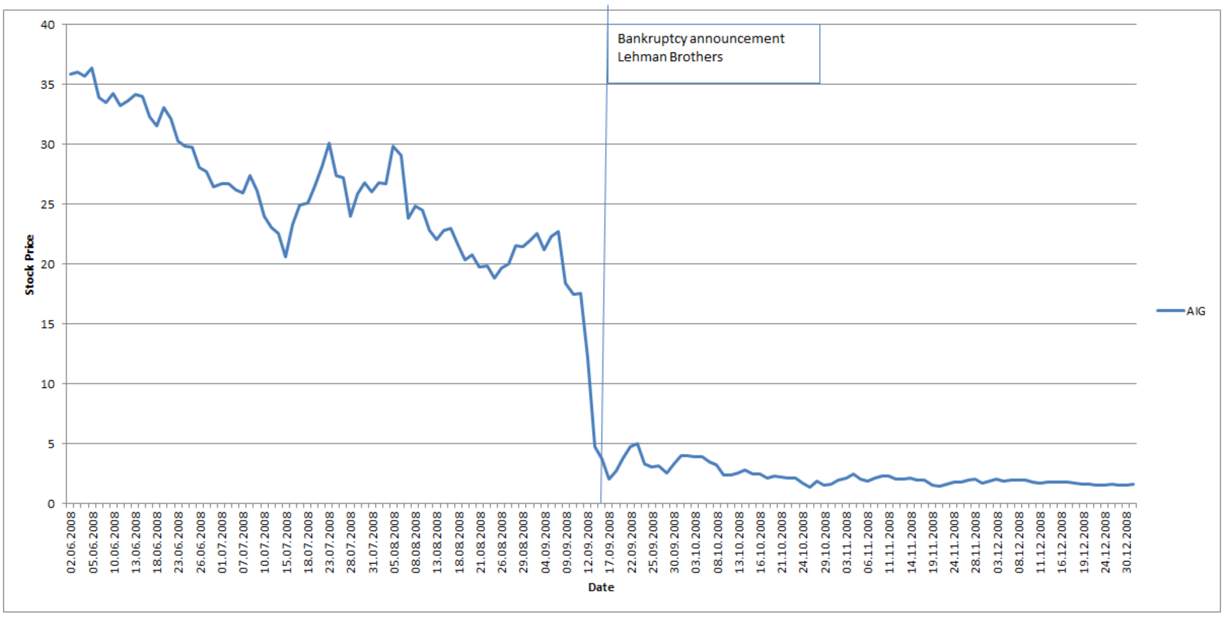

Figure 40: Daily stock price for AIG

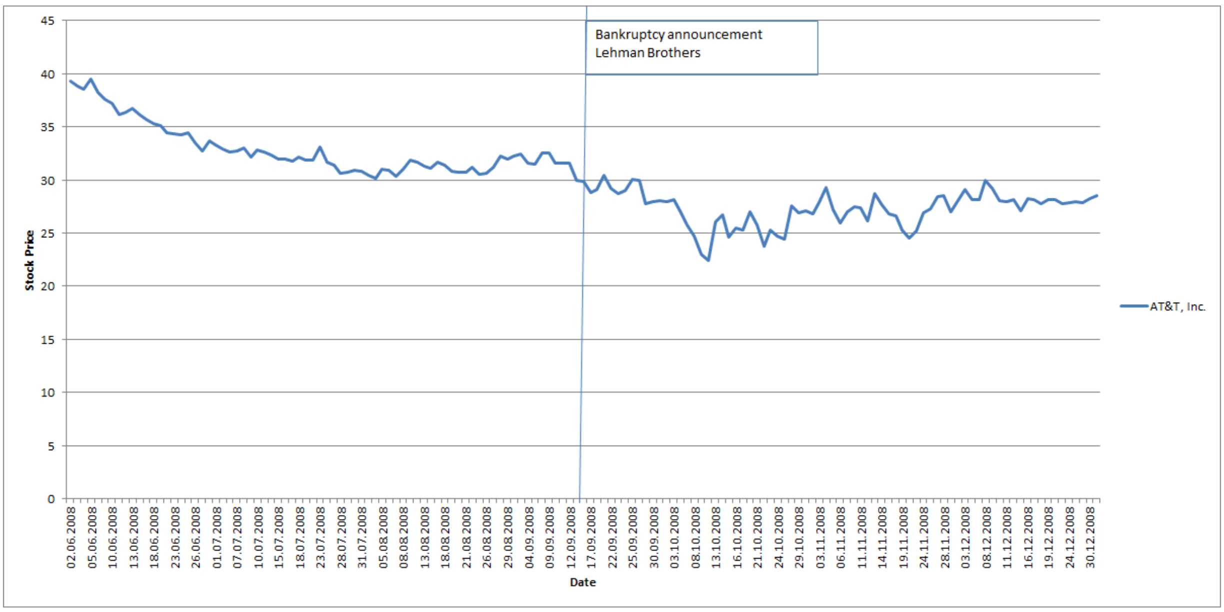

Figure 41: Daily stock price for AT&T, Inc.

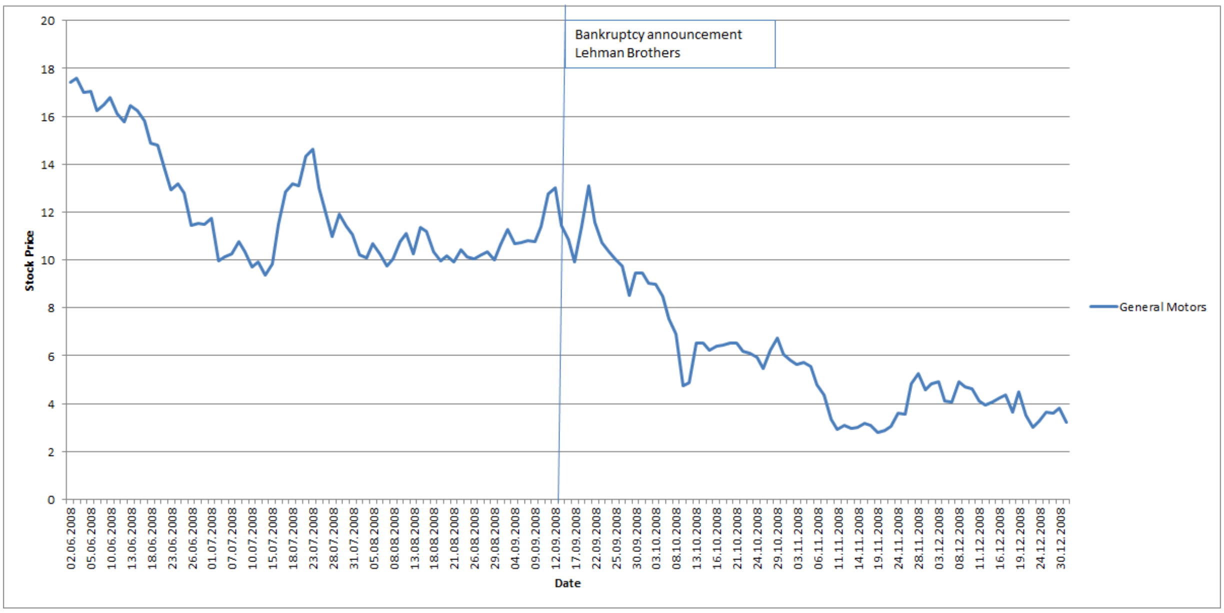

Figure 42: Daily stock price for General Motors Company

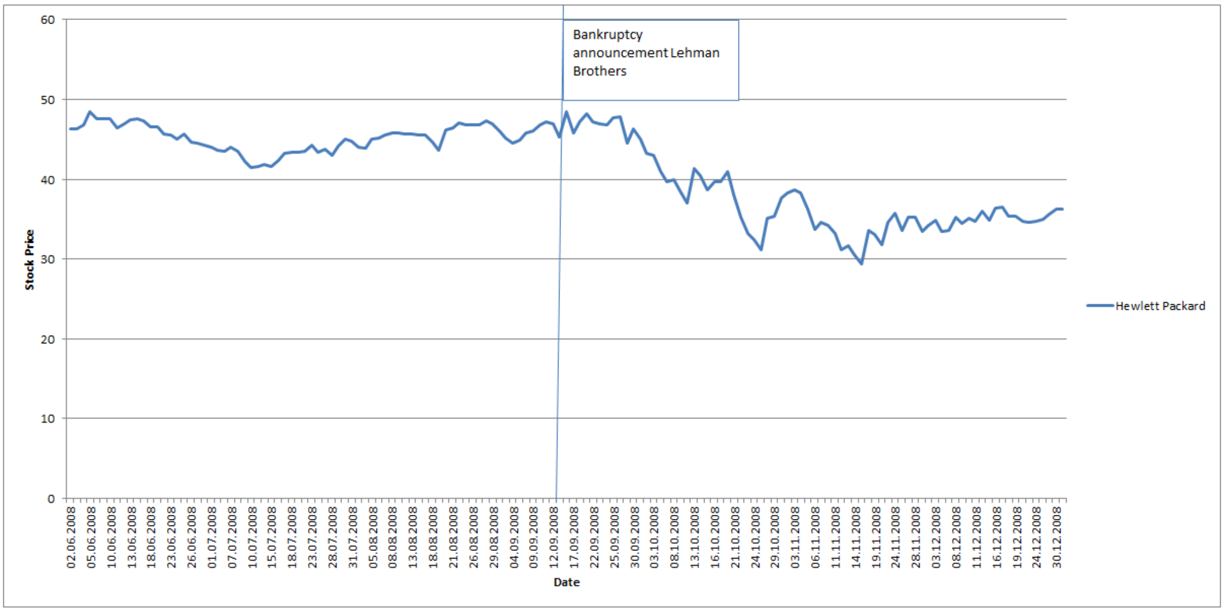

Figure 43: Daily stock price for Hewlett Packard Company

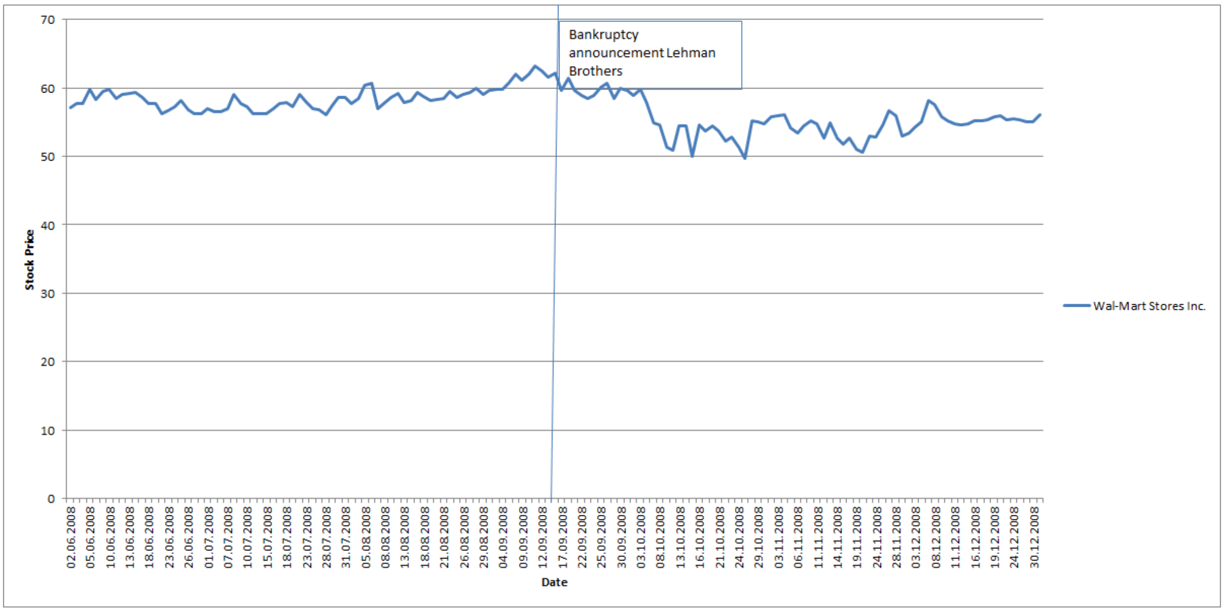

Figure 44: Daily stock price for Wal-Mart Stores, Inc.

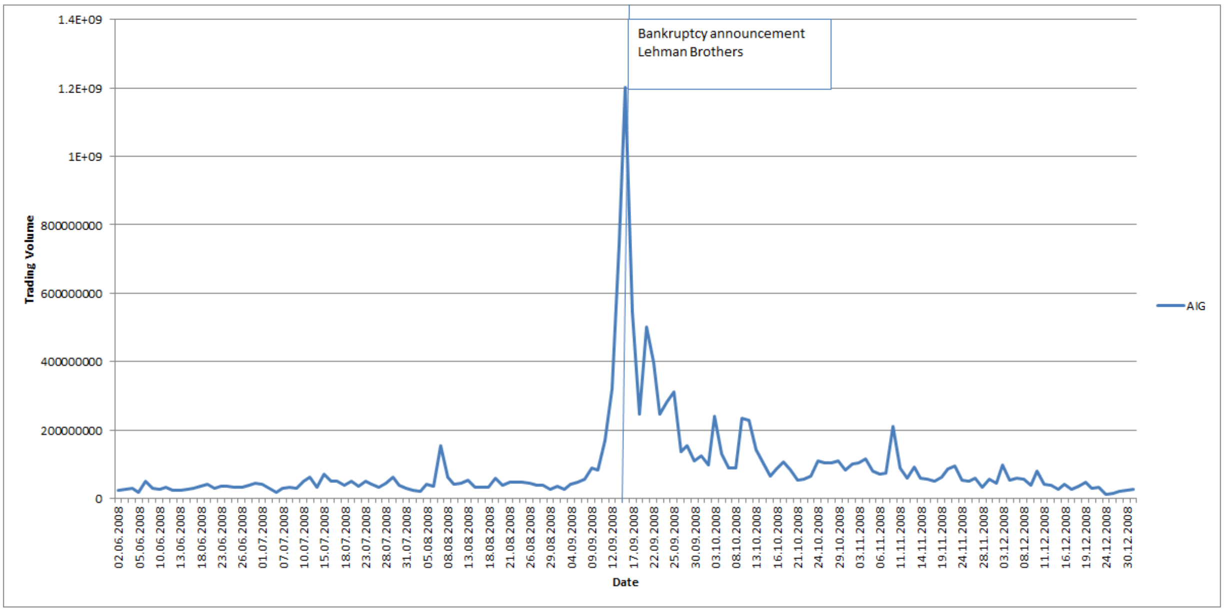

Figure 45: Daily trading volume for AIG

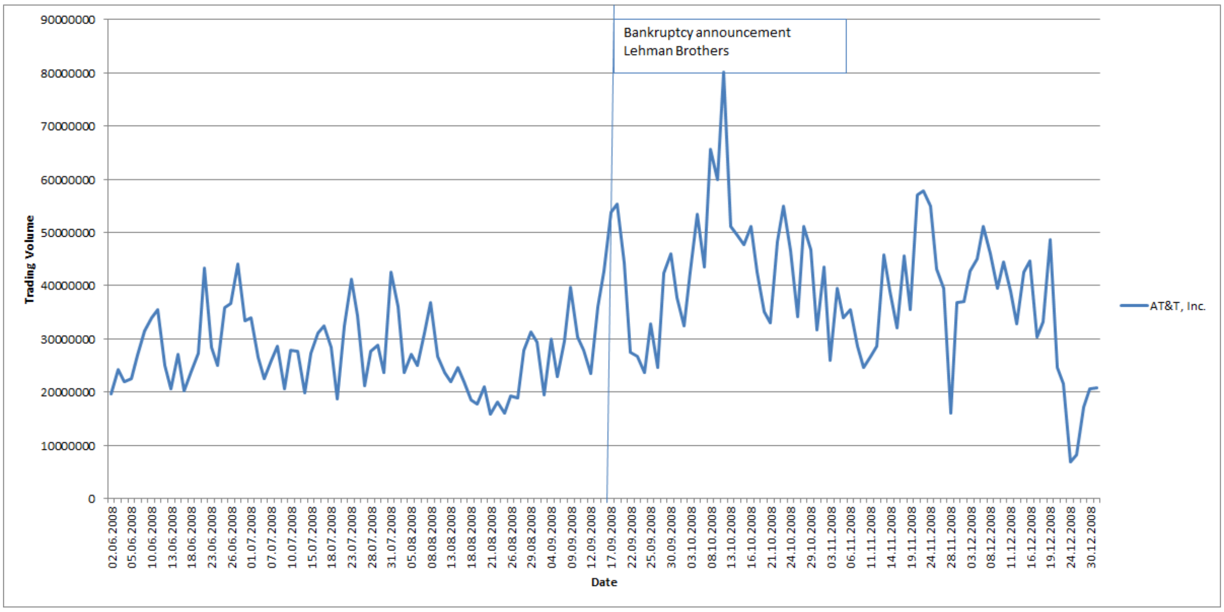

Figure 46: Daily trading volume for AT&T, Inc.

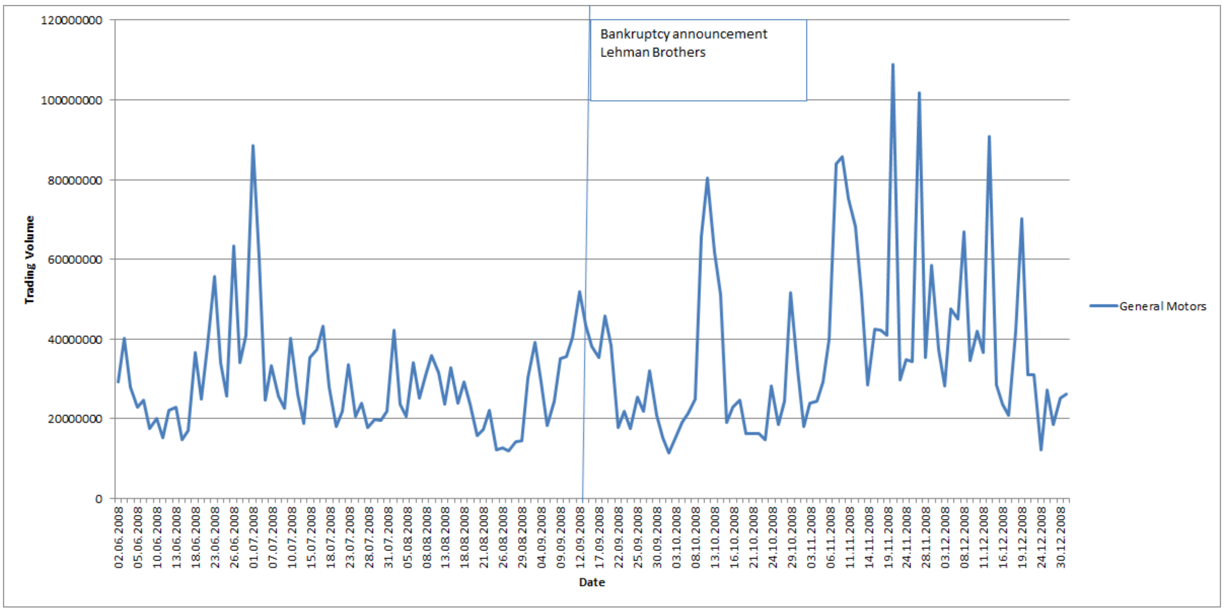

Figure 47: Daily trading volume for General Motors Company

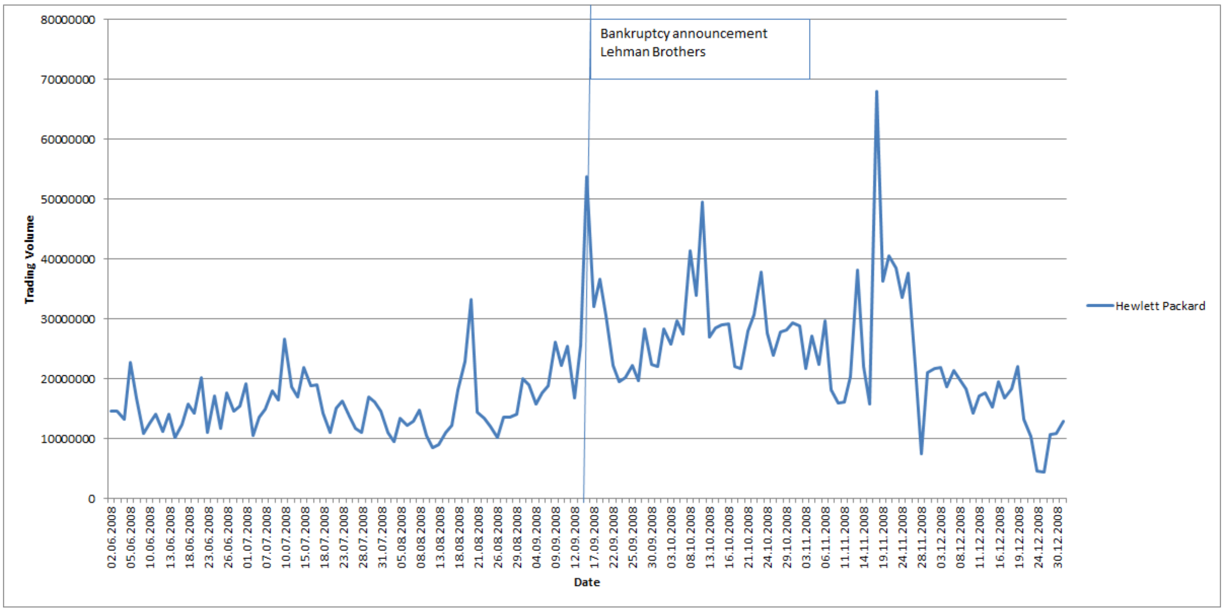

Figure 48: Daily trading volume for Hewlett Packard Company

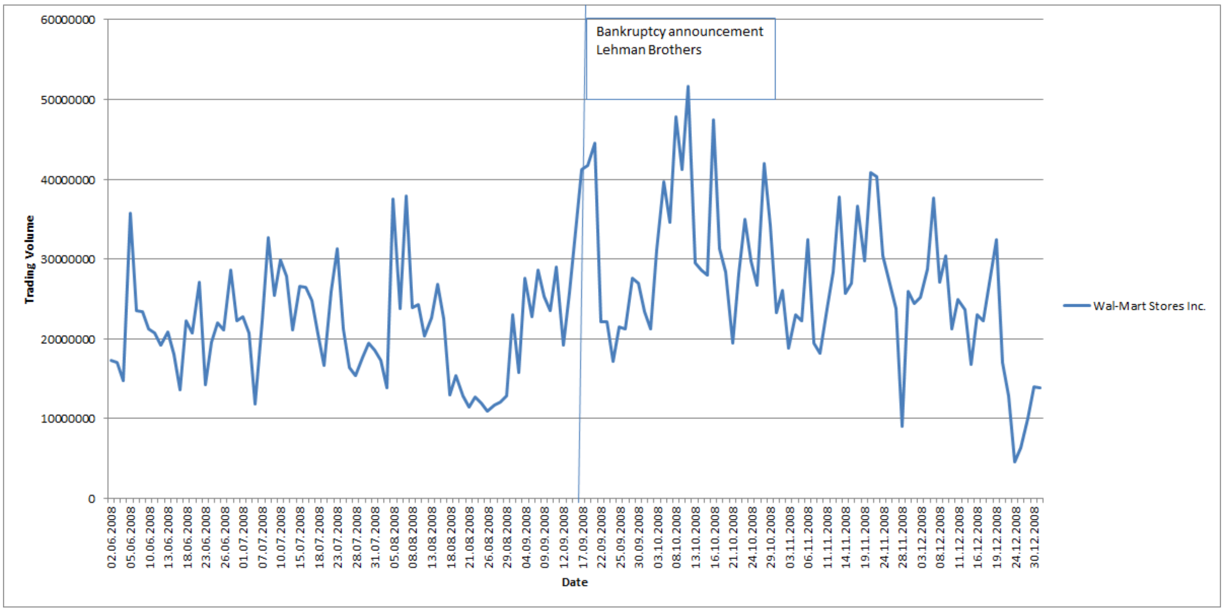

Figure 49: Daily trading volume for Wal-Mart Stores, Inc.

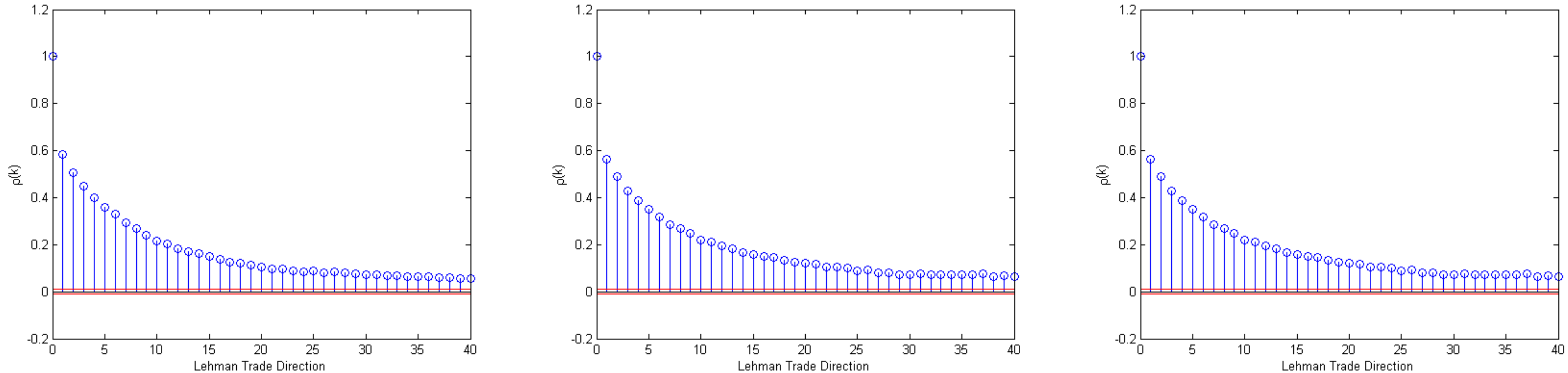

Figure 50: Persistence in Sign of Lehman Brothers' Trades: September 02, 03, & 04, 2008

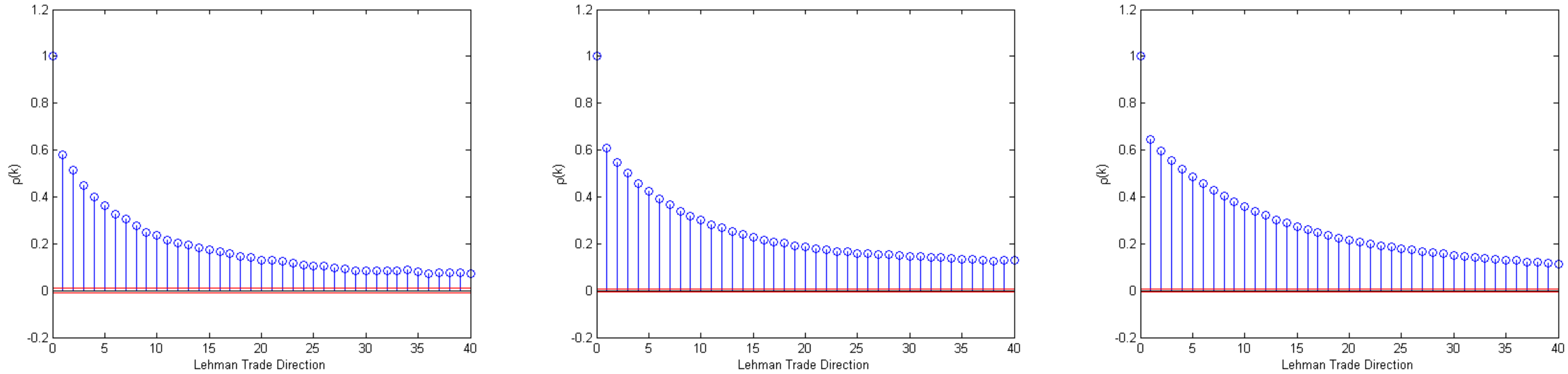

Figure 51: Persistence in Sign of Lehman Brothers' Trades: September 05, 08, & 09, 2008

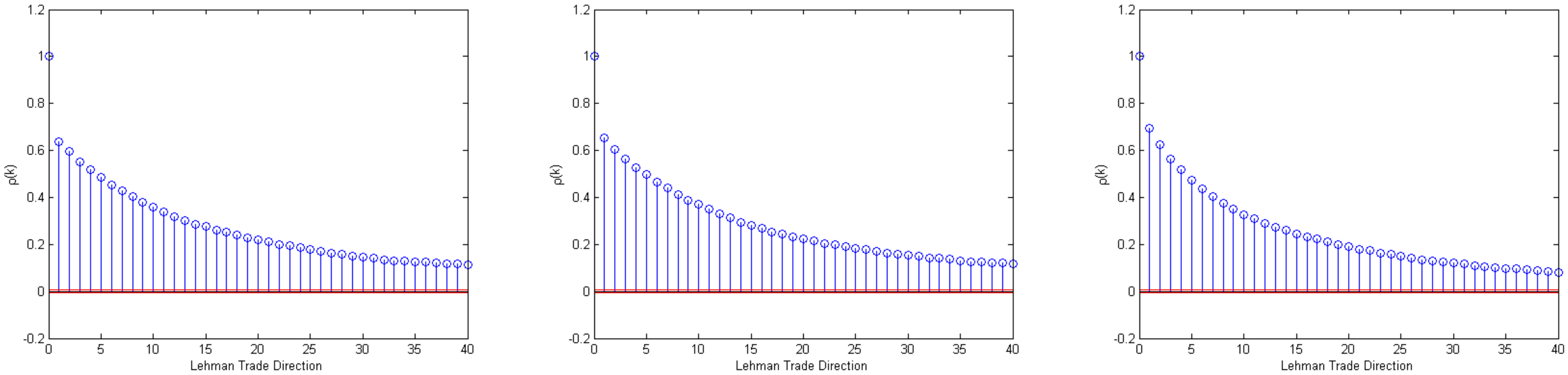

Figure 52: Persistence in Sign of Lehman Brothers' Trades: September 10, 11, & 12, 2008

Table 2: Mean-Comparison Test for Relative Bid-Ask Spreads of Bank of America

Time Period	Observations	Mean	Std. Error
09/02/2008 to 09/12/2008	301,530	0.0007	0.00004
10/21/2008 to 10/31/2008	777,115	0.0012	0.00005
Combined	1,078,465	0.0010	0.00007
Difference		-0.0005	0.00006**
09/02/2008 to 09/12/2008	301,530	0.0007	0.00004
12/17/2008 to 12/31/2008	787,173	0.0010	0.00001
Combined	1,088,523	0.0009	0.00004
Difference		-0.0003	0.00004**

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Mean-Comparison Test for Relative Bid-Ask Spreads of Barclays PLC

Time Period	Observations	Mean	Std. Error
09/02/2008 to 09/12/2008	243,644	0.0010	0.00004
10/21/2008 to 10/31/2008	174,779	0.0023	0.00023
Combined	418,423	0.0016	0.00019
Difference		-0.0013	0.00024**

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Mean-Comparison Test for Relative Bid-Ask Spreads of Citigroup

Time Period	Observations	Mean	Std. Error
09/02/2008 to 09/12/2008	362,287	0.0009	0.00002
10/21/2008 to 10/31/2008	576,358	0.0015	0.00007
Combined	938,645	0.0012	0.00008
Difference		-0.0006	0.00007**
09/02/2008 to 09/12/2008	362,287	0.0009	0.00002
12/17/2008 to 12/31/2008	410,657	0.0018	0.00001
Combined	772,944	0.0013	0.00011
Difference		-0.0009	0.00002***

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Mean-Comparison Test for Relative Bid-Ask Spreads of Goldman Sachs

Time Period	Observations	Mean	Std. Error
09/02/2008 to 09/12/2008	198,808	0.0009	0.00004
10/21/2008 to 10/31/2008	521,379	0.0015	0.00007
Combined	720,187	0.0012	0.00009
Difference		-0.0007	0.00008**
09/02/2008 to 09/12/2008	198,808	0.0009	0.00004
12/17/2008 to 12/31/2008	238,510	0.0010	0.00004
Combined	437,318	0.0009	0.00003
Difference		-0.0008	0.00006

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Mean-Comparison Test for Relative Bid-Ask Spreads of JP Morgan Chase

Time Period	Observations	Mean	Std. Error
09/02/2008 to 09/12/2008	405,754	0.0007	0.00002
10/21/2008 to 10/31/2008	736,195	0.0010	0.00004
Combined	1,141,949	0.0009	0.00004
Difference		-0.0003	0.00004**
09/02/2008 to 09/12/2008	405,754	0.0007	0.00002
12/17/2008 to 12/31/2008	582,126	0.0007	0.00004
Combined	987,880	0.0007	0.00002
Difference		-0.0002	0.00004

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Mean-Comparison Test for Relative Bid-Ask Spreads of Lehman Brothers

Time Period	Observations	Mean	Std. Error
08/06/2008 to 08/22/2008	316,549	0.0016	0.00006
08/26/2008 to 09/12/2008	434,203	0.0023	0.00034
Combined	750,752	0.0020	0.00018
Difference		-0.0006	0.00034*

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Mean-Comparison Test for Relative Bid-Ask Spreads of Merrill Lynch

Time Period	Observations	Mean	Std. Error
09/02/2008 to 09/12/2008	444,924	0.0013	0.00015
10/21/2008 to 10/31/2008	299,073	0.0019	0.00011
Combined	743,997	0.0016	0.00012
Difference		-0.0007	0.00018*
09/02/2008 to 09/12/2008	444,924	0.0013	0.00015
12/17/2008 to 12/31/2008	208,014	0.0013	0.00006
Combined	652,938	0.0013	0.00008
Difference		-0.00006	0.00016

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Mean-Comparison Test for Relative Bid-Ask Spreads of Morgan Stanley

Time Period	Observations	Mean	Std. Error
09/02/2008 to 09/12/2008	147,872	0.0010	0.00005
10/21/2008 to 10/31/2008	311,231	0.0029	0.00023
Combined	459,103	0.0019	0.00026
Difference		-0.0020	0.00023**
09/02/2008 to 09/12/2008	147,872	0.0010	0.00005
12/17/2008 to 12/31/2008	202,793	0.0014	0.00009
Combined	350,665	0.0011	0.00007
Difference		-0.0004	0.00010*

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Mean-Comparison Test for Relative Bid-Ask Spreads of Wells Fargo

Time Period	Observations	Mean	Std. Error
09/02/2008 to 09/12/2008	301,775	0.0008	0.00003
10/21/2008 to 10/31/2008	636,018	0.0012	0.00005
Combined	937,793	0.0010	0.00006
Difference		-0.0004	0.00006**
09/02/2008 to 09/12/2008	301,775	0.0008	0.00003
12/17/2008 to 12/31/2008	401,499	0.0007	0.00003
Combined	703,274	0.0007	0.00002
Difference		-0.0000	0.00004

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

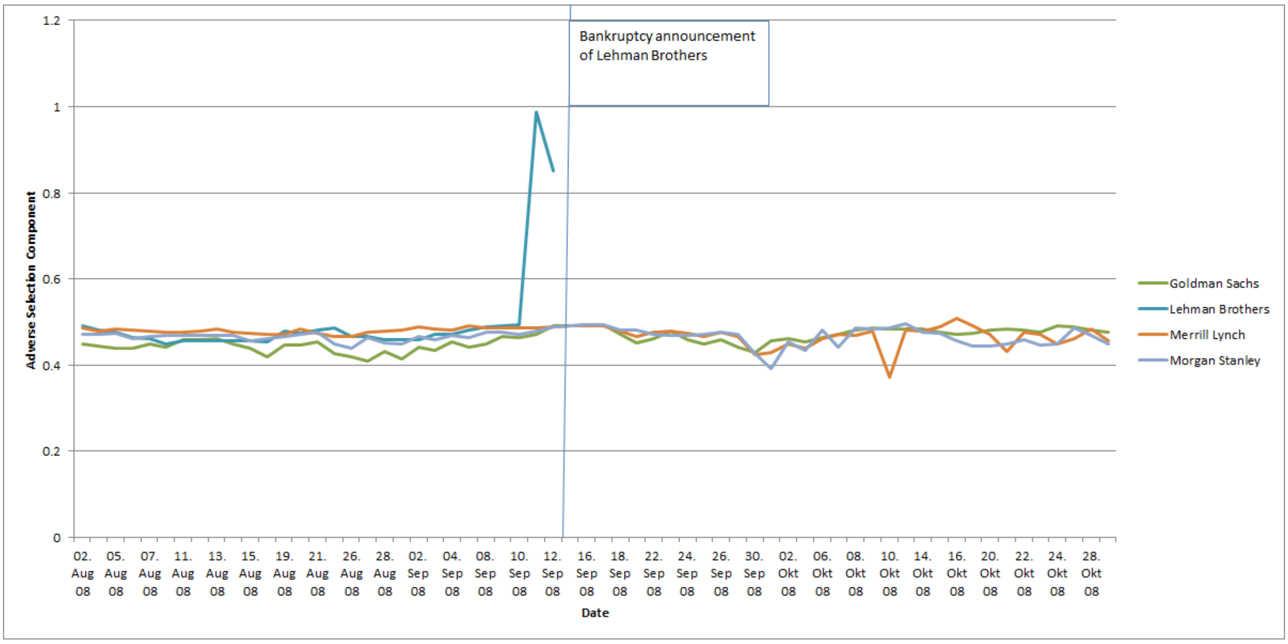

Figure 53: Evolution of the Adverse Selection Component of Investment Banks: The lines plot the evolution of the adverse selection component *sa* of all investment banks in our sample.

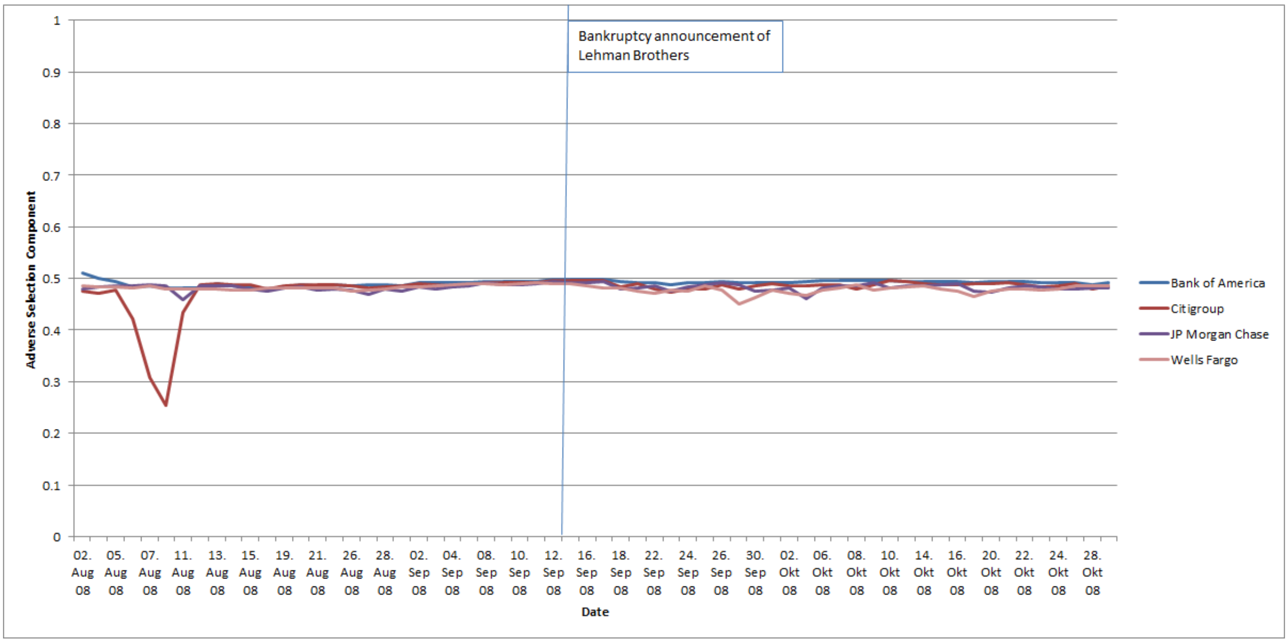

Figure 54: **Evolution of the Adverse Selection Component of Commercial Banks:** The lines plot the evolution of the adverse selection component *sa* of all commercial banks in our sample.

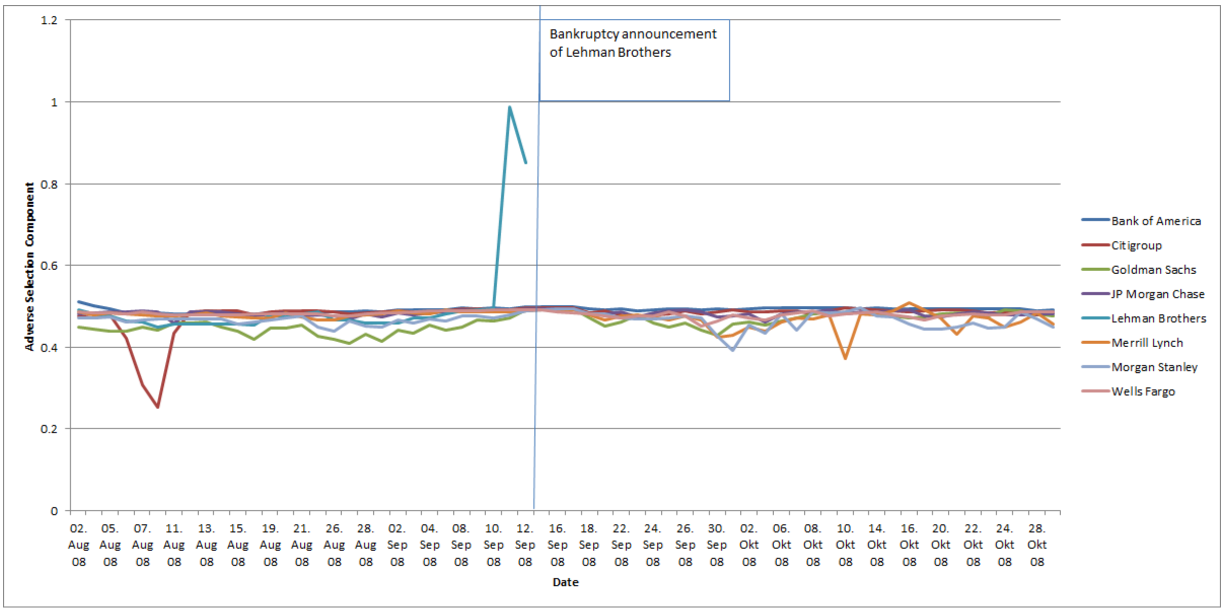

Figure 55: **Evolution of the Adverse Selection Component of U.S. Banks:** The lines plot the evolution of the adverse selection component *sa*.

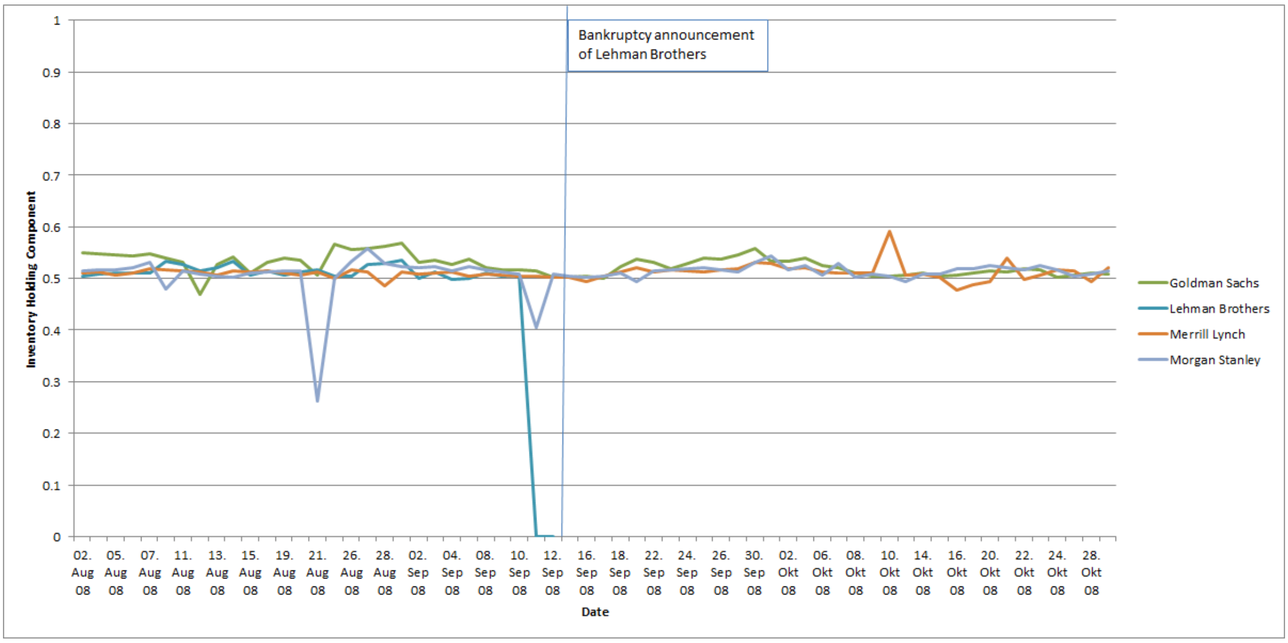

Figure 56: Evolution of the Inventory Holding Component of Investment Banks: The lines plot the evolution of the inventory holding component si of all investment banks in our sample.

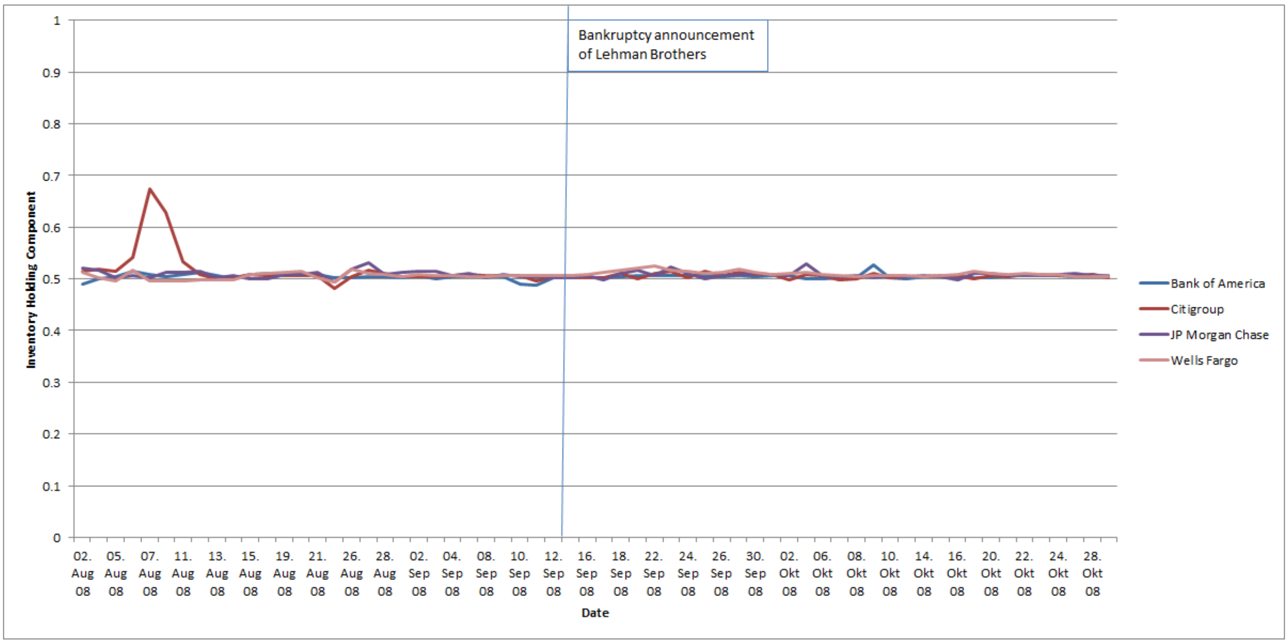

Figure 57: Evolution of the Inventory Holding Component of Commercial Banks: The lines plot the evolution of the inventory holding component si of all commercial banks in our sample.

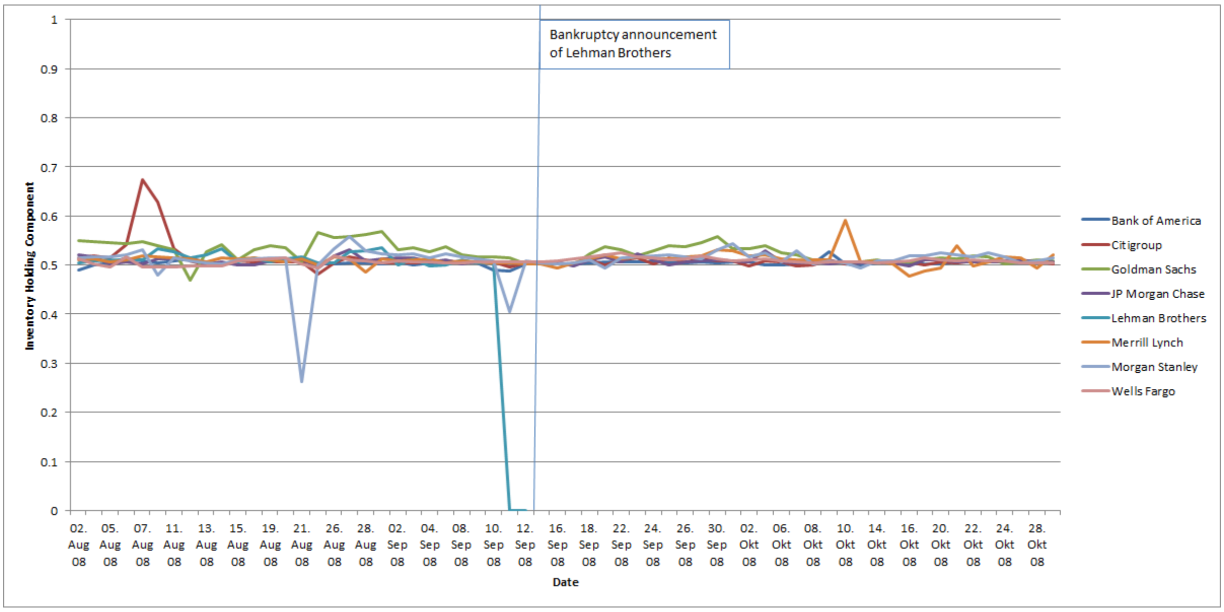

Figure 58: Evolution of the Inventory Holding Component of U.S. Banks: The lines plot the evolution of the inventory holding component *si*.

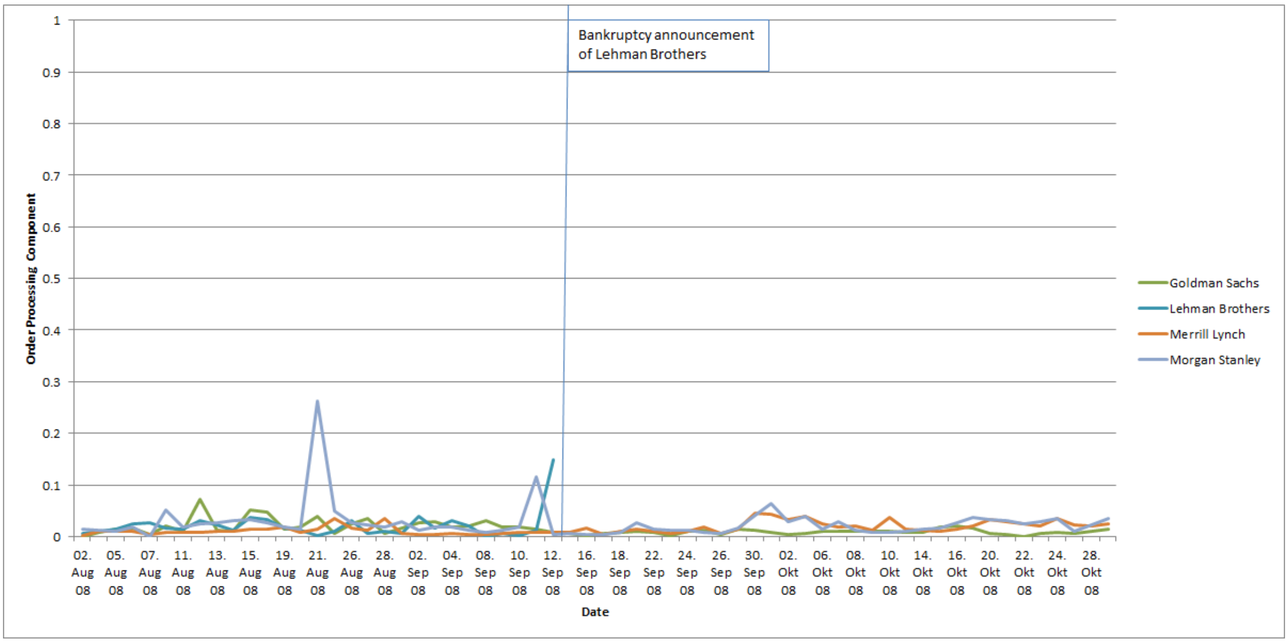

Figure 59: Evolution of the Order Processing Component of Investment Banks: The lines plot the evolution of the order processing component *so* of all investment banks in our sample.

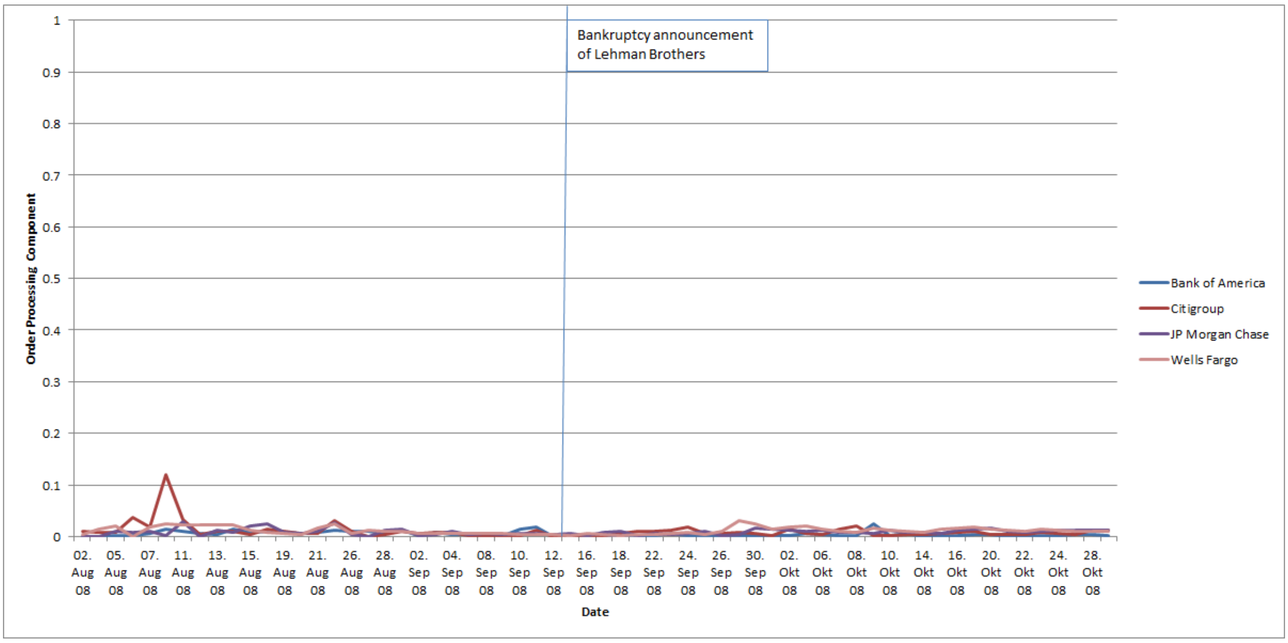

Figure 60: Evolution of the Order Processing Component of Commercial Banks: The lines plot the evolution of the order processing component *so* of all commercial in our sample.

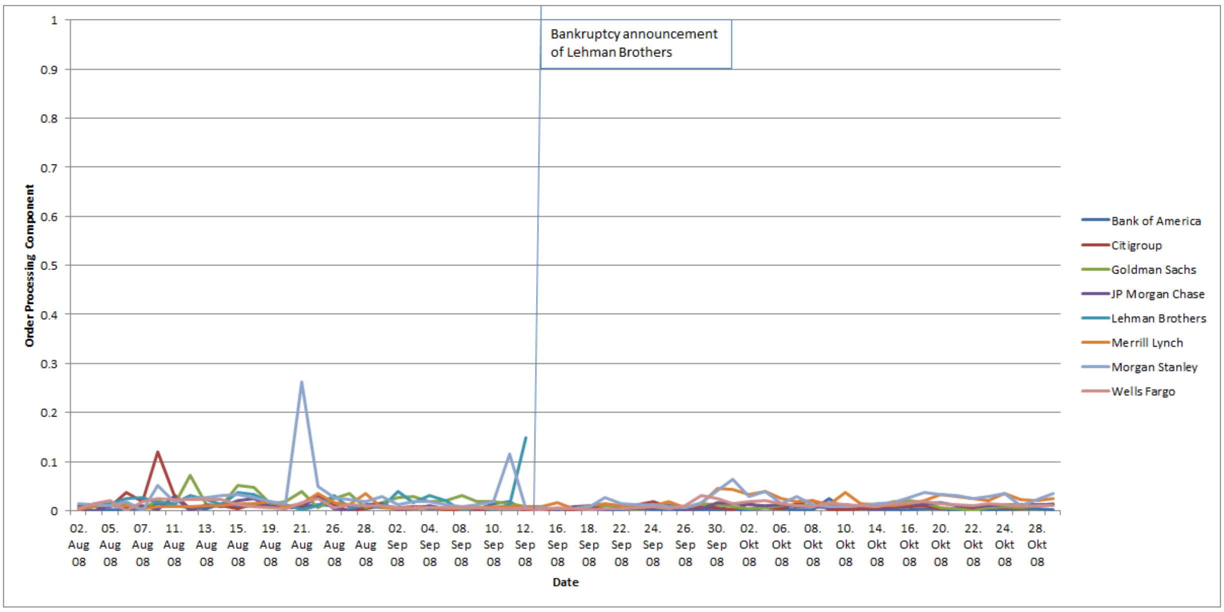

Figure 61: Evolution of the Order Processing Component of U.S. Banks: The lines plot the evolution of the order processing component *so*.

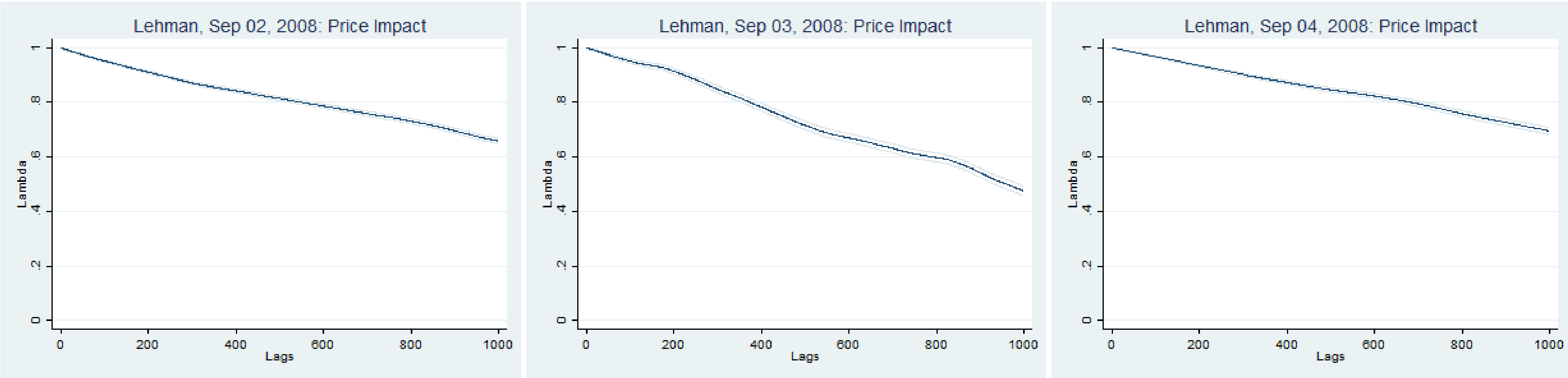

Figure 62: Evolution of Lambda: September 02, 03, & 04, 2008

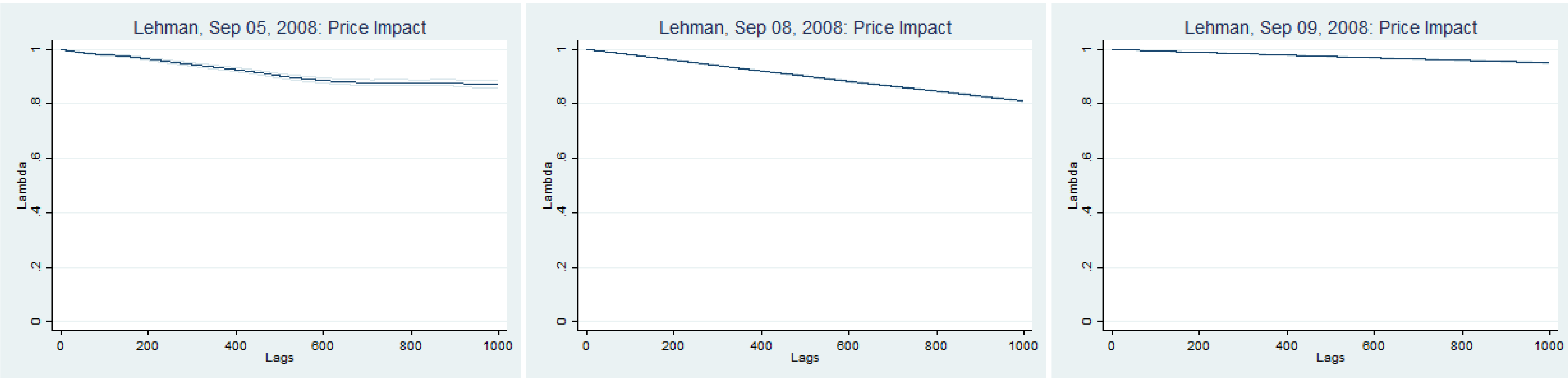

Figure 63: Evolution of Lambda: September 05, 08, & 09, 2008

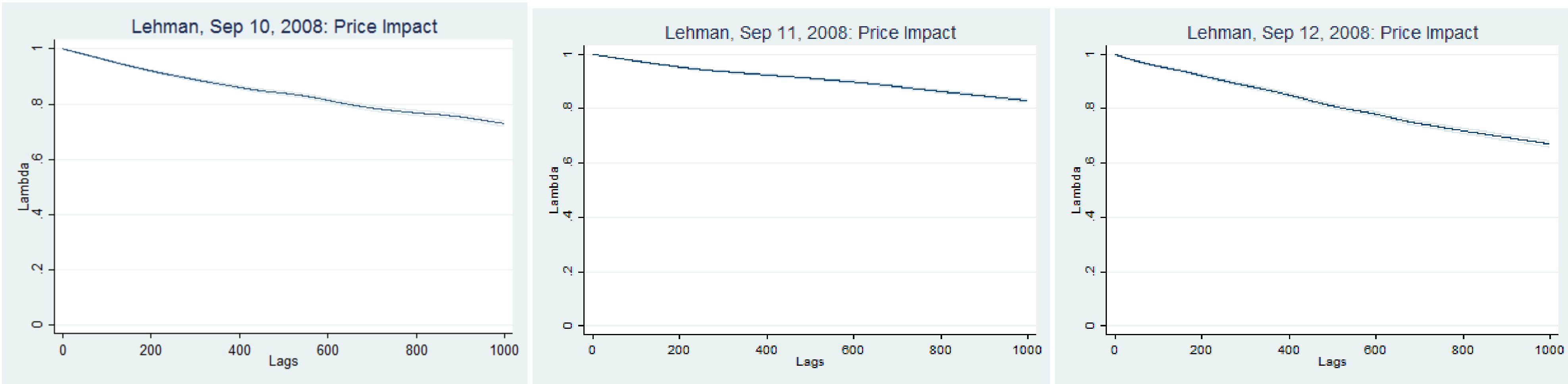

Figure 64: Evolution of Lambda: September 10, 11, & 12, 2008

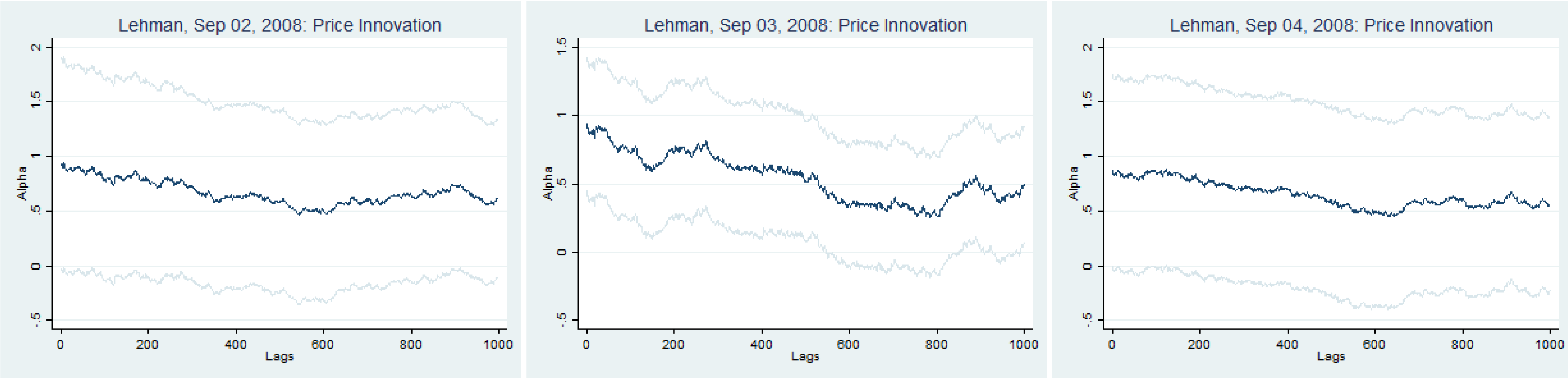

Figure 65: Evolution of Alpha: September 02, 03, & 04, 2008

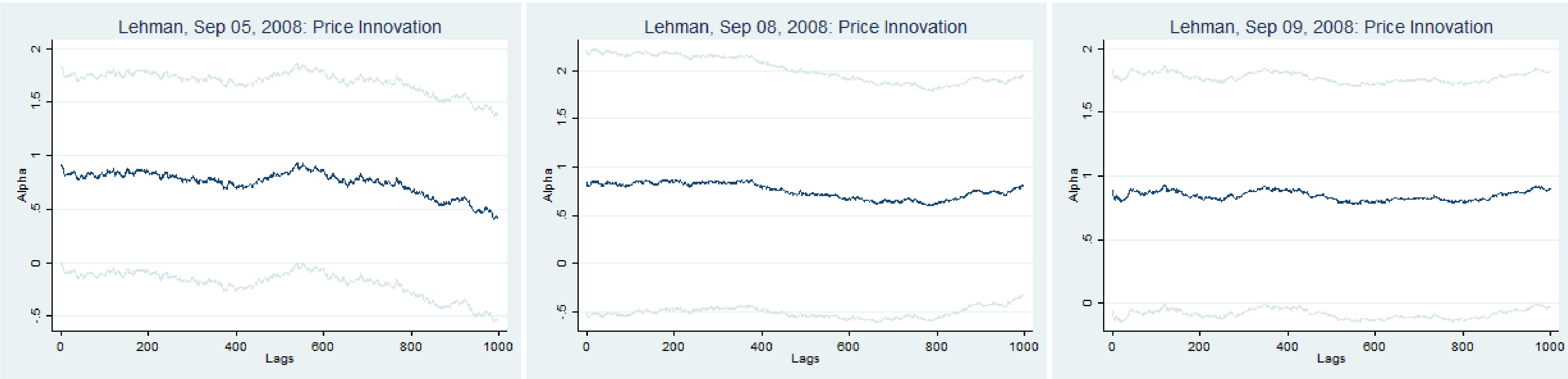

Figure 66: Evolution of Alpha: September 05, 08, & 09, 2008

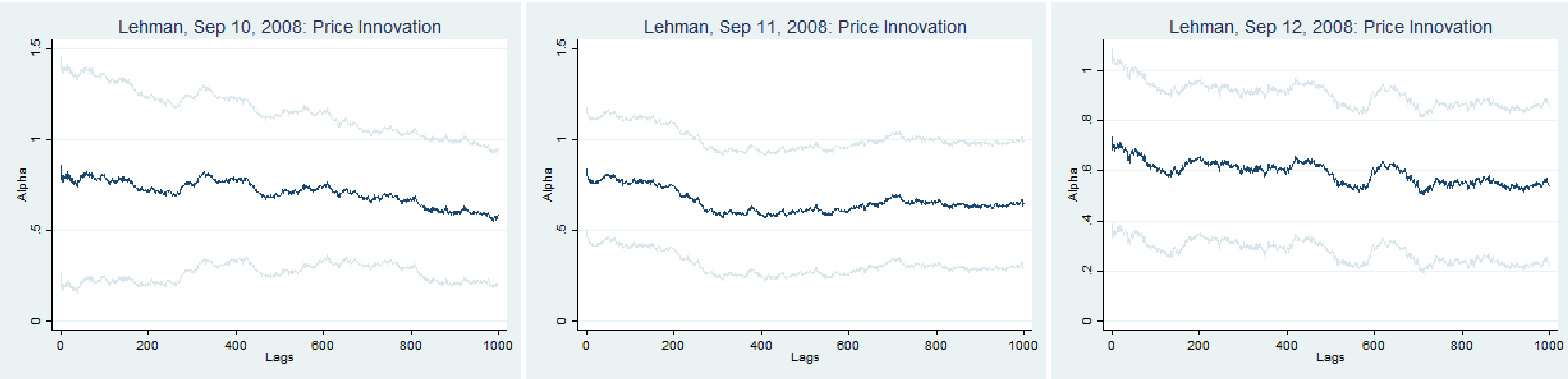

Figure 67: Evolution of Alpha: September 10, 11, & 12, 2008

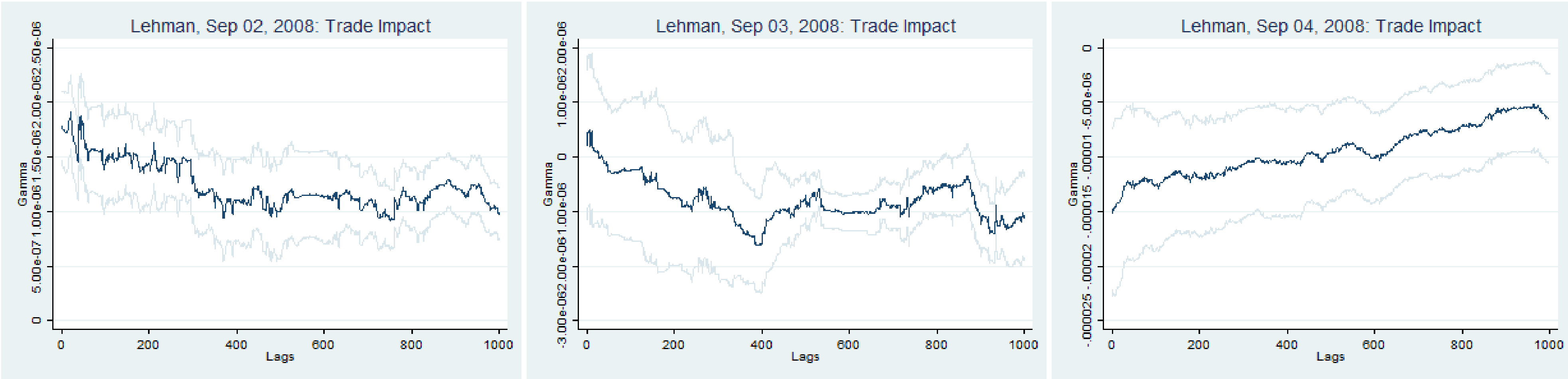

Figure 68: Evolution of Gamma: September 02, 03, & 04, 2008

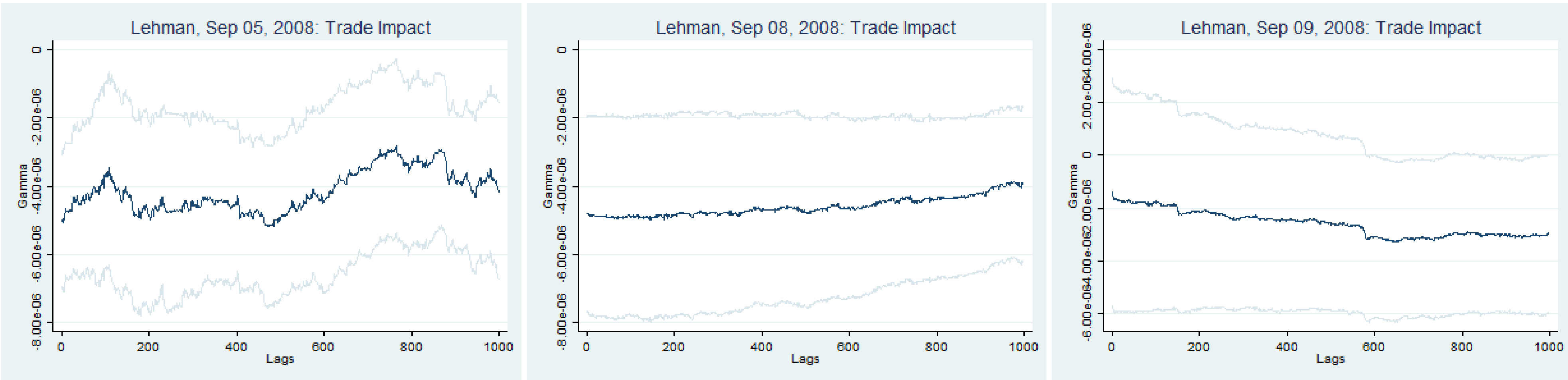

Figure 69: Evolution of Gamma: September 05, 08, & 09, 2008

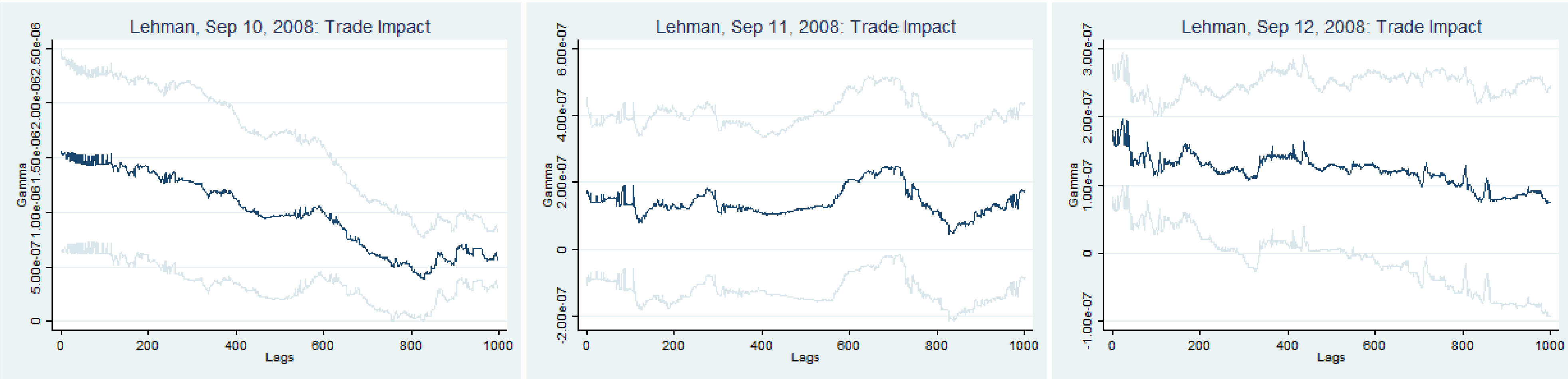

Figure 70: Evolution of Gamma: September 10, 11, & 12, 2008

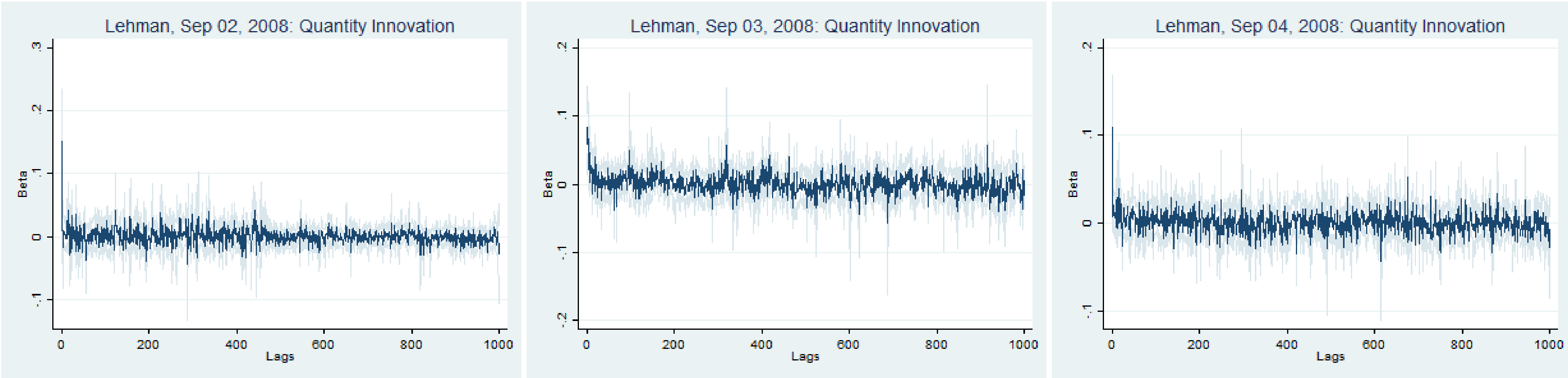

Figure 71: Evolution of Beta: September 02, 03, & 04, 2008

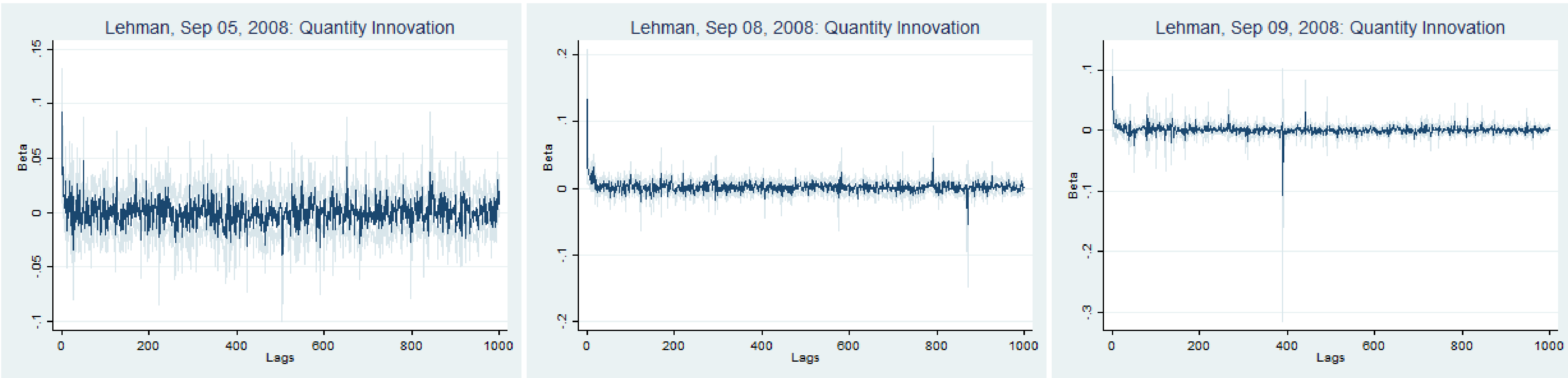

Figure 72: Evolution of Beta: September 05, 08, & 09, 2008

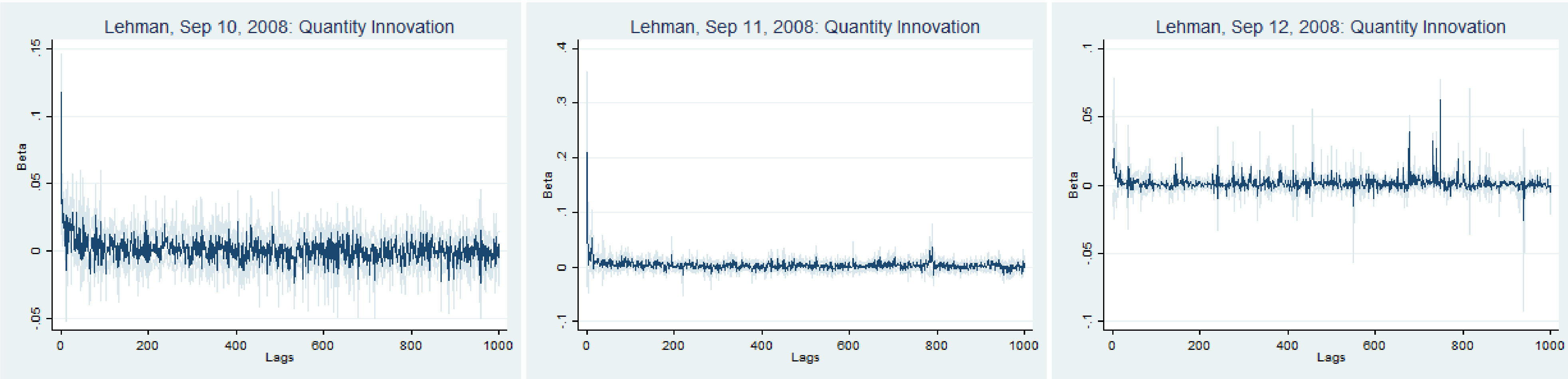

Figure 73: Evolution of Beta: September 10, 11, & 12, 2008

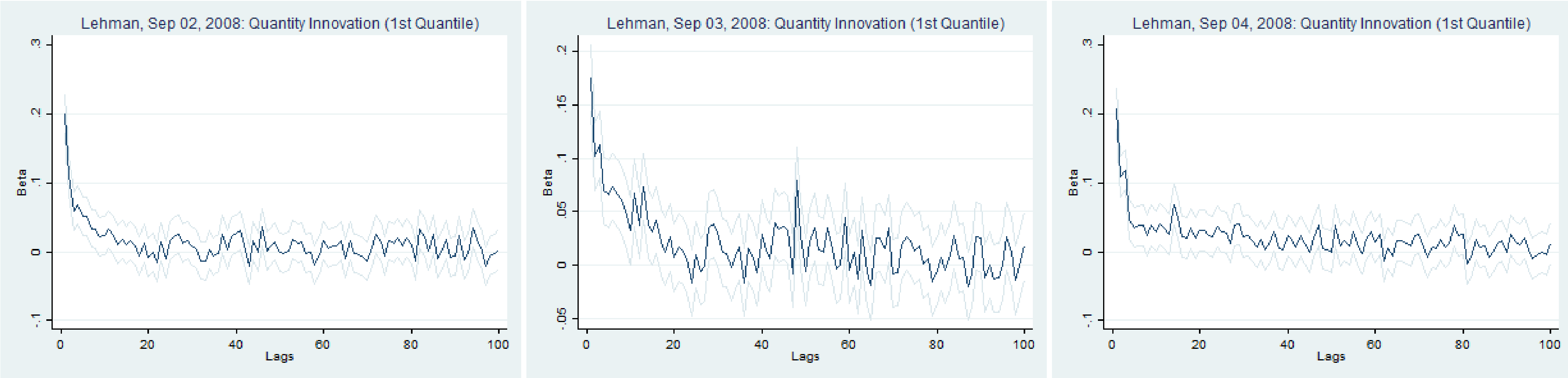

Figure 74: Evolution of Beta of Small Trades: September 02, 03, & 04, 2008

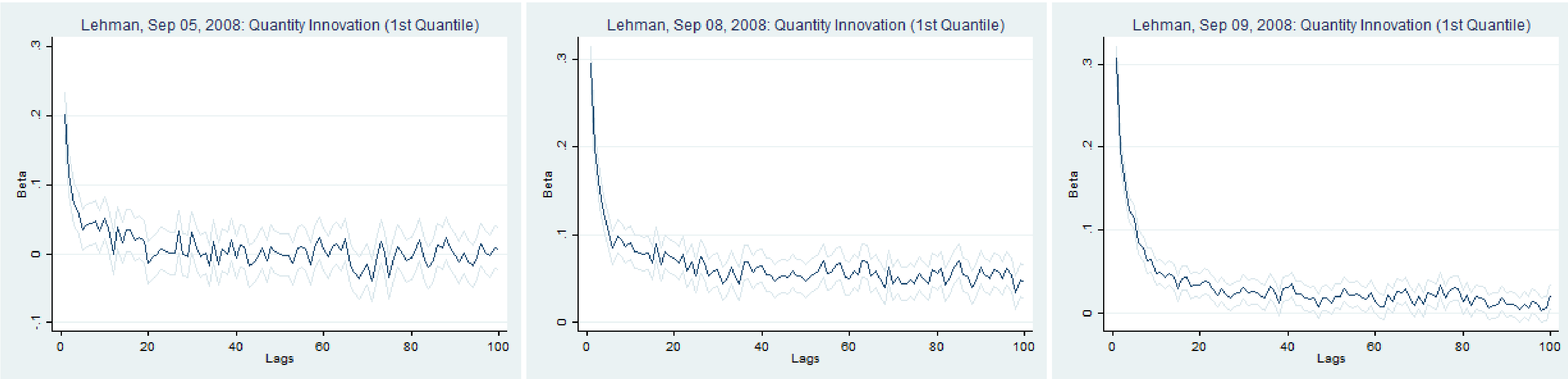

Figure 75: Evolution of Beta of Small Trades:: September 05, 08, & 09, 2008

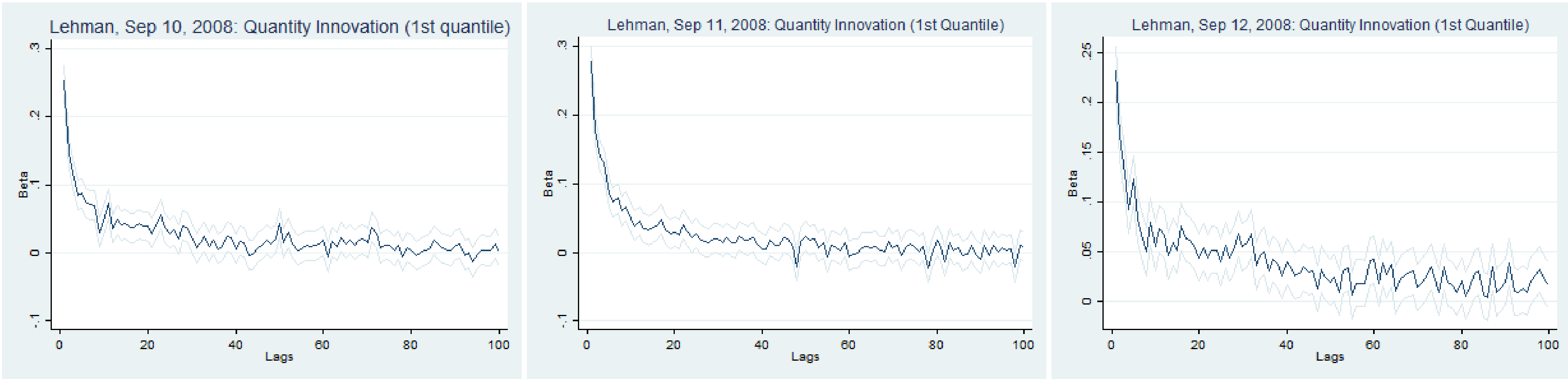

Figure 76: Evolution of Beta of Small Trades:: September 10, 11, & 12, 2008

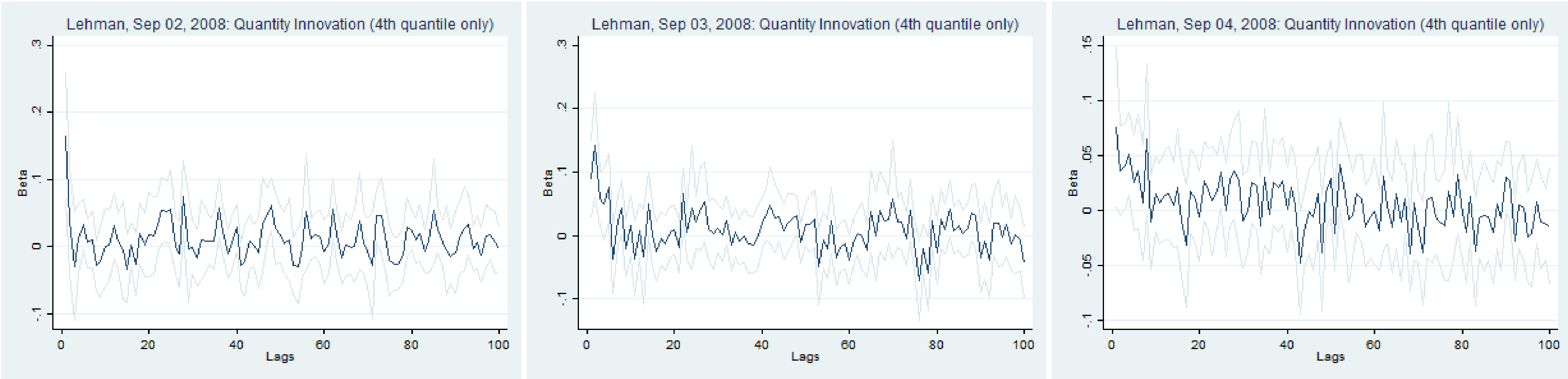

Figure 77: Evolution of Beta of Large Trades: September 02, 03, & 04, 2008

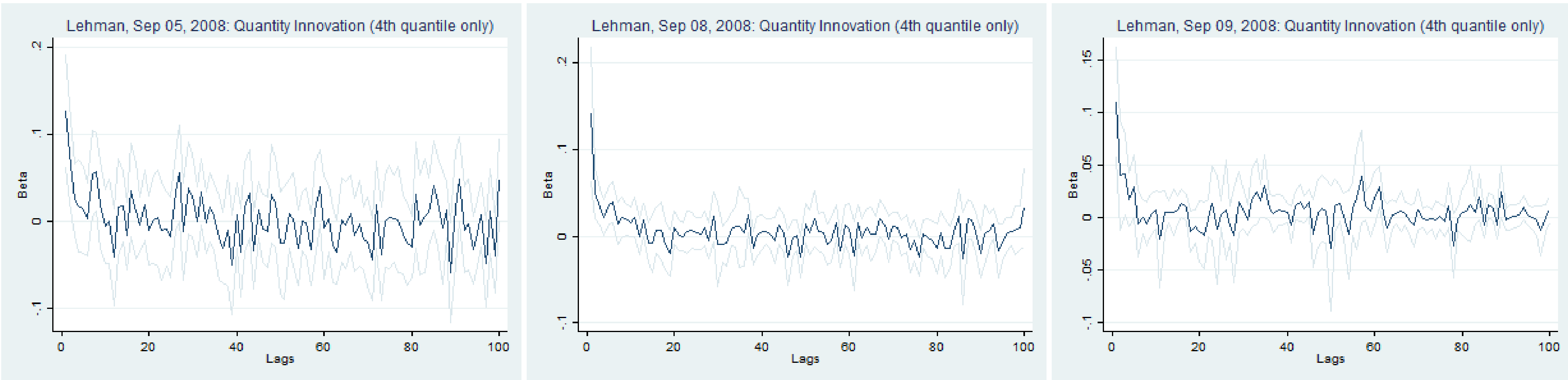

Figure 78: Evolution of Beta of Large Trades: September 05, 08, & 09, 2008

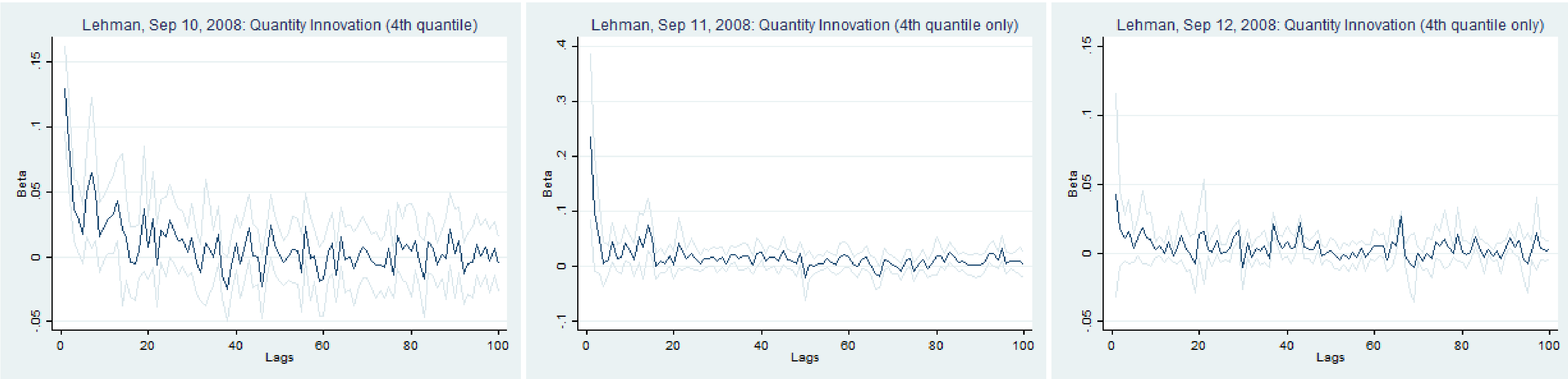

Figure 79: Evolution of Beta of Large Trades: September 10, 11, & 12, 2008