Essays on Hybrid Debt Instruments and Market Microstructure

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The President:

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To Tamara and my parents,

Barbara & Bernhard Kohler

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Summary

This dissertation comprises three articles. The first article analyzes the announcement effects of the issuance of trust preferred securities, a hybrid debt instrument bearing bond-like and stock-like features, for the stocks of the issuing bank. We find negative abnormal returns for the stocks of the issuing bank, where the negative effects are stronger for announcements during the recent financial crisis and for announcements during periods of increased financial distress of the issuing bank.

The second and third article cover topics from market microstructure. In the second article we analyze effects of the implementation of MiFID on liquidity. There is no evidence for a worsening of market quality associated with the implementation of MiFID. In contrast, liquidity measures indicate a general increase in market quality. Given the non-existence of a consolidated tape in Europe, we examine whether trade-throughs prevent the emergence of a consolidated market. We find evidence that trade-throughs originate from traders with a priority of execution speed over price and conclude that the occurrence of trade-throughs does not indicate inferior market quality.

In the third article information processing in the fragmented market after the implementation of MiFID is analyzed for a sample of Swiss stocks on the Swiss exchange and on Chi-X. According to Hasbrouck information shares, the determination of a leading market is not possible. By applying an autoregressive conditional intensity model that explicitly takes the asynchronous structure of order arrivals into account, we find strong evidence that Chi-X is the leading market in terms of intensity based information shares.

Zusammenfassung

Die vorliegende Dissertation umfasst drei Artikel. Im ersten Artikel wird untersucht, welchen Effekt die Ankündigung einer Emission von trust preferred securities, einem hybriden Schuldinstrument, auf die Aktien der emittierenden Bank hat. Die Analyse zeigt, dass der Effekt auf die Aktien der emittierenden Bank negativ ist und während der Finanzmarktkrise und während Perioden mit erhöhter Unsicherheit noch verstärkt wird.

Der zweite und dritte Artikel befassen sich mit Themen der Markt Mikrostruktur. Im zweiten Artikel werden die Auswirkungen von MiFID auf die Liquidität untersucht. Es zeigt sich, dass mit der Einführung von MiFID die Liquidität gestiegen ist. Des Weiteren wird aufgezeigt, dass Trade-Throughs nicht auf eine ungenügende Marktintegration hinweisen, sondern auf die Priorisierung von Handelsgeschwindigkeit über Preis.

Der dritte Artikel befasst sich mit der Informationsverarbeitung in fragmentierten Märkten nach der Implementierung von MiFID. Die Informationsverarbeitung für Schweizer Aktien, welche sowohl an der Schweizer Börse als auch an Chi-X gehandelt werden, wird mittels Hasbrouck Information Shares untersucht. Dieser Standardansatz liefert jedoch keine eindeutigen Ergebnisse hinsichtlich der Frage, welcher Markt in der Informationsverarbeitung führend ist. Das alternative Autoregressive Conditional Intensity Modell, welches die asynchrone Struktur der Daten berücksichtigt, zeigt, dass Chi-X in Bezug auf die Informationsverarbeitung führt.

Part I.
Announcement Effects of Trust Preferred Securities - Evidence from the Financial Crisis

Abstract

Trust preferred securities are hybrid financial instruments that bear bond-like and stock-like features. We analyze the announcement effects of the issuance of trust preferred securities for the stocks of the issuing bank in an event study framework. Significantly negative abnormal returns for the stocks of the issuing banks can be found for multiple sampling intervals within the event window. We find stronger negative effects for announcements during the financial crisis and for announcements during periods of increased financial distress of the issuing bank.

1. Introduction

Trust preferred securities (TruPS) are hybrid financial instruments that combine features of stocks and bonds. Bond-like features are fixed or floating rate coupons which are tax deductible for the issuing company and that the holder of TruPS has no voting or control rights. On the other hand, the interest payment is deferrable without triggering a default which is similar to a dividend payment, the maturity is typically very long and the instruments are deeply subordinated, which are stock-like features of TruPS. In October 1996 the Federal Reserve (FED) allowed banks to include TruPS in the calculation of their Tier-1 capital[1], although the fraction of Tier-1 capital that can be held in TruPS is limited[2]. This declaration led to a growth in the number and volume of issued TruPS in the banking sector, which was especially high in the period before the financial crisis, i.e., before mid-2007[3].

There are several reasons for banks to issue TruPS, e.g., the possibility to raise Tier-1 capital without a dilution effect or loss of control for the existing shareholders, which is discussed in Balasubramanian and Cyree (2006).

[1] The requirements of the FED for TruPS to be included in the Tier-1 capital are that the TruPS must provide for a minimum of five-year consecutive deferral period on dividends, that the TruPS must be subordinated to all subordinated debt and that they must have the longest feasible maturity, see FED (1996).

[2] The Federal Reserve Press Release, dated October 21, 1996 states that the amount of cumulative preferred stock instruments a bank may include in Tier-1 capital is limited to 25%, see FED (1996). In a survey, the Committee of European Banking Supervision (CEBS) states that the majority of European countries has a limit to the inclusion of hybrids in original own funds of 15%, see CEBS (2007).

[3] Under the Basel III capital requirements released by the Bank for International Settlements (BIZ) additional Tier-1 capital must be perpetual without incentives to redeem, like, e.g., step-ups of coupon payments, see BIZ (2010). This means that the majority of TruPS, issued before the change in the regulatory framework, does not qualify for additional Tier-1 capital under Basel III.

Furthermore, they find differences in the capital structure characteristics for issuers and non-issuers, suggesting that capital structure decisions are a motivation for banks to issue TruPS. The hybrid character of TruPS, i.e., the equity-like treatment for financial reporting purposes and the debt-like treatment for tax issues is also discussed in Engel et al. (1999). They find that firms pay on average 4.2% of the issue size for an average reduction of the debt-to-asset ratio of 12.8%. By restricting their sample to firms that used TruPS to retire existing preferred stock they isolate the net tax benefits from TruPS against preferred stock. Net tax benefits are quantified as 18%-28% of the issue size.

Empirical studies show mixed results for the question whether the issuance of TruPS is enhancing or decreasing bank shareholders' wealth. Benston et al. (2003) analyze in an event study framework the stock market's reaction to the issuance of TruPS and test two sets of competing hypotheses. Hypotheses which predict an increase in shareholders' wealth are the realization of tax advantages, the reduction in the costs of financial distress as the TruPS serve as additional cushion in the capital structure of the issuing bank and the realization of growth opportunities. However, as stated in Benston et al. (2003), no bank had issued TruPS before the FED granted Tier-1 capital status to these instruments in 1996. Therefore, tax advantages as sole motivation for the issuance of TruPS seem unlikely.

On the other hand, the main hypothesis predicting a decrease in shareholders' wealth is moral-hazard. A moral-hazard situation appears if banks which are undercapitalized would not issue TruPS to strengthen their capital structure because the losses that would be absorbed by the TruPS might be imposed on the Federal Deposit Insurance Corporation (FDIC). Holders of TruPS on the other hand require a premium for the bankruptcy risk they bear. Issuing TruPS would therefore decrease shareholders' wealth. The motivation for banks in this setting to issue TruPS would be executives of the banks that seek to protect their reputation and position, although the issuance is suboptimal for the shareholders.

Benston et al. (2003) find evidence for an increase in shareholders' wealth after the announcement of the issuance of TruPS. Furthermore, they find a significantly positive abnormal return for issuing banks around October 21, 1996, the day when the FED declared that it would accept TruPS as Tier-1 capital. In contrast, Harvey et al. (2003) find weak support for negative stock market returns around the individual announcement dates. However, around the announcement of the FED to grant Tier-1 capital status to TruPS they find evidence of declining default premia and increasing shareholders' wealth. Previous event studies yield inconclusive results whether the issuance of TruPS increases or decreases shareholder value. Furthermore, as the main focus in previous studies lies on the determination of abnormal returns around the day the FED granted Tier-1 capital status to TruPS, the underlying sample periods do not cover periods of financial turbulences, like the recent financial crisis, nor do they capture the period with the strongest increase in the number and volume of issued TruPS before 2007.

We contribute to the literature by the analysis of a comprehensive sample of TruPS, which covers the period of strong growth in these hybrid instruments, as well as the period of the financial crisis, which started in mid-2007. This allows us to analyze the overall announcement effect of the issuance of TruPS and to focus on the difference in the announcement effects before and during the financial crisis. To our best knowledge, our study is the first one comparing announcement effects of TruPS during the financial crisis with pre-crisis effects.

The analysis is done in a classical event study framework. We analyze a sample of 99 TruPS, issued between 1996 and 2009 by using a Constant Mean Return Model and a Market Model to determine the abnormal returns of the stocks of the issuing banks around the announcement dates. The abnormal returns for multiple sampling intervals and individual days within the event window are tested for significance with parametric and nonparametric tests. To compare the effects of pre-crisis announcements and announcements during the financial crisis, we perform the analysis on different subsamples. We hypothesize that during the financial crisis the issuance of TruPS was a signal of the need to strengthen the Tier-1 capital and was therefore interpreted by the market as a bad signal, accompanied by a decrease in shareholders' wealth. Furthermore, bank-specific and issue-specific characteristics are used to analyze the determinants of the cumulative abnormal returns.

The paper proceeds as follows. Section 2 outlines the data and Section 3 explains the methods used for the analysis. The results for the full sample, for the subsamples and for the determinants of the abnormal returns are presented and discussed in Section 4. Finally, Section 5 concludes.

2. Data

We obtain a sample of TruPS from Reuters [4]. The initial sample contains 143 TruPS, issued by 78 banks. Individual announcement dates for the TruPS are determined by Bloomberg, where either the date of the first Bloomberg News, which contains details about the issuance of TruPS by a bank, or the announcement date according to Bloomberg is used[5]. Equity market data which includes stock prices for the issuing banks and market indices for the Market Model is taken from Thomson Reuters Datastream and balance sheet information of the issuing banks from BankScope.

From the initial sample 44 TruPS were omitted due to incomplete stock price history either in the estimation or the event window (2), a missing event date (30) or missing balance sheet information for the year-end before the announcement date (12). The final sample contains 99 TruPS, issued by 48 banks with announcement dates between January 1997 and July 2009. Table 1 shows the number of issues for each year in the sample period together with the issued volume and the average issue size. From the final sample of 99 TruPS, 6 were issued in EURO, 1 in GBP, 2 in CAD and 90 in US$. For simplicity we convert all amounts into US$ with the current exchange rate.

The total face amount of the 99 TruPS of our full sample equals 60,339 million US$. The average issue volume increases from 86 million US$ in 1997 to 637 million US$ in 2009 and equals 450 million US$ for the full sample period. As

[4] The sample was taken on October 5, 2009. All non-bank issuers are excluded.

[5] For 3 TruPS the announcement date according to Bloomberg was a Saturday. For the calculations these 3 announcement dates were set to the Friday before.

Table 1 – Final Sample
The table shows descriptive statistics of our full sample of 99 TruPS with announcement dates between January 1997 and July 2009. The sample is taken from Reuters and the individual announcement dates from Bloomberg. The aggregated dollar volume per year and the average volume per issue are presented.

Year	Dollar volume (in million US$)[a]	Average size (in million US$)	Issues (number)	Banks (number)
1997	86	86	1	1
1998	2,497	416	6	4
1999	162	162	1	1
2000	5,425	904	6	6
2001	1,770	442	4	4
2002	102	34	3	3
2003	3,528	392	9	9
2004	526	263	2	2
2005	2,275	379	6	5
2006	11,780	693	17	13
2007	21,114	782	27	15
2008	8,524	656	13	11
2009[b]	2,549	637	4	3
Total/Average	60,339	450	99	48[c]

[a]Converted to US$ with the current exchange rate.
[b]Until October 5, 2009
[c]Corrected for multiple issues

can be seen from Table 1, the average issuance volume and the growth rate of the aggregated issued volume were higher in later years compared to the beginning of the sample period, immediately after the FED granted Tier-1 capital status to TruPS.

For the calculation of normal returns with the Market Model we need a proxy for the market return. We use the FTSE sector indices for banks for the respective stock exchange where the stock of the issuing bank is listed. Table 2 presents the indices that are used as proxy.

Table 2 – **Market Indices**
The table shows the stock market indices, which are used as proxy for the market indices in the Market Model.

Market	Index used as proxy
Australia	FTSE Australia Banks - Total Return Index
Canada	FTSE Canada Banks - Total Return Index
France	FTSE France Banks - Total Return Index
Germany	FTSE Germany Banks - Total Return Index
Holland	FTSE Netherlands Banks - Total Return Index
Italy	FTSE Italy Banks - Total Return Index
Sweden	FTSE Sweden Banks - Total Return Index
Switzerland	FTSE Switzerland Banks - Total Return Index
United Kingdom	FTSE UK Banks - Total Return Index
United States	FTSE USA Banks - Total Return Index

The FTSE Bank indices are free float adjusted, market capitalization weighted indices and are therefore representative for the banking sector of a market. See FTSE (2008) and FTSE (2009) for more details on the index construction.

3. Methods

A classical event study framework is used to analyze the announcement effects of the issuance of TruPS on the stock price of the issuing bank. We follow the event study design, as proposed by Campbell et al. (1997) with the day a bank announces the issuance of TruPS as event date. Our analysis is performed with an estimation window of 250 days length, which starts 270 days before the event date and ends 21 days before the event date and is denoted by [-270,-21]. The event window (denoted by [-20, 20]) covers 20 pre-event days, the event date and 20 post-event days (a total of 41 days). This choice of window lengths for the estimation and the event window is typical for event study designs, see for instance Peterson (1989).

3.1. Determination of Normal Returns

For the calculation of abnormal returns in the event window normal returns based on the estimation window observations have to be estimated. We use two different models for the calculation of normal returns: the Constant Mean Return Model and the Market Model.

Constant Mean Return Model For $R_{i,t}$, the return of stock i at day t, the Constant Mean Return Model proposes the following relation

$$R_{i,t} = \mu_i + \xi_{i,t}, \tag{3.1}$$

with

$$\mathbf{E}[\xi_{i,t}] = 0 \tag{3.2}$$

and

$$\mathrm{Var}[\xi_{i,t}] = \sigma^2_{\xi_i}, \tag{3.3}$$

i.e., the return of stock i at day t is explained as sum of the constant mean return for stock i which is denoted by μ_i and a random error term which is denoted by $\xi_{i,t}$.

Market Model The Market Model relates the return of stock i at day t to the return of the corresponding market index at day t. Formally this means

$$R_{i,t} = \alpha_i + \beta_i R_{m,t} + \epsilon_{i,t}, \tag{3.4}$$

with

$$\mathbf{E}[\epsilon_{i,t}] = 0 \tag{3.5}$$

and

$$\text{Var}[\epsilon_{i,t}] = \sigma^2_{\epsilon_i}, \tag{3.6}$$

where $R_{m,t}$ denotes the return of the market index[6]. The potential improvement of the Market Model compared to the Constant Mean Return Model lies in the reduction of the variance of the abnormal returns. The variance is reduced because the portion of the return that can be explained by the market return is removed (see Chandra et al. (1990) for an analytical derivation). Campbell et al. (1997) argue that often the simple Constant Mean Return Model yields results comparable to those of more sophisticated models, like the Market Model[7]. On the other hand Chandra et al. (1990) argue that the Market Model has higher power than the simple Constant Mean Return

[6] As follows from the comparison of Equation 3.1 and Equation 3.4, the Constant Mean Return Model is a special case of the more general Market Model with the constraints that β_i equals zero and α_i equals μ_i for all i, see also Chandra et al. (1990).

[7] In an earlier version of this paper broad stock market indices were used as proxy for the market index instead of the FTSE sector indices for banks. The R^2s of the regressions were so low that the results of the Constant Mean Return Model were indeed very close. However, with the FTSE sector indices for banks as market indices R^2s and the explanatory power of the Market Model are significantly higher.

Model[8]. Brown and Weinstein (1985) compare the one factor market model to a general multi factor model and conclude that the improvement of using a multi factor model is only marginal compared to the one factor market model, which is also confirmed by Campbell et al. (1997). We use and compare both approaches to compute the normal returns, i.e., a Constant Mean Return Model and a one factor Market Model, simply referred to as Market Model in the remainder of this paper.

3.2. Determination of Abnormal Returns and Variance Estimators

To determine the effect of the announcement of the issuance of TruPS on the stock of the issuing bank, abnormal returns which are denoted by $AR_{i,t}$ are calculated. For this calculation we subtract the expected normal returns (either from the Constant Mean Return Model or from the Market Model) from the actual observed return for each stock i and every day t, i.e.,

$$AR_{i,t} = R_{i,t} - R_{i,t}^{N}, \tag{3.7}$$

where $AR_{i,t}$ denotes the abnormal return of stock i at day t, $R_{i,t}$ is the actual observed return of stock i at day t and $R_{i,t}^{N}$ is the expected normal return

[8] Brown and Warner (1980) state that the power of the Constant Mean Return Model and the Market Model are similar. However, Chandra et al. (1990) show that this is due to the fact that in Brown and Warner (1980) a Patell t-test is used to test for significance in the case of the Constant Mean Return Model, but significance in the case of the Market Model was tested with an ordinary t-test. See also Binder (1998), who discusses this problem.

from the Constant Mean Return Model or the Market Model, respectively, i.e.,

$$R_{i,t}^{N} = \begin{cases} \hat{\mu}_i, & \text{for the Constant Mean Return Model,} \\ \hat{\alpha}_i + \hat{\beta}_i R_{m,t}, & \text{for the Market Model,} \end{cases}$$

and $\hat{\mu}_i$, $\hat{\alpha}_i$ and $\hat{\beta}_i$ denote the parameter estimates for μ_i, α_i and β_i. $\hat{\mu}_i$ is the mean return over the estimation window, i.e.,

$$\hat{\mu}_i = \frac{1}{250} \sum_{s=-270}^{-21} R_{i,s} \tag{3.8}$$

and $\hat{\alpha}_i$ and $\hat{\beta}_i$ denote the OLS estimation coefficients for the Market Model. The individual abnormal returns of the stocks are aggregated across the sample by calculating the average abnormal return at day t as

$$AAR_t = \frac{1}{n} \sum_{j=1}^{n} AR_{j,t}, \tag{3.9}$$

where n denotes the number of stocks in the sample. A second dimension to aggregate abnormal returns is across time. The cumulative average abnormal return between day i_1 and i_2, denoted by $CAAR[i_1, i_2]$, is calculated as the sum of the average abnormal returns between day i_1 and i_2, i.e.,

$$CAAR[i_1, i_2] = \sum_{s=i_1}^{i_2} AAR_s. \tag{3.10}$$

Analyzing an event which simultaneously affects all companies in the sample (e.g., a change in the accounting standards) leads to identical estimation and event windows for all companies. In this case the covariances between the abnormal returns have to be taken into account in the calculation of the variance of the abnormal returns [9]. However, Chandra et al. (1990) show in a simulation study that even if event dates are clustered, ignoring cross-sectional dependence, i.e., assuming independence, has little effect when applying the Market Model. Applying the Constant Mean Return Model on the other hand while ignoring cross-sectional dependence leads to an underestimation of the variance of the abnormal returns and therefore the rejection rates for the test statistics exceed the upper limit. As the event dates in our sample are distributed over time, i.e., they are non-synchronous, we can assume abnormal returns of individual stocks to be uncorrelated and ignore cross-sectional dependence for both models. Therefore, we calculate the variance estimator of the average abnormal returns, denoted by $\hat{\sigma}^2_{AAR}$, as

$$\hat{\sigma}^2_{AAR} = \frac{1}{n^2} \sum_{j=1}^{n} \hat{\sigma}^2_j, \tag{3.11}$$

where $\hat{\sigma}^2_i$ denotes the empirical variance of the abnormal returns of stock i in the estimation window and n denotes the number of stocks in the sample, i.e.,

$$\hat{\sigma}_i = \sqrt{\frac{1}{249} \sum_{s=-270}^{-21} \left(AAR_s - \overline{AAR}\right)^2}, \tag{3.12}$$

[9] Bernard (1987) and Campbell et al. (1997) discuss the problem of cross-sectional dependencies due to clustering.

where

$$\overline{AAR} = \frac{1}{250} \sum_{s=-270}^{-21} AAR_s. \tag{3.13}$$

The variance estimator of the cumulative average abnormal return between day i_1 and i_2 is calculated as

$$\hat{\sigma}^2_{CAAR}[i_1, i_2] = (i_2 - i_1 + 1)\hat{\sigma}^2_{AAR}, \tag{3.14}$$

see Campbell et al. (1997) for more details.

3.3. Tests for Significant Abnormal Returns

Two different approaches are applied to test for significance of the abnormal returns: parametric tests according to Campbell et al. (1997) and nonparametric rank tests according to Corrado (1989).

Parametric tests The null hypothesis is that the event does not have an effect on the stock price of the issuing company in the event window. Therefore, the standardized average abnormal returns during the event window have a standard normal distribution under the null hypothesis, i.e.,

$$\frac{AAR_t}{\sqrt{\hat{\sigma}^2_{AAR}}} \sim N(0,1), \quad \text{for all } t, \tag{3.15}$$

where AAR_t is given by (3.9), $\hat{\sigma}^2_{AAR}$ is given by (3.11) and $N(0,1)$ denotes a standard normal distribution. Similarly, the test statistic for an aggregation across time, i.e., for the cumulative average abnormal return, is constructed as

$$\frac{CAAR[i_1, i_2]}{\sqrt{\hat{\sigma}^2_{CAAR}[i_1, i_2]}} \sim N(0, 1), \tag{3.16}$$

where $CAAR[i_1, i_2]$ is given by (3.10) and $\hat{\sigma}^2_{CAAR}[i_1, i_2]$ is given by (3.14). This means that the standardized AAR_t and the standardized $CAAR[i_1, i_2]$ are asymptotically standard normally distributed under H_0, see also Campbell et al. (1997) and Brown and Warner (1985). To test for significant abnormal returns during the event window a t-test is applied on the standardized AAR_t and the standardized $CAAR[i_1, i_2]$.

Nonparametric tests Statistical problems can arise by applying a parametric approach as outlined above in an event study framework (e.g., assumptions on the underlying distribution). Brown and Warner (1980, 1985), Campbell et al. (1997) and Peterson (1989) discuss related problems. However, the application of the Market Model with the outlined parametric approach yields robust results for a variety of situations. Still, we use a nonparametric model to test for the robustness of the results obtained by the parametric tests. Corrado (1989) proposes a nonparametric rank test, which does not depend on assumptions regarding the distribution of the abnormal returns[10].

For the application of the nonparametric tests the abnormal returns have to be ranked. Denote by L the number of abnormal returns for each security i, i.e., the length of the estimation and the event window together. Under the

[10]Another widely used nonparametric test is the sign test, which requires symmetric distributions, i.e., the probability of an abnormal return to be positive has to be the same as the probability of being negative. As the Rank Test, as proposed by Corrado (1989), does not have this constraint, we use the rank test.

null hypothesis that there is no abnormal return, the expected rank is $\frac{L+1}{2}$ for every day. We define $K_{i,t}$ as the rank of the abnormal return $AR_{i,t}$ among the L abnormal returns of security i. The Rank Test is calculated as

$$\text{Rank Test}[i_1, i_2] = \sum_{s=i_1}^{i_2} \left[\frac{1}{n} \sum_{j=1}^{n} \left(K_{j,s} - \frac{L+1}{2} \right) \right], \tag{3.17}$$

i.e., the Rank Test for the sampling interval between day i_1 and day i_2 is the arithmetic mean of the ranks of all n stocks, corrected for the mean rank $\frac{L+1}{2}$ and summed up between day i_1 and i_2. Under the null hypothesis the following relation holds

$$\frac{\frac{1}{n}\sum_{j=1}^{n}\left(K_{j,t} - \frac{L+1}{2}\right)}{\sqrt{\frac{1}{291}\sum_{s=-270}^{20}\left[\frac{1}{n}\sum_{j=1}^{n}\left(K_{j,s} - \frac{L+1}{2}\right)\right]^2}} \sim N(0,1), \tag{3.18}$$

i.e., the standardized arithmetic mean of the ranks of all n stocks on day t, corrected for the mean rank $\frac{L+1}{2}$, has a standard normal distribution. The denominator of (3.18) denotes the empirical standard deviation using the full sample period. For a sampling interval between day i_1 and i_2, a similar relation holds under the null hypothesis

$$\frac{\sum_{s=i_1}^{i_2}\left[\frac{1}{n}\sum_{j=1}^{n}\left(K_{j,s} - \frac{L+1}{2}\right)\right]}{\sqrt{\frac{i_2-i_1+1}{291}\sum_{s=-270}^{20}\left[\frac{1}{n}\sum_{j=1}^{n}\left(K_{j,s} - \frac{L+1}{2}\right)\right]^2}} \sim N(0,1). \tag{3.19}$$

A t-test is applied on (3.18) to test for significant abnormal returns within the nonparametric framework for single days within the event window and on (3.19) to test for significant abnormal returns for the sampling interval between day i_1 and i_2 within the event window. See Corrado (1989) for further details.

4. Empirical Results

4.1. Analysis of the Full Sample

The upper panel of Table 3 shows abnormal returns for different sampling intervals calculated with the Constant Mean Return Model and with the Market Model. Additionally, nonparametric rank tests are given for both models as robustness checks. Significance is tested using a t-test for the respective t-values. The results for three symmetric sampling intervals around the event date, $[-20, 20]$, $[-5, 5]$ and $[-1, 1]$, are presented. Additionally, we analyze four intervals which are asymmetric around the event date, the 20 day pre-event interval $[-20, -1]$, the 20 day post-event interval $[1, 20]$ and two shorter intervals, $[-1, 5]$, covering one day prior to the announcement, the announcement day itself and five post-event days and $[1, 5]$ which covers five days following the announcement. Furthermore, the lower panel of Table 3 presents abnormal returns and rank tests for individual days around the event date.

Figure 1 shows the CAAR in the event window for the Constant Mean Return Model (left hand side) and the Market Model (right hand side), respectively. The abnormal returns are negative for all sampling intervals in Table 3. The CAAR for the whole event window is -2.56% for the Constant Mean Re-

Table 3 – **Abnormal Returns for Full Sample**

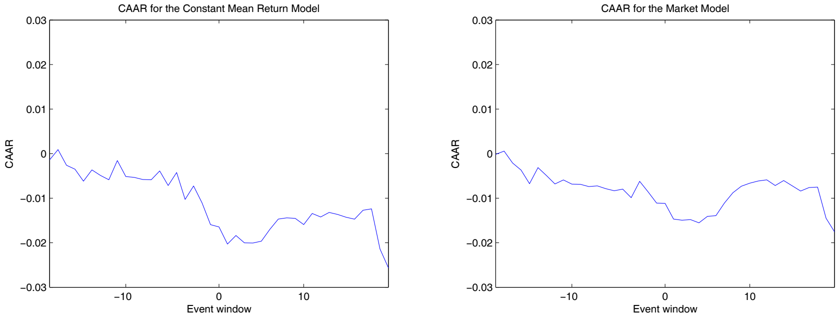
The table shows abnormal returns for different sampling intervals (upper panel) and individual days (lower panel) within the event window for the full sample of 99 TruPS with announcement dates between January 1997 and July 2009. Results from the Constant Mean Return Model and for the Market Model are presented.

	Constant Mean Return Model						Market Model					
Interval/ Day	CAAR/ AAR	t-value	sig.	Rank Test	t-value	sig.	CAAR/ AAR	t-value	sig.	Rank Test	t-value	sig.
[-20,20]	-2.56%	-1.95	*	-117	-2.00	**	-1.75%	-2.01	**	-65	-1.11	
[-5, 5]	-1.25%	-1.83	*	-43	-1.44		-0.58%	-1.27		-15	-0.50	
[-1, 1]	-0.92%	-2.59	**	-28	-1.75	*	-0.61%	-2.57	**	-20	-1.26	
[-20, -1]	-1.59%	-1.73	*	-80	-1.98	**	-1.11%	-1.82	*	-74	-1.79	*
[1, 20]	-0.92%	-1.00		-44	-1.08		-0.64%	-1.05		-7	-0.16	
[1, 5]	-0.32%	-0.70		-30	-1.45		-0.29%	-0.96		-17	-0.80	
[-1, 5]	-0.86%	-1.58		-45	-1.89	*	-0.55%	-1.52		-17	-0.71	
[-5]	0.29%	1.42		16.3	1.79	*	0.04%	0.26		-1.0	-0.11	
[-4]	-0.60%	-2.93	***	-11.6	-1.27		-0.19%	-1.39		7.6	0.82	
[-3]	0.30%	1.47		11.2	1.23		0.37%	2.68	***	-0.3	-0.03	
[-2]	-0.38%	-1.85	*	-13.7	-1.51		-0.24%	-1.74	*	-4.4	-0.48	
[-1]	-0.49%	-2.37	**	-23.5	-2.58	**	-0.25%	-1.83	*	-15.9	-1.73	*
[0]	-0.05%	-0.25		7.5	0.83		-0.01%	-0.05		15.2	1.64	
[1]	-0.38%	-1.87	*	-11.6	-1.28		-0.35%	-2.58	**	-19.4	-2.10	**
[2]	0.19%	0.93		11.6	1.27		-0.03%	-0.19		1.7	0.18	
[3]	-0.16%	-0.80		-13.4	-1.48		0.01%	0.10		-2.6	-0.28	
[4]	0.00%	-0.02		-5.9	-0.65		-0.07%	-0.53		-1.5	-0.17	
[5]	0.04%	0.20		-10.2	-1.12		0.14%	1.05		5.3	0.58	

n=99 observations

***/**/* denotes significance at the 1%/5%/10% level

Figure 1 – CAAR for Full Sample
The figure shows the CAAR for the full sample of 99 TruPS with announcement dates between January 1997 and July 2009 for the 41 day event window (20 pre-event days, the event date, and 20 post-event days), where day 0 denotes the event date. The left panel shows the CAAR calculated with the Constant Mean Return Model and the right panel shows the CAAR calculated with the Market Model.



turn Model and −1.75% for the Market Model, i.e., the stocks in the sample underperformed the mean return by 2.56% and the market indices by 1.75% during the 41 day event window. The Constant Mean Return Model shows significant negative cumulative average abnormal returns for the symmetric intervals $[-20, 20]$, $[-5, 5]$ and $[-1, 1]$. As for the asymmetric intervals, the 20 day pre-event interval $[-20, -1]$ shows significant negative CAAR at the 10% level. The nonparametric rank test confirmes the results for the symmetric intervals $[-20, 20]$ and $[-1, 1]$ and for the asymmetric interval $[-20, -1]$. The abnormal return on the event day itself is negative but insignificant. Significant abnormal returns can be found around the event day, e.g., AAR_{-4}, AAR_{-2}, AAR_{-1} and AAR_1 are significantly negative. The significance of AAR_{-1} is also confirmed by the nonparametric rank test. We find negative abnormal returns for different sampling intervals in the whole event window, around the event date and also in the pre-event period[11]. According to the findings from the Constant Mean Return Model, the announcement of the issuance of TruPS results in negative abnormal returns for the stocks of the issuing banks.

The results from the Market Model confirm the findings for the CAAR with significantly negative abnormal returns at the 5% level for the symmetric intervals $[-20, 20]$ and $[-1, 1]$ and at the 10% level for the asymmetric interval $[-20, -1]$. However, the rank test confirmes only the significance of the negative abnormal return for the sampling interval $[-20, -1]$ at the 10% level. The nonparametric rank tests for the individual days around the event date are significant for negative returns on the days immediately before and after the event, i.e., AAR_{-1} and AAR_1.

The analysis of the full sample provides evidence for a decrease in shareholders' wealth after the announcement of the issuance of TruPS. These findings are supported by the Constant Mean Return Model and the Market Model with parametric and nonparametric tests. Support from the Market Model is generally weaker in the sense that the nonparametric rank test only shows significantly negative abnormal returns for the pre-event window $[-20, -1]$ and the days immediately before and after the event date. Graphical evidence for negative effects on shareholders' wealth is presented in Figure 1, which shows the CAAR according to the Constant Mean Return Model and the Market

[11] This could be caused due to information leakage prior to the announcement or because Bloomberg is not the fastest information channel.

Model for the event window.

Our results contradict the results of Benston et al. (2003), who find evidence for positive abnormal returns around the event date. They calculate a significant abnormal return of 1.07% over the three day period $[-1, 1]$ around the individual announcement date of the banks. We provide clear evidence for negative abnormal returns for the stocks of banks that announce the issuance of TruPS. These findings support the results from Harvey et al. (2003), which also state negative abnormal returns over certain sampling intervals around the announcement date.

4.2. Analysis of Subsamples

The second research question is, whether the announcement effect is different during periods of increased financial stress. To address this question we split the sample in two disjoint subsamples. The first subsample covers the period of the financial crisis (Subsample crisis), which started mid-2007, and the second subsample covers the period before the crisis (Subsample pre-crisis), which covers the period of the strong growth of the number and volume of issues of TruPS. Following Beltratti and Stultz (2009) and Fahlenbrach and Stultz (2011) issues with announcement dates after July 1st, 2007 are included in Subsample crisis (29 out of the 99 TruPS in the full sample). Subsample pre-crisis consists of TruPS with announcement dates between January 1997 and June 2007 (70 out of the 99 TruPS in the full sample). The abnormal returns and the rank tests for the same sampling intervals as for the full sample in Table 3 are given in Table 4 for Subsample crisis and in Table 5 for Subsample pre-crisis.

The results for Subsample crisis are similar to the results for the full sample. Again, for the Constant Mean Return Model the symmetric intervals around the event date show a significant negative CAAR of -3.08% with significance at the 1% level for $[-1, 1]$, of -3.30% with significance at the 5% level for $[-5, 5]$ and of -5.44% with significance at the 10% level for $[-20, 20]$. The asymmetric interval $[-1, 5]$ also shows a significant negative abnormal return of -2.54%.

The nonparametric rank test confirms the significant negative abnormal returns for the interval $[-20, 20]$ and shows significant negative abnormal returns for the 20 day pre- and post-event windows $[-20, -1]$ and $[1, 20]$. Moreover, abnormal returns that are not significant are all negative. Abnormal returns according to the Constant Mean Return Model for the first subsample for individual days around the event date are shown in the lower panel of Table 4. The event day and the following day show significant negative abnormal returns with the Constant Mean Return Model with $AAR_0 = -0.87\%$ (significant at the 10% level) and $AAR_1 = -1.73\%$ (significant at the 1% level).

The Market Model again confirms the results. The abnormal return of the sampling interval $[-1, 1]$ equals -2.03% and is highly significant at the 1% level. The abnormal returns of the tighter intervals around the event date show generally higher significance. The sampling intervals $[1, 5]$ and $[-1, 5]$ reveil both significant negative abnormal returns at the 5% level. The lower panel of Table 4 presents abnormal returns according to the Market Model

Table 4 – **Abnormal Returns for Subsample Crisis**

The table shows abnormal returns for different sampling intervals (upper panel) and individual days (lower panel) within the event window for Subsample crisis, which contains TruPS issued between mid-2007 and 2009. Results from the Constant Mean Return Model and for the Market Model are presented.

	Constant Mean Return Model						Market Model					
Interval/ Day	CAAR/ AAR	t-value	sig.	Rank Test	t-value	sig.	CAAR/ AAR	t-value	sig.	Rank Test	t-value	sig.
[-20,20]	-5.44%	-1.73	*	-300	-2.71	***	-3.22%	-1.80	*	-133	-1.21	
[-5, 5]	-3.30%	-2.03	**	-54	-0.94		-1.54%	-1.66	*	2	0.04	
[-1, 1]	-3.08%	-3.63	***	-35	-1.18		-2.03%	-4.19	***	-12	-0.42	
[-20, -1]	-1.21%	-0.55		-164	-2.13	**	-0.26%	-0.21		-104	-1.35	
[1, 20]	-3.36%	-1.53		-153	-1.98	**	-2.34%	-1.87	*	-59	-0.77	
[1, 5]	-1.20%	-1.09		-41	-1.05		-1.36%	-2.17	**	-62	-1.60	
[-1, 5]	-2.54%	-1.96	*	-49	-1.07		-1.85%	-2.50	**	-23	-0.51	
[-5]	0.99%	2.02	**	42.5	2.46	**	0.15%	0.53		15.1	0.87	
[-4]	-0.63%	-1.29		-32.2	-1.87	*	0.43%	1.55		15.7	0.91	
[-3]	-0.44%	-0.90		-3.3	-0.19		0.14%	0.51		-12.8	-0.74	
[-2]	-0.68%	-1.39		-12.1	-0.70		-0.41%	-1.46		7.7	0.44	
[-1]	-0.48%	-0.98		-25.4	-1.47		0.13%	0.46		8.6	0.49	
[0]	-0.87%	-1.77	*	17.1	0.99		-0.63%	-2.24	**	30.0	1.74	*
[1]	-1.73%	-3.54	***	-26.9	-1.56		-1.54%	-5.49	***	-51.1	-2.95	***
[2]	0.01%	0.01		11.7	0.68		-0.33%	-1.16		-17.0	-0.99	
[3]	-0.28%	-0.56		-21.4	-1.24		-0.11%	-0.38		-24.2	-1.40	
[4]	0.65%	1.32		15.2	0.88		0.29%	1.05		23.1	1.33	
[5]	0.16%	0.32		-19.1	-1.11		0.32%	1.13		7.2	0.42	

n=29 observations

***/**/* denotes significance at the 1%/5%/10% level

for individual days around the event day. The event day AAR_0 and the following day AAR_1 show both significant negative abnormal returns at the 1% level (AAR_1) and at the 5% level (AAR_0). The significance of both one-day abnormal returns is additionally confirmed by the nonparametric rank test. The results for Subsample crisis indicate a significant negative abnormal return. The abnormal returns around the event date, as well as different symmetric and asymmetric sampling intervals around the event date confirm these findings.

The abnormal returns for Subsample pre-crisis are presented in Table 5.

The signs of the abnormal returns for Subsample pre-crisis are mixed for different sampling intervals. However, significant CAARs are negative. Overall significance is lower than in Subsample crisis and in the full sample. Only the sampling interval $[-20, -1]$ shows significant negative abnormal returns for the Constant Mean Return Model (at the 10% level) and for the Market Model (at the 5% level), but this significance is not confirmed by the respective nonparametric rank tests. Abnormal returns for individual days around the event date for Subsample pre-crisis are shown in the lower panel of Table 5. In contrast to Subsample crisis, significant abnormal returns appear predominantly in the pre-event period, e.g., AAR_{-4} and AAR_{-1} are significantly negative for the Constant Mean Return Model and the Market Model. The significance of AAR_{-1} is also confirmed by the nonparametric rank test for both models. Overall, the results for Subsample pre-crisis show weak evidence for negative abnormal returns for issues between 1997 and June 2007. Figure 2 shows the CAAR in the event window, calculated by the Con-

Table 5 – **Abnormal Returns for Subsample Pre-Crisis**

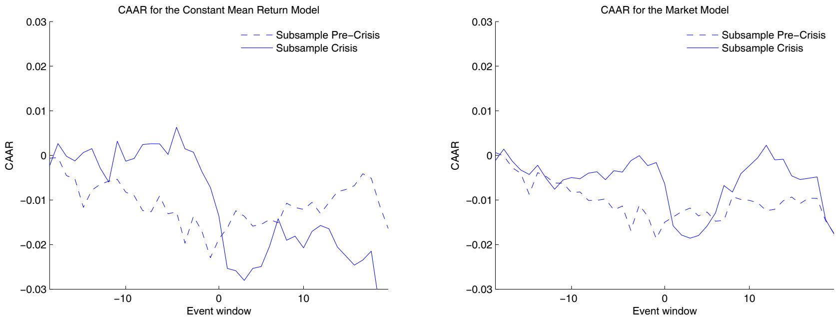
The table shows the abnormal returns for different sampling intervals (upper panel) and individual days (lower panel) within the event window for Subsample pre-crisis, which contains TruPS issued between January 1997 and June 2007. Results from the Constant Mean Return Model and for the Market Model are presented.

	Constant Mean Return Model						Market Model					
Interval/ Day	CAAR/ AAR	t-value	sig.	Rank Test	t-value	sig.	CAAR/ AAR	t-value	sig.	Rank Test	t-value	sig.
[-20,20]	-1.38%	-1.03		-41	-0.61		-1.15%	-1.16		-37	-0.54	
[-5, 5]	-0.40%	-0.58		-39	-1.12		-0.18%	-0.35		-23	-0.64	
[-1, 1]	-0.03%	-0.08		-24	-1.35		-0.02%	-0.07		-23	-1.26	
[-20, -1]	-1.75%	-1.88	*	-46	-0.98		-1.46%	-2.11	**	-62	-1.28	
[1, 20]	0.09%	0.10		1	0.03		0.06%	0.09		15	0.32	
[1, 5]	0.04%	0.09		-25	-1.07		0.15%	0.43		2	0.10	
[-1, 5]	-0.16%	-0.29		-44	-1.59		-0.01%	-0.02		-15	-0.52	
[-5]	0.00%	0.02		5.4	0.52		-0.01%	-0.07		-7.6	-0.71	
[-4]	-0.59%	-2.84	***	-3.0	-0.29		-0.45%	-2.91	***	4.2	0.39	
[-3]	0.61%	2.92	***	17.2	1.64		0.46%	2.96	***	4.9	0.46	
[-2]	-0.26%	-1.24		-14.4	-1.38		-0.17%	-1.08		-9.4	-0.87	
[-1]	-0.49%	-2.35	**	-22.7	-2.17	**	-0.41%	-2.63	***	-26.1	-2.43	**
[0]	0.29%	1.38		3.6	0.34		0.25%	1.62		9.0	0.84	
[1]	0.17%	0.84		-5.3	-0.51		0.14%	0.89		-6.3	-0.59	
[2]	0.27%	1.28		11.6	1.10		0.10%	0.63		9.5	0.88	
[3]	-0.12%	-0.56		-10.1	-0.97		0.06%	0.41		6.3	0.59	
[4]	-0.27%	-1.31		-14.6	-1.40		-0.22%	-1.45		-11.7	-1.09	
[5]	-0.01%	-0.04		-6.5	-0.62		0.07%	0.47		4.6	0.43	

n=70 observations

***/**/* denotes significance at the 1%/5%/10% level

Figure 2 – CAAR for Subsamples
The figure shows the CAAR for the two subsamples for the 41 day event window (20 pre-event days, the event date, and 20 post-event days), where day 0 denotes the event date. The left panel shows the CAAR calculated with the Constant Mean Return Model and the right panel shows the CAAR calculated with the Market Model. The solid lines refer to results for Subsample crisis and the dashed lines to results for Subsample pre-crisis.



stant Mean Return Model and the Market Model, respectively, for the two subsamples.

A direct comparison of Subsample crisis and Subsample pre-crisis is presented in Table 6, which shows abnormal returns for different sampling intervals within the event window and statistical tests for the differences in the abnormal returns between Subsample crisis and Subsample pre-crisis, i.e., the difference is negative if the abnormal return of Subsample crisis is less than the abnormal return of Subsample pre-crisis for the same sampling interval. As can be seen from Table 6, the difference between the cumulative abnormal returns of the two subsamples is negative for all sampling intervals but the 20-day pre-event window $[-20, -1]$. The difference for the sampling interval $[1, 20]$ is statistically significant for the Constant Mean Return Model and the

Table 6 – **Comparison of Subsamples**

The table shows the comparison of Subsample crisis and Subsample pre-crisis. The abnormal returns for different sampling intervals within the event window are shown for the Constant Mean Return Model in the upper panel and for the Market Model in the lower panel. Diff. denotes the difference of the abnormal return of Subsample crisis and Subsample pre-crisis. Significance of the difference between the two subsamples is tested with a parametric t-test and with a nonparametric Wilcoxon rank-sum test. The respective p-values for the Null-hypothesis of no difference between the two subsamples are given for the t-test (ttest) and the Wilcoxon rank-sum test (WRS).

			Constant Mean Return Model				
Interval	Subsample Crisis	Subsample Pre-Crisis	Diff.	ttest	sig.	WRS	sig.
[-20,20]	-5.44%	-1.38%	-4.06%	0.31		0.56	
[-5, 5]	-3.30%	-0.40%	-2.90%	0.19		0.50	
[-1, 1]	-3.08%	-0.03%	-3.05%	0.14		0.74	
[-20, -1]	-1.21%	-1.75%	0.54%	0.82		0.72	
[1, 20]	-3.36%	0.09%	-3.45%	0.09	*	0.06	*
[1, 5]	-1.20%	0.04%	-1.24%	0.21		0.98	
[-1, 5]	-2.54%	-0.16%	-2.38%	0.14		0.99	
			Market Model				
Interval	Subsample Crisis	Subsample Pre-Crisis	Diff.	ttest	sig.	WRS	sig.
[-20,20]	-3.22%	-1.15%	-2.08%	0.40		0.78	
[-5, 5]	-1.54%	-0.18%	-1.36%	0.26		0.46	
[-1, 1]	-2.03%	-0.02%	-2.02%	0.15		0.26	
[-20, -1]	-0.26%	-1.46%	1.20%	0.39		0.81	
[1, 20]	-2.34%	0.06%	-2.40%	0.07	*	0.20	
[1, 5]	-1.36%	0.15%	-1.50%	0.00	***	0.02	**
[-1, 5]	-1.85%	-0.01%	-1.85%	0.07	*	0.82	

***/**/* denotes significance at the 1%/5%/10% level

differences for the sampling intervals $[1, 20]$, $[1, 5]$ and $[-1, 5]$ are statistically significant for the Market Model, where the significance of the difference of sampling interval $[1, 5]$ is also confirmed by the nonparametric Wilcoxon rank-sum test. The difference of sampling interval $[1, 5]$ equals -1.50%, i.e., the abnormal return during the five day post-event period for Subsample crisis lies 1.50% below the abnormal return during the same sampling period for the Subsample pre-crisis. The direct comparison of the two subsamples shows that the wealth decreasing effects which we found for the full sample are stronger during the period of the recent financial crisis, i.e., that an announcement of the issuance of TruPS during this period is accompanied by a stronger decrease of the stock price of the issuing bank.

4.3. Analysis of Cumulative Abnormal Returns

A multiple regression analysis is performed to analyze determinants of cumulative abnormal returns for the symmetric sampling interval $[-20, 20]$ and the asymmetric post-event sampling interval $[1, 20]$. We include bank-specific and issue-specific characteristics, where bank-specific characteristics are taken from BankScope at the year-end before the announcement. The characteristics for the first regression model include a size variable ($Assets$), which is defined as logarithm of the total assets, a variable which indicates the ratio of face amount to total assets ($IssueSize$), the variable $TaxRate$, which measures the ratio of taxes to profit before taxes, the ratio of equity to total assets ($CapitalRatio$) and the return on assets (ROA) as a proxy for profitability.

The second regression model additionally includes the variable VOL, which is calculated as ratio of the standard deviation of the log-returns in the pre-event[12] sampling interval $[-20, -1]$ to the standard deviation of the log-returns in the estimation window. If VOL is larger (smaller) than one, the volatility in the month prior to the announcement is larger (smaller) than the volatility during the estimation window. The variable VOL therefore proxies the level of uncertainty or financial stress of the respective bank at the time of the announcement.

The third regression model includes interactive terms for the variables ROA and VOL with an indicator variable $Crisis$, where $Crisis$ equals one for announcements in Subsample crisis and zero for announcements in Subsample pre-crisis. Table 7 presents the results for the two different sampling intervals. Consistent with Benston et al. (2003), we find negative coefficients for the variable $CapitalRatio$, indicating that the abnormal return of poorly capitalized banks is higher. This relation is significant for the CARs of both sampling intervals for Model (1) and Model (2), however significance is weak. Also for the coefficient ROA, which is a measure for the profitability of a bank, our results are consistent with Benston et al. (2003). We find positive coefficients for ROA for all three models. The coefficients are significant for both sampling intervals for Model (1) and Model (2) and highly significant for the post-event sampling interval $[1, 20]$ for Model (2). This evidence suggests that stocks of highly profitable banks exhibit higher abnormal returns upon

[12] To exclude possible effects of the announcement on the volatility of the stock of the issuing bank, only the pre-event period within the event window is used for the calculation of VOL.

Table 7 – **Analysis of Abnormal Returns**
Results from three multiple regression models are presented where the dependent variable is CAR$[-20, 20]$ (upper panel) and CAR$[1, 20]$ (lower panel). Regressors of Model (1) include the log of total assets ($Assets$), the ratio of face amount to total assets ($IssueSize$), the variable $TaxRate$, the ratio of equity to total assets ($CapitalRatio$) and the return on assets (ROA). Model (2) additionally includes the variable VOL, calculated as ratio of the standard deviation of the log-returns in $[-20, -1]$ to the standard deviation of the log-returns in the estimation window. Model (3) includes the two interactive terms $Crisis \times ROA$ and $Crisis \times VOL$, where $Crisis$ is an indicator variable equaling one for event dates in Subsample crisis and zero for event dates in Subsample pre-crisis. Bank-specific characteristics are taken from BankScope at the year-end before the announcement. Standard errors are calculated according to Newey and West (1987).

CAR[-20,20]	Model (1)			Model (2)			Model (3)		
	Coeff.	t-val.	sig.	Coeff.	t-val.	sig.	Coeff.	t-val.	sig.
$Intercept$	-0.10	-0.62		-0.08	-0.54		-0.07	-0.52	
$Assets$	0.01	0.66		0.01	0.68		0.01	0.73	
$IssueSize$	3.01	0.97		2.92	0.95		1.81	0.84	
$TaxRate$	-0.03	-0.53		-0.03	-0.45		-0.03	-0.55	
$CapitalRatio$	-0.01	-1.78	*	-0.01	-1.76	*	-0.01	-1.64	
ROA	0.05	2.50	**	0.05	2.55	**	0.02	1.57	
VOL				-0.02	-1.10		0.01	0.21	
$Crisis \times ROA$							0.09	3.37	***
$Crisis \times VOL$							-0.07	-2.24	**
Adj.R^2	6.3%			6.1%			17.2%		
CAR[1,20]	Model (1)			Model (2)			Model (3)		
	Coeff.	t-val.	sig.	Coeff.	t-val.	sig.	Coeff.	t-val.	sig.
$Intercept$	0.01	0.18		0.02	0.26		-0.03	-0.36	
$Assets$	0.00	0.00		0.00	0.00		0.00	0.42	
$IssueSize$	1.22	1.24		1.20	1.23		1.03	1.12	
$TaxRate$	-0.03	-0.50		-0.02	-0.47		-0.02	-0.49	
$CapitalRatio$	-0.01	-1.97	*	-0.01	-1.94	*	0.00	-1.64	
ROA	0.03	2.69	**	0.03	2.71	***	0.01	1.70	*
VOL				0.00	-0.69		0.02	0.92	
$Crisis \times ROA$							0.03	2.14	**
$Crisis \times VOL$							-0.04	-2.35	**
Adj.R^2	3.1%			2.2%			5.7%		

***/**/* denotes significance at the 1%/5%/10% level

the announcement of the issuance of TruPS.

The coefficients of $TaxRate$ are negative for all three regression models, but not significant. This suggests that the abnormal return is not significantly higher for banks with high tax rates and, therefore, the benefits from the tax shield are not the main driver of abnormal returns. The variable $IssueSize$ has positive coefficients, which means that the larger the volume of TruPS in relation to total assets, the stronger the market reaction in terms of abnormal returns. This is consistent with Benston et al. (2003) and Cornett and Tehranian (1994) who find a positive relation between the ratio of offer size to total assets and the stock market reaction. However, this relation is not significant for our sample and the three regression models.

The second regression model includes the ratio of the standard deviation of the log-returns in the sampling interval $[-20, -1]$ to the standard deviation of the log-returns in the estimation window (VOL). As can be seen from Table 7, the coefficient of VOL is negative for both sampling intervals. This indicates that a decrease of the stock price of the issuing bank is higher in periods of increased uncertainty for the issuing bank. However, this result is not significant for Model (2).

The third regression model includes interactive terms which measure the additional effect of the variables ROA and VOL during the financial crisis. The sign of the variable VOL changes from negative to positive, but is still insignificant. The coefficient of the interactive term $Crisis \times ROA$ is significantly positive, which means that the market rewarded banks with a high profitability in the past during the financial crisis stronger than before.

The coefficient of the interactive term $Crisis \times VOL$ however is significantly negative for both sampling periods, which suggests that during the financial crisis banks with an increase in its stock price volatility over the month prior to the announcement show stronger negative abnormal returns. We hypothesize that market participants interpret the increased volatility prior to the announcement of the issuance of TruPS as indicator of increased financial stress for the individual bank and the announcement itself as the need of a recapitalization, i.e., as a sign of relative weakness of the issuing bank. This finding contradicts Benston et al. (2003), who conclude that market participants do not interpret the issuance of TruPS as sign of financial distress of a bank. Our results however, suggest that during the recent financial crisis market participants interpreted the issuance of TruPS by banks with increased stock price volatility as sign of financial distress. The adjusted R^2s of the third regression model increase for both sampling intervals compared to Model (1) and Model (2), which suggests that due to the inclusion of the variable VOL and the interactive terms the goodness of fit of the regression model is increased.

5. Conclusion

TruPS are hybrid financial instruments that combine bond-like and equity-like characteristics. This article analyzes the announcement effects of TruPS based on a sample of 99 TruPS with announcement dates between 1997 and 2009. The main question is whether the announcement of the issuance of TruPS by a bank is wealth enhancing or decreasing, i.e., whether the effect on a bank's stock price is positive or negative. A second question is whether the financial crisis affects the magnitude of the announcement effect. The full sample and two subsamples, the first covering the period of the financial crisis and the second covering the period prior to the crisis, are analyzed separately. We compare the announcement effects for announcements which took place before and during the financial crisis, which started in mid-2007. Abnormal returns are calculated in a classical event study framework, where normal returns are modeled with a Constant Mean Return Model and a Market Model. Significance is tested by parametric and nonparametric tests.

We find significantly negative abnormal returns of the stocks of the issuing banks for individual days around the announcement, as well as for multiple sampling intervals within the event window. The analysis of the subsamples supports our preliminary findings that the announcement of the issuance of TruPS has a negative impact on shareholders' wealth. The direct comparison of the announcement effects of the two subsamples shows an even stronger negative reaction during the financial crisis. Finally, an analysis of the cumulative abnormal returns reveals stronger negative effects in periods of increased uncertainty.

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Part II.
Fragmentation in European Equity Markets and Market Quality - Evidence from the Analysis of Trade-Throughs

Abstract

The implementation of MiFID has lead to fragmentation of liquidity in European equity trading. We analyze longterm effects of MiFID on liquidity with a new sample of Swiss stocks and do not find evidence for a worsening of market quality. In contrast, liquidity measures indicate a general increase in market quality. Given the non-existence of a consolidated tape in Europe, we examine whether trade-throughs prevent the emergence of a consolidated market. We find evidence that trade-throughs originate from traders with a priority of execution speed over price and conclude that the occurrence of trade-throughs does not indicate inferior market quality.

1. Introduction

The Markets in Financial Instruments Directive (MiFID) was adopted by the European Parliament and Council in 2004. Aim of the initiative is the protection of investors and the promotion of fair, transparent and efficient financial markets[1]. MiFID had to be implemented by all member countries of the European Union by November 2007. The new regulation replaced a directive of 1993 on investment services in the securities field[2], which included a concentration rule[3] that allowed member countries to require the execution of certain orders at a regulated market. Therefore, the concentration rule was beneficial for established national exchanges.

By removing the concentration rule, MiFID enabled the competition among trading venues, which lead to the emergence of alternative trading platforms and their gain of market share. A similar development took place in the United States over the last decade, where ECNs[4] like Archipelago, Island and Instinet could increase their market share in the trading of U.S. stocks on the cost of established exchanges like the NYSE and NASDAQ. As a consequence, a consolidation on the level of exchanges took place with the purchase of the ECN Island by Instinet in 2002, the merger of NYSE with Archipelago to the NYSE Group and the purchase of Instinet by NASDAQ in 2005.

In the course of the implementation of MiFID several multilateral trading fa-

[1] See Council Directive 2004/39/EC of 21 April 2004 on markets in financial instruments, EC (2004).

[2] See Council Directive 93/22/EEC of 10 May 1993 on investment services in the securities field, ECC (1993).

[3] See Art. 14(3) of the directive.

[4] Electronic Communication Networks (ECNs) are alternative trading platforms.

cilities (MTFs) were launched in Europe[5], starting in March 2007 with Chi-X, a pan-European MTF owned by a consortium of global financial institutions[6]. In 2008 several MTFs followed like BATS Europe and Nasdaq OMX Europe, two European subsidiaries of American exchanges and Turquoise, a MTF owned by nine investment banks[7]. The increasing number of trading platforms and the possibility, as well as the pressure to choose the most efficient trading channel lead to a fragmentation of trading volume. In June 2010 more than 25% of the overall trading volume for European equities was traded on four MTFs[8].

Swiss stocks encountered the same development without regulatory pressure.[9] According to the Fidessa Fragmentation Index[10] about 75% of the aggregated trading volume of the SMI stocks in June 2008 was traded on the Swiss exchange and about 1.3% on Chi-X (the rest was traded on dark venues, OTC and through systematic internalisers). In June 2009 the share of the Swiss exchange had dropped to 65% and in June 2010 to 51% of the overall trading volume. The share of Chi-X has risen to almost 13% and other MTFs could increase their market share as well (BATS Europe accounts for almost

[5] See Gresse (2010) for a detailed timetable of the development of MTFs in Europe.

[6] See www.chi-x.com.

[7] See www.tradeturquoise.com

[8] According to the Equity Market Share Report for June 2010 of Thomson Reuters, the fraction of the aggregated trading volume in June 2010 of Chi-X, Nasdaq OMX Nordic, BATS Europe and Turquoise equals 26.9%. The report includes on-exchange and MTF reported trading volume.

[9] The implementation of MiFID is only mandatory for companies in the European Economic Area (EEA) but the emergence of additional trading platforms like MTFs has also affected the trading of Swiss stocks, as they are also traded on these platforms.

[10] The Fidessa Fragmentation Index is a measure for the concentration of trading in one market vs. the fragmentation of trading across different trading venues. For more information we refer to fragmentation.fidessa.com.

6%, Turquoise for almost 3%, Nyse Arca and Nasdaq Europe together for 0.5%).

In this article we analyze several questions around liquidity fragmentation in Europe. How is market quality in Europe as a whole affected by fragmentation? Are the effects similar for large and mid caps or do we observe differences related to company size? Do we observe a similar development as in the United States or does the lack of a trade-through prohibition prevent the emergence of a virtual consolidated market as discussed by Hendershott and Jones (2005) and O'Hara and Ye (2011) and, therefore, deteriorate market quality? To address these questions, we analyze measures of liquidity fragmentation and market quality with a new sample covering intraday data from the Swiss stock exchange and three MTFs for 29 Swiss stocks between November 3, 2008 and June 30, 2010.

We contribute to the literature on the effects of liquidity fragmentation in Europe in three important aspects. First, our study helps to understand the effects of liquidity fragmentation in the European equities markets. Although a number of studies analyzed liquidity fragmentation in U.S. markets, there is a gap in the analysis of long-term effects of the implementation of MiFID and the related fragmentation of liquidity for European stocks. Second, we concentrate on institutional differences between U.S. and European equities markets by the analysis of trade-throughs. In Europe there is neither a consolidated tape nor a rule prohibiting trade-throughs. But still literature analyzing these differences is insufficient. Hendershott and Jones (2005) analyze the relaxation of the trade-through prohibition for the three most active

ETFs in the U.S. market and its effects on market quality. Although they find no evidence for negative effects on market quality, they conclude that this could be related to the high liquidity of the ETFs analyzed. Our study is related to Storkenmaier and Wagener (2011) who analyze quote quality and trade-throughs for a sample of UK blue-chip stocks. However, our contribution is to provide evidence that trade-throughs originate from informed traders with a priority of execution speed over price. Third, we analyze a new and comprehensive long-term set of data. Where most studies on competition and fragmentation are laid out as event studies with a comparably short after event period, our analysis covers 20 months, which makes an investigation of long-term effects possible. Additionally, to our best knowledge, we are the first to analyze explicitly stocks from Switzerland, which is not a member of the European Union and, therefore, to a lesser extent affected by MiFID.

The remainder of this paper is organized as follows. The next section reviews the literature and Section 3 outlines the data. Section 4 presents measures of liquidity and fragmentation, while Section 5 analyzes trade-throughs. Finally, Section 6 concludes.

2. Literature Review

There is a large body of literature, which analyzes the effects of liquidity fragmentation on market quality on a theoretical and empirical level. However, it is inconclusive about the question, whether fragmentation leads to an increase or decrease in market quality (see also Degryse (2009), Storkenmaier and Wagener (2010) and Chlistalla and Lutat (2011)).

Centralized trading reduces search and coordination costs for traders and could, therefore, be the optimal framework regarding market quality. Pagano (1989) and Chowdhry and Nanda (1991) argue that liquidity tends to concentrate on one trading venue. Mendelson (1987) and Madhavan (1995) analyze theoretically the effects of liquidity fragmentation and show that fragmentation can decrease market quality. In Madhavan (1995) a model which explains liquidity fragmentation in the context of disclosure is proposed. In this model fragmentation can decrease market quality, but due to heterogeneous preferences of market participants regarding disclosure of their trades, liquidity not necessarily concentrates. Amihud et al. (2003) provide empirical evidence for benefits of consolidation by the analysis of corporate warrants from the Tel-Aviv Stock Exchange. However, they state that the cost of fragmentation is likely to be reduced under advanced trading systems.

Bennett and Wei (2006) find improved market quality in terms of liquidity provision and price efficiency for stocks that switched from NASDAQ to the NYSE. This improvement is attributed to order flow concentration. It increases market quality in particular for less liquid stocks while the competition among trading platforms could still improve market quality for highly liquid stocks. With a sample of NYSE and Nasdaq stocks O'Hara and Ye (2011) find no evidence for a decrease in market quality due to fragmentation. Moreover, fragmentation appears to be most beneficial for small stocks[11]. Christie

[11] Regarding the findings of Bennett and Wei (2006), O'Hara and Ye (2011) state that the findings of improved measures of market quality related to the move of the listing from Nasdaq to NYSE could be due to size effects of the stocks, rather than a consolidation

and Schultz (1994) find evidence that NASDAQ market makers were able to earn rents by posting too wide spreads. When this was made public, spreads suddenly narrowed as shown in Christie et al. (1994). These studies show that the concentration of liquidity in one market place does not necessarily lead to competition among market makers and, therefore, does not fully enforce liquidity. In contrast, competition among trading venues may lead to better conditions, related services and lower prices for traders which could finally result in enhanced market quality. Boehmer and Boehmer (2003) find evidence for improved market quality for ETFs that started to trade on the NYSE after having been traded on other platforms, which they attribute to enhanced competition for order flow.

Several studies analyze the competition between NASDAQ and ECNs. Barclay et al. (2003), e.g., conclude that ECN trading explains more of the stock-price variance than trading on NASDAQ and thus ECNs are able to attract more informed traders. Fink et al. (2006) also find evidence for positive effects of enhanced competition between NASDAQ and ECNs and state that cost-competition for trading outweighs potentially negative effects driven by fragmentation.

The theoretical underpinning for effects of fragmentation on market quality follows two main strands. On the one hand positive network externalities through consolidation are emphasized, which means that fragmentation of

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of liquidity. According to O'Hara and Ye (2011) the stocks that move from Nasdaq to NYSE tend to be the larger Nasdaq firms due to the listing standards of the two exchanges. For larger Nasdaq firms O'Hara and Ye (2011) find no significant differences between fragmentation and consolidation.

liquidity should have negative effects on market quality. On the other hand competition among trading venues is seen as the main driver for enhanced market quality for the market participants. O'Hara and Ye (2011) argue that smart order routing, the existence of a consolidated tape and a rule prohibiting trade-throughs[12] lead to a virtual consolidation of U.S. equity markets although fragmentation has increased. This hypothesis combines the two strands of argumentation by explaining how increased competition through fragmentation leads to increased market quality without the negative effects due to the loss of consolidation.

MiFID however neither requires a consolidated tape, nor prohibits trade-throughs. The emergence of a virtual consolidated market for European equities is thus questionable. If the lack of a consolidated tape and a rule prohibiting trade-throughs prevents the emergence of a virtual consolidated market as discussed by O'Hara and Ye (2011), trade-throughs would be evidence for market participants which do not monitor all trading venues and, therefore, trade at suboptimal prices. However, if trade-throughs express traders' priority of execution speed over price, the existence of trade-throughs would not provide evidence for a deterioration in market quality nor against the concept of a virtual consolidated market. Therefore, the analysis of trade-throughs is important for the understanding of the consequences of the different regulations in the U.S. and Europe on liquidity fragmentation and market quality.

[12] A trade-through is the execution of an order at a certain price, although a better price is offered on another exchange. Foucault and Menkveld (2008) ascribe high trade-through rates to investors not using smart routers to route their trades to the market offering the best available price. See Section 5 for more details.

There are comparably few empirical studies analyzing the effects of fragmentation of European equity trading related to the implementation of MiFID. Hengelbrock and Theissen (2009) analyze the simultaneous market entry of Turquoise in 14 European countries, the determinants of its market share and the effects on market quality in terms of liquidity and bid-ask spreads. Their main findings are that the market share of Turquoise is higher for firms with higher market capitalization, higher free float and lower volatility. A panel analysis provides evidence for a decrease in spreads and weak evidence for increased volume after the introduction of Turquoise. In another event study Chlistalla and Lutat (2011) analyze the market entry of Chi-X in France. They provide evidence that market quality does not suffer from the entrance of a new competitor and the accompanying fragmentation of liquidity. Gresse (2010) analyzes measures of liquidity and market quality on regulated markets and MTFs for a sample of 140 LSE and Euronext listed stocks over four one month periods between October 2007 and September 2009 and finds no evidence for a decrease in market quality.

Foucault and Menkveld (2008) study the entrance of the London Stock Exchange with its MTF EuroSETS in the Dutch stock market and the implications on the limit order market operated by Euronext. They find that the consolidated order book after the entry of EuroSETS is deeper, i.e., overall liquidity is higher. Furthermore, they describe a negative relation between the rate of trade-throughs at the expense of EuroSETS and the liquidity supply on this market. With a high rate of trade-throughs for a particular stock, the probability of execution on EuroSETS is lower. Accordingly, the liquidity supply on EuroSETS would also be lower.

Riordan et al. (2010) analyze competition and market quality in fragmented markets for the FTSE 100 constituents across the London Stock Exchange (LSE) and the three MTFs Chi-X, BATS Europe and Turquoise with a sample covering 29 trading days. They find evidence for an increase in market quality in terms of quoted spreads and a shift of price discovery from LSE towards Chi-X. Storkenmaier and Wagener (2011) analyze market coordination, i.e., arbitrage opportunities (crossed market quotes) and suboptimal executions (trade-throughs) within the same sample period and conclude that the competition among trading venues lead to an alignment of prices. A similar conclusion is drawn by Spankowski et al. (2012), who analyze intraday patterns on the LSE and three MTFs and find evidence for a convergence across different trading venues. Degryse et al. (2011) focus on the effects of dark trading on liquidity. They find a negative impact of dark trading on liquidity, while evidence is provided that fragmentation increases liquidity.

3. Data

We conduct our analysis for the constituents of the SMI Expanded index that includes the 50 largest Swiss stocks. Stocks that are not traded on the three MTFs Chi-X, BATS Europe and Turquoise and stocks where data is not available are excluded. Our final sample in Table 1 consists of 29 stocks. We obtain intraday trade and quote data from Thomson Reuters Tick History for the Swiss exchange and the MTFs Chi-X, BATS Europe and Turquoise.

Table 1 – Final Sample

The table shows the final sample of 29 companies. It consists of the constituents of the SMI Expanded index that are listed on the MTFs Chi-X, BATS Europe and Turquoise. The SMI Expanded covers the SMI and SMIM indices and contains the 50 largest capitalized stocks of the Swiss market. We use the index constituents as on June 15, 2010. Additionally, we show the attribution of the stocks to the subsamples. It is based on the average daily market capitalization (MCAP) over the sample period November 3, 2008 until June 30, 2010. Market capitalization is retrieved from Thomson Reuters Datastream and is reported in billion Swiss francs. Subsample Stocks L contains the ten largest stocks of the final sample, Stocks S contains the nine smallest stocks and Stocks M the ten remaining stocks.

Company	**Symbol**	**MCAP**	**Subsample**
Nestle	NESN	168.1	
Novartis	NOVN	135.2	Stocks L
Roche	ROG	113.8	Avg. MCAP: 66.0
Credit Suisse	CSGN	53.2	
UBS	UBSN	51.3	
ABB	ABBN	43.0	
Zurich Financial Services	ZURN	32.4	
Syngenta	SYNN	24.1	
Holcim	HOLN	19.9	
Swisscom	SCMN	18.8	
Swiss Re	RUKN	15.2	
Synthes	SYST	15.1	Stocks M
Richemont	CFR	14.9	Avg. MCAP: 10.2
Kuehne + Nagel	KNIN	10.6	
SGS	SGSN	10.2	
Adecco	ADEN	9.2	
Swatch Group I	UHR	6.9	
Actelion	ATLN	6.9	
Givaudan	GIVN	6.6	
Geberit	GEBN	6.3	
Swatch Group N	UHRN	5.3	
Lonza	LONN	4.9	Stocks S
Baloise	BALN	4.2	Avg. MCAP: 3.2
Swiss Life Holding	SLHN	3.5	
Nobel Biocare	NOBN	3.2	
Logitech	LOGN	3.1	
Clariant	CLN	2.1	
Petroplus	PPHN	1.6	
OC Oerlikon	OERL	0.8	

Our sample covers a period of 433 trading days between November 3, 2008 and June 30, 2010 (20 months) and is, therefore, significantly larger than in comparable studies. The trade data contains the number of stocks traded and the price. The quotes data contains changes in the order book on the best bid and ask level[13]. Trade and quote data is timestamped to the millisecond. The data covers trades executed in the limit order book of the Swiss exchange or the three MTFs Chi-X, BATS Europe and Turquoise, but it does not include trades executed by systematic internalizers, dark pools or OTC venues.

For our analysis we build one-second snapshots of historical order books containing the best bid and ask price and the corresponding volumes. Historical trade data is aggregated to one-second intervals by summing up trading volume and calculating the volume weighted average price. Historical trade and quote data is calculated for every stock on every trading venue from 09:00:00 (CET) until 17:15:00 (CET) on each trading day[14].

To analyze size effects, we group the stocks into three subsamples according to their average daily market capitalization during the sample period. Table 1 shows the attribution of the stocks to the subsamples. Stocks L contains the 10 largest stocks, Stocks M contains the 10 following stocks and Stocks S the remaining 9 stocks. The daily market capitalization per company during the sample period is retrieved from Thomson Reuters Datastream.

[13] Our data does not include iceberg orders and hidden liquidity.

[14] Continuous trading on the Swiss exchange takes place between 09:00:00 (CET) and 17:20:00 (CET) followed by the closing auction, see SIX Swiss Exchange (2010). We exclude the closing auction from our analysis and discard trade and quote data with a timestamp after 17:15:00 (CET).

4. Fragmentation and Market Quality

Table 2 shows the fragmentation of liquidity. Panel A presents the market share in terms of average daily trading volume, Panel B in terms of average daily number of trades for the four trading venues.

The fragmentation index (FI) is the reciprocal of a Herfindahl index[15] based on the market share on different trading venues, i.e.,

$$FI = \left(\sum_{k \in K} MS_k^2 \right)^{-1},$$

where $k \in K = \{SWX, BS, CHI, TQ\}$ denotes the trading venue Swiss exchange (SWX), BATS Europe (BS), Chi-X (CHI) and Turquoise (TQ), respectively. MS_k denotes the market share of trading venue k for $k \in K$ in terms of the trading volume and the number of trades, respectively. FI is, therefore, a measure for the concentration and takes a minimum of 1 if trading is fully concentrated on one market. An increase in the fragmentation index FI is related to an increase in the dispersion on different venues.

The Swiss exchange as the traditional and established market attracts the highest fraction in terms of trading volume (80.86%) as well as the number of trades (72.34%). The three MTFs exhibit a substantially and statistically highly significant lower market share in average daily trading volume with 11.49% for Chi-X, 5.01% for Turquoise and 2.64% for BATS Europe and in the average daily number of trades with 16.29% for Chi-X, 6.98% for Turquoise

[15] The Fidessa Fragmentation Index is calculated analogously. See also Gresse (2010) who uses the same measure for fragmentation.

Table 2 – **Market Share**

The table shows market share figures in terms of trading volume (turnover in CHF) and number of trades for the Swiss exchange (SWX), BATS Europe (BS), Chi-X (CHI), Turquoise (TQ) and for all trading venues (Total) over the sample period November 3, 2008 until June 30, 2010. Panel A shows the fraction of the different trading venues in the average daily trading volume. Panel B shows the market share in terms of the average daily number of trades over the sample period. The fragmentation index (FI) is the reciprocal of a Herfindahl index based on the market share on the different trading venues. Additionally, statistical significance for the mean differences of the market share between the Swiss exchange and the three MTFs is tested with a standard t-test.

Panel A: Average daily trading volume (in 1'000)

		Total		SWX			BS		
		Volume	FI	Volume	Fraction		Volume	Fraction	sig.
Pooled Sample	Mean	2,914,066	1.52	2,336,969	80.86%		85,733	2.64%	***
	Std			113,709			8,510		
Stocks L	Mean	2,330,061	1.55	1,846,450	79.85%		73,229	2.83%	***
	Std			140,518			13,273		
Stocks M	Mean	421,388	1.44	346,787	83.16%		10,344	2.17%	***
	Std			29,167			2,058		
Stocks S	Mean	162,617	1.26	143,731	89.06%		2,160	1.22%	***
	Std			15,214			531		
				CHI			TQ		
				Volume	Fraction	sig.	Volume	Fraction	sig.
Pooled Sample	Mean			350,284	11.49%	***	141,080	5.01%	***
	Std			22,574			8,609		
Stocks L	Mean			290,672	11.99%	***	119,710	5.33%	***
	Std			31,466			11,480		
Stocks M	Mean			46,948	10.51%	***	17,309	4.16%	***
	Std			6,210			2,166		
Stocks S	Mean			12,664	7.43%	***	4,062	2.30%	***
	Std			2,009			808		

Table continued on next page

Table 2 – continued from previous page

Panel B: Average daily number of trades									
		Total		SWX			BS		
		Trades	FI	Trades	Fraction	Trades	Fraction	sig.	
Pooled Sample	Mean	128,644	1.85	91,530	72.34%		6,395	4.40%	***
	Std			2,992			492		
Stocks L	Mean	83,814	1.97	57,174	69.22%		4,632	4.96%	***
	Std			3,539			727		
Stocks M	Mean	29,393	1.76	21,532	74.98%		1,376	3.97%	***
	Std			1,509			265		
Stocks S	Mean	15,437	1.43	12,825	84.11%		387	2.25%	***
	Std			1,003			92		
				CHI			TQ		
				Trades	Fraction	sig.	Trades	Fraction	sig.
Pooled Sample	Mean			21,960	16.29%	***	8,759	6.98%	***
	Std			1,147			401		
Stocks L	Mean			15,692	18.04%	***	6,317	7.79%	***
	Std			1,517			495		
Stocks M	Mean			4,659	14.73%	***	1,826	6.31%	***
	Std			642			201		
Stocks S	Mean			1,610	9.89%	***	616	3.75%	***
	Std			251			101		

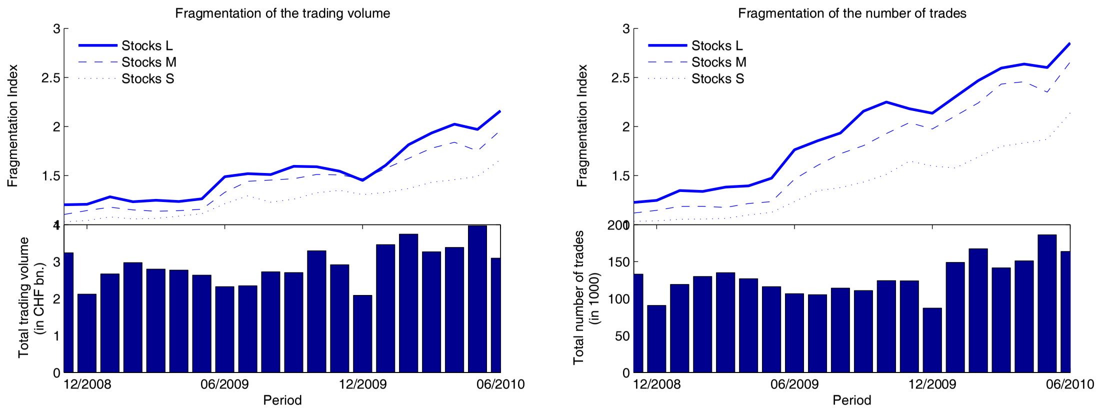
***/**/* denotes significance at the 1%/5%/10% level

and 4.40% for BATS Europe. As the market share in terms of the number of trades is higher for all MTFs than the market share in terms of trading volume, it follows that the average trade size is lower on the MTFs than on the Swiss exchange. For the Swiss exchange the average trading volume per trade equals TCHF 25.5, whereas the average trading volume per trade on the MTFs is TCHF 13.4 for BATS Europe, TCHF 16.0 for Chi-X and TCHF 16.1 for Turquoise, i.e., on average 40% less on the MTFs than on the Swiss exchange.

The results for the subsamples show that fragmentation increases for the higher capitalized stocks. The fragmentation index is 1.55 for the trading volume and 1.97 for the number of trades for Stocks L. Stocks M exhibits a lower degree of fragmentation for trading volume ($FI = 1.44$) and for the number of trades ($FI = 1.76$) and the highest concentration in trading can be found for Stocks S with $FI = 1.26$ for trading volume and $FI = 1.43$ for the number of trades. Figure 1 shows the development of the fragmentation index (FI) over the sample period together with the corresponding trading volume and the corresponding number of trades.

Figure 1 shows a steady increase in fragmentation over the sample period. For trading volume the fragmentation is rather stable until June 2009 and increases between June 2009 and June 2010. A temporary decrease of FI in December 2009, which is more pronounced for the trading volume than for the number of trades, coincides with a decrease in the overall trading activity reflected in total trading volume and the total number of trades. Overall, the fragmentation is increasing for all subsamples, however, the increase is more

Figure 1 – **Fragmentation of Trading Volume and Number of Trades**
The figure shows the fragmentation index (FI) over the sample period November 3, 2008 until June 30, 2010 for total trading volume (left panel) and for the total number of trades (right panel). FI is the reciprocal of a Herfindahl index based on the market share of the four trading venues Swiss exchange, Chi-X, BATS Europe and Turquoise. Additionally, the total trading volume (in billion CHF) is shown in the left panel. The total trading volume is the monthly average of the aggregated daily trading volume on all trading venues. In the right panel, the total number of trades (in 1,000) is shown, calculated as monthly average of the aggregated number of trades per day on all four trading venues.



pronounced for the higher capitalized stocks.

To assess market quality we calculate four liquidity measures that capture different dimensions of liquidity[16]: tightness, time and depth of the order book. Two spread measures are used to describe tightness, the relative spread (RS_s), calculated as

$$RS_s = \frac{p_s^A - p_s^B}{p_s^M},$$

and the relative effective spread (RS_s^{eff}) calculated as

$$RS_s^{eff} = \frac{\left|p_s - p_s^M\right|}{p_s^M},$$

where s denotes the one-second intraday interval and p_s^A and p_s^B denote the ask price and the bid price, respectively, related to interval s. p_s^M denotes the mid price of interval s and is calculated as

$$p_s^M = \frac{p_s^A + p_s^B}{2}.$$

p_s denotes the volume weighted average price in interval s. Therefore, the spread measure RS_s is based on the quotes at the time of the trade and RS_s^{eff} on the realized execution price, which makes RS_s^{eff} the relevant measure from the point of view of a market participant[17]. Turnover (V_s) takes the time

[16] Liquidity is well established as a multi-dimensional concept. Therefore, most authors use multiple measures for capturing different dimensions of liquidity, e.g., Chordia et al. (2000) and Chordia et al. (2001).

[17] See also Hendershott and Jones (2005) and O'Hara and Ye (2011).

dimension of liquidity into account and is calculated as

$$V_s = \sum_{j=1}^{N_s} p_j \cdot q_j,$$

where p_i and q_i denote the price and the number of stocks traded and N_s the number of trades within the one-second interval s. The depth dimension of liquidity is captured by calculating the dollar depth ($D\$_s$) as

$$D\$_s = \frac{q_s^A \cdot p_s^A + q_s^B \cdot p_s^B}{2},$$

where q_s^A and q_s^B denote the quoted number of stocks in interval s on the ask side and bid side, respectively, i.e., the dollar depth measures the average quoted volume of the bid and ask side of the order book in every one-second interval. With these liquidity measures we gather the same information as Bessembinder and Kaufman (1997), however, we are able to process the full sample at once and, therefore, do not rely on their multistage methodology. Average liquidity measures across trading venues and subsamples are presented in Table 3.

The Swiss exchange provides the highest liquidity according to all liquidity measures. The relative spread RS for the pooled sample on Chi-X, BATS Europe and Turquoise is $0.33\% - 0.38\%$ which equals approximately two times the relative spread on the Swiss exchange of 0.16%. The relative effective spread RS^{eff} on the Swiss exchange for the pooled sample is 0.06% which equals approximately one third of the relative spread. The same proportion

Table 3 – **Liquidity Measures**
The table shows liquidity measures for the Swiss exchange (SWX), BATS Europe (BS), Chi-X (CHI), Turquoise (TQ) across different subsamples. Two spread measures are presented, RS denotes the relative spread and RS^{eff} denotes the relative effective spread, calculated with the prevailing mid-price. V denotes the average turnover per hour in CHF and $D\$$ is the dollar depth, measured as average posted volume on the bid and ask side of the order book. Additionally, statistical significance for the mean differences between the Swiss exchange and the three MTFs is tested with a standard t-test.

			RS					
		SWX	BS	sig.	CHI	sig.	TQ	sig.
Pooled Sample	Mean	0.16%	0.34%	***	0.38%	***	0.33%	***
	Std	0.09%	0.46%		1.07%		1.08%	
Stocks L	Mean	0.10%	0.29%	***	0.18%	***	0.19%	***
	Std	0.04%	0.47%		0.21%		0.41%	
Stocks M	Mean	0.15%	0.35%	***	0.29%	***	0.33%	***
	Std	0.05%	0.39%		0.86%		1.34%	
Stocks S	Mean	0.23%	0.39%	***	0.83%	***	0.56%	***
	Std	0.12%	0.52%		1.81%		1.34%	
			RS^{eff}					
		SWX	BS	sig.	CHI	sig.	TQ	sig.
Pooled Sample	Mean	0.06%	0.09%	***	0.08%	***	0.08%	***
	Std	0.04%	0.15%		0.12%		0.11%	
Stocks L	Mean	0.04%	0.07%	***	0.05%	***	0.05%	***
	Std	0.01%	0.14%		0.06%		0.09%	
Stocks M	Mean	0.05%	0.10%	***	0.08%	***	0.08%	***
	Std	0.02%	0.16%		0.09%		0.09%	
Stocks S	Mean	0.08%	0.12%	***	0.14%	***	0.13%	***
	Std	0.05%	0.14%		0.19%		0.15%	

Table continued on next page

Table 3 – continued from previous page

		SWX	BS	sig.	CHI	sig.	TQ	sig.
			V					
Pooled Sample	Mean	9,767,894	358,340	***	1,464,092	***	589,678	***
	Std	13,782,305	1,031,524		2,736,155		1,043,423	
Stocks L	Mean	22,381,217	887,624	***	3,523,297	***	1,451,030	***
	Std	17,030,503	1,608,674		3,813,634		1,391,390	
Stocks M	Mean	4,203,483	125,381	***	569,065	***	209,806	***
	Std	3,534,994	249,377		752,690		262,516	
Stocks S	Mean	1,935,770	29,091	***	170,560	***	54,701	***
	Std	1,843,876	64,301		243,436		97,949	
			$D\$$					
		SWX	BS	sig.	CHI	sig.	TQ	sig.
Pooled Sample	Mean	182,093	28,128	***	52,316	***	32,204	***
	Std	393,843	78,010		121,840		52,583	
Stocks L	Mean	389,160	54,674	***	111,850	***	66,574	***
	Std	616,209	110,127		191,748		76,366	
Stocks M	Mean	92,245	11,341	***	27,021	***	18,443	***
	Std	53,250	15,476		23,172		15,719	
Stocks S	Mean	51,849	17,286	***	14,273	***	9,305	***
	Std	34,308	68,220		16,986		10,374	

***/**/* denotes significance at the 1%/5%/10% level

can be seen in RS^{eff} for Chi-X, BATS Europe and Turquoise with RS^{eff} between $0.08\% - 0.09\%$. The fact that the relative effective spread is smaller than the relative spread shows that trades are executed within the quote, i.e., not at the offered prices according to the order book[18]. The spread measures decrease with increasing market capitalization. Turnover V and dollar depth $D\$$ show a similar pattern, as they are higher on the Swiss exchange than on the MTFs and increasing with market capitalization. The differences between the liquidity measures on the Swiss exchange and the MTFs are all highly significant.

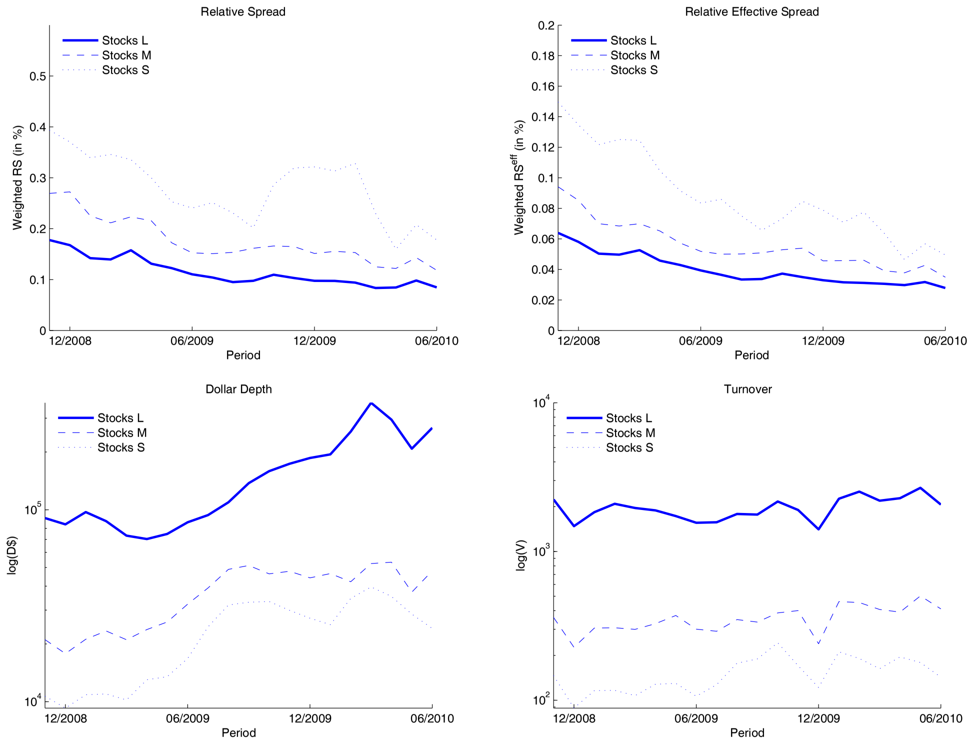
According to the analyzed liquidity measures, Chi-X is the MTF with the highest market quality, followed by Turquoise and BATS Europe. Figure 2 shows how the liquidity measures evolve over the sample period. The upper panel shows the relative spread RS and the relative effective spread RS^{eff}, weighted with the corresponding turnover per trading venue. The lower panel shows turnover V and dollar depth $D\$$, both in log-scales.

According to Figure 2 the spread measures are decreasing over the sample period for all subsamples and the spreads for the higher capitalized stocks are consistently lower than for the smaller stocks. Turnover does not show a clear trend over the sample period while dollar depth, especially for Stocks L, is increasing over time which is consistent with Foucault and Menkveld (2008), who also find a deeper consolidated order book after the entrance of the MTF EuroSETS in the Dutch stock market. Figure 2 clearly shows an increase in

[18] See Chordia et al. (2000) and Chordia et al. (2001) who also find substantially lower relative effective spreads compared to the relative spreads.

Figure 2 – **Liquidity Measures**

The figure shows the development of the liquidity measures relative spread RS, relative effective spread RS^{eff}, dollar depth $D\$$ and turnover V over the sample period November 3, 2008 until June 30, 2010 for all trading venues. RS and RS^{eff} are weighted with the corresponding turnover. $D\$$ and V are reported in log scale.



market quality which coincides with a steady increase in fragmentation.

We follow Gresse (2010) and provide a multivariate regression analysis of the liquidity measures. Two multivariate fixed effects regression models of spread and depth measures are presented, where fragmentation enters as independent variable in the second regression model. We define the first regression model as

$$LM_{i,t}^{k} = \alpha_1 + \beta_1 V_{i,t} + \beta_2 \sigma_{i,t} + \beta_3 \log MCAP_{i,t} + \beta_4 D_i + \epsilon_{i,t},$$

where $LM_{i,t}^{k}$ denotes the liquidity measures RS, RS^{eff} and $\log D\$$ for stock i and month t, respectively. The regressors are monthly averages of daily turnover, denoted by $V_{i,t}$, daily volatility $\sigma_{i,t}$ which is measured as standard deviation of the log returns and the logarithm of daily market capitalization $\log MCAP_{i,t}$.

We expect market quality to deteriorate in turbulent market phases, i.e., increasing spread measures and a decreasing depth for high volatility and, therefore, a positive sign for the coefficient of σ for the spread measures and a negative sign for the depth measure. Market quality is expected to be higher for large stocks, which implies a negative sign of the coefficient of $\log MCAP$ and V for the spread measures and a positive sign for the depth measure. We include company fixed effects, denoted by D_i, in the regression model and use Newey-West standard errors to account for heteroskedasticity and autocorrelation. We define the second regression model as

$$LM_{i,t}^{k} = \alpha_1 + \beta_1 FI_{i,t} + \beta_2 V_{i,t} + \beta_3 \sigma_{i,t} + \beta_4 \log MCAP_{i,t} + \beta_5 D_i + \epsilon_{i,t},$$

i.e., the fragmentation index $FI_{i,t}$ is also incorporated as independent variable. From Figure 2, we expect fragmentation to be an indication of enhanced competition, which improves market quality for investors. Therefore, we expect the coefficient of FI to be negative for the spread measures and positive for the depth measure. The results for the two regression models are given in Table 4 for RS, in Table 5 for RS^{eff} and in Table 6 for $\log D\$$.

The upper panel of Table 4 shows that the coefficient for $\log MCAP$ is negative and significant at the 1% level for the pooled sample which means that the relative spread is decreasing for higher capitalized stocks. This relation holds for the subsamples Stocks M and Stocks S. The coefficient for Stocks L is positive, although not significant. The sign of σ is positive which indicates an increasing relative spread for increasing intraday volatility. It is highly significant for the pooled sample and all subsamples. The coefficient of turnover is negative for the pooled sample and the subsamples and highly significant for the three subsamples, which indicates decreasing relative spreads for increasing trading activity. The adjusted R^2 for the pooled sample with the first regression model is 82%.

The second regression model in the lower panel of Table 4 includes fragmentation as independent variable. The coefficient of $\log MCAP$ remains negative and highly significant for the pooled sample. The signs of the coefficients for the subsamples do not change, however the result for subsample Stocks M loses significance. The results for σ and V are similar to the first regression model. The coefficient of FI is negative and significant for the pooled sample and the subsamples Stocks M and Stocks S which indicates decreasing spreads

Table 4 – **Relative Spread**

The table shows the results from a regression analysis with relative spread RS (in bps) as dependent variable. The regressors are monthly averages of daily turnover V (in 1,000 CHF), the standard deviation of daily log returns σ (in %) and the logarithm of daily market capitalization $\log MCAP$. Panel B also includes the fragmentation index FI, measured as reciprocal of a Herfindahl index based on the market share of the four trading venues Swiss exchange, Chi-X, BATS Europe and Turquoise, as independent variable. The regression model includes company specific fixed effects, which are omitted for brevity. Results are presented for the full sample and for three subsamples of stocks, where Newey-West standard errors are used to test for significance.

Panel A: Regression Analysis without Fragmentation

	Pooled Sample			**Stocks L**			**Stocks M**			**Stocks S**		
	coeff.	t-stat.	sig.	coeff.	t-stat.	sig.	coeff.	t-stat.	sig.	coeff.	t-stat.	sig.
V	-0.034	-0.31		-0.169	-2.81	***	-2.150	-3.56	***	-6.997	-3.27	***
σ	2.047	8.40	***	2.071	10.03	***	2.370	5.74	***	2.999	9.61	***
$\log MCAP$	-8.809	-5.11	***	0.658	0.46		-3.965	-2.33	**	-9.577	-2.83	***
Adjusted R^2	82.17%			74.40%			60.26%			80.84%		

Panel B: Regression Analysis with Fragmentation

	Pooled Sample			**Stocks L**			**Stocks M**			**Stocks S**		
	coeff.	t-stat.	sig.	coeff.	t-stat.	sig.	coeff.	t-stat.	sig.	coeff.	t-stat.	sig.
FI	-2.253	-2.27	**	-1.223	-1.30		-4.375	-5.00	***	-5.349	-2.42	**
V	0.030	0.31		-0.148	-2.44	**	-1.554	-3.47	***	-5.488	-2.79	***
σ	1.884	7.42	***	1.960	8.54	***	2.007	5.20	***	2.703	7.00	***
$\log MCAP$	-7.983	-4.20	***	1.302	0.97		-2.292	-1.82	*	-9.508	-2.67	***
Adjusted R^2	82.46%			75.02%			65.01%			81.18%		
Cross sections	29			10			10			9		
Observations	577			200			200			177		

***/**/* denotes significance at the 1%/5%/10% level

Table 5 – **Relative Effective Spread**

The table shows the results from a regression analysis with relative effective spread RS^{eff} (in bps) as dependent variable. Independent variables include monthly averages of daily turnover V (in 1,000 CHF), the standard deviation of daily log returns σ (in %) and the logarithm of daily market capitalization $\log MCAP$. Panel B also includes the fragmentation index FI, measured as reciprocal of a Herfindahl index based on the market share of the four trading venues Swiss exchange, Chi-X, BATS Europe and Turquoise, as independent variable. The regression model includes company specific fixed effects, which are omitted for brevity. Results are presented for the full sample and for three subsamples of stocks, where Newey-West standard errors are used to test for significance.

Panel A: Regression Analysis without Fragmentation

	Pooled Sample			**Stocks L**			**Stocks M**			**Stocks S**		
	coeff.	t-stat.	sig.	coeff.	t-stat.	sig.	coeff.	t-stat.	sig.	coeff.	t-stat.	sig.
V	0.003	0.06		-0.064	-2.13	**	-0.874	-3.89	***	-2.684	-2.85	***
σ	0.889	8.99	***	0.871	10.30	***	1.029	6.41	***	1.324	11.70	***
$\log MCAP$	-3.553	-4.87	***	0.628	0.84		-1.201	-2.07	**	-4.394	-2.96	***
Adjusted R^2	81.14%			64.88%			64.56%			83.24%		

Panel B: Regression Analysis with Fragmentation

	Pooled Sample			**Stocks L**			**Stocks M**			**Stocks S**		
	coeff.	t-stat.	sig.	coeff.	t-stat.	sig.	coeff.	t-stat.	sig.	coeff.	t-stat.	sig.
FI	-0.726	-1.63		-0.341	-0.72		-1.632	-5.16	***	-2.548	-2.92	***
V	0.023	0.50		-0.058	-1.96	*	-0.652	-4.01	***	-1.965	-2.40	**
σ	0.836	8.14	***	0.840	8.14	***	0.894	5.94	***	1.183	8.51	***
$\log MCAP$	-3.287	-4.01	***	0.808	1.19		-0.577	-1.32		-4.361	-2.79	***
Adjusted R^2	81.31%			65.11%			69.11%			83.67%		
Cross sections	29			10			10			9		
Observations	577			200			200			177		

***/**/* denotes significance at the 1%/5%/10% level

Table 6 – **Dollar Depth**

The table shows the results from a regression analysis with logarithm of dollar depth $\log D\$$ as dependent variable. The independent variables are the monthly averages of daily turnover V (in 1,000 CHF), the standard deviation of daily log returns σ (in %) and the logarithm of daily market capitalization $\log MCAP$. Panel B also includes the fragmentation index FI, measured as reciprocal of a Herfindahl index based on the market share of the four trading venues Swiss exchange, Chi-X, BATS Europe and Turquoise, as independent variable. The regression model includes company specific fixed effects, which are omitted for brevity. Results are presented for the full sample and for three subsamples of stocks, where Newey-West standard errors are used to test for significance.

Panel A: Regression Analysis without Fragmentation

	Pooled Sample			**Stocks L**			**Stocks M**			**Stocks S**		
	coeff.	t-stat.	sig.	coeff.	t-stat.	sig.	coeff.	t-stat.	sig.	coeff.	t-stat.	sig.
V	0.051	2.55	**	0.027	1.65		-0.032	-0.49		0.995	4.48	***
σ	-0.127	-5.71	***	0.004	0.09		-0.117	-2.78	***	-0.178	-6.92	***
$\log MCAP$	0.710	4.08	***	1.688	4.51	***	0.816	4.00	***	0.043	0.16	
Adjusted R^2	85.40%			78.10%			53.18%			72.11%		

Panel B: Regression Analysis with Fragmentation

	Pooled Sample			**Stocks L**			**Stocks M**			**Stocks S**		
	coeff.	t-stat.	sig.	coeff.	t-stat.	sig.	coeff.	t-stat.	sig.	coeff.	t-stat.	sig.
FI	0.679	6.71	***	0.628	3.16	***	0.801	6.91	***	0.677	3.56	***
V	0.027	1.37		0.016	0.93		-0.141	-2.48	**	0.624	4.53	***
σ	-0.069	-3.57	***	0.061	1.41		-0.050	-1.27		-0.130	-5.70	***
$\log MCAP$	0.579	4.89	***	1.357	3.95	***	0.510	2.39	**	0.309	2.33	**
Adjusted R^2	88.53%			81.61%			67.29%			76.06%		
Cross sections	29			10			10			9		
Observations	578			200			200			178		

***/**/* denotes significance at the 1%/5%/10% level

for increasing fragmentation. This is evidence for a positive effect of fragmentation on market quality. The adjusted R^2s for all subsamples are higher for the second regression model which includes fragmentation as independent variable.

Table 5 presents the results for the relative effective spread. They are similar to the results for the relative spread. The coefficient for $\log MCAP$ in both regression models is significantly negative for the pooled sample. The positive sign for Stocks L is not significant. σ has a positive and highly significant coefficient in both regression models for the pooled sample and all subsamples and the coefficients for V are significantly negative for the subsamples and insignificant for the pooled sample. The lower panel of Table 5 presents results for the second regression model where fragmentation is included as independent variable. The coefficient of FI is negative for the pooled sample and all the subsamples and significant for the subsamples Stocks M and Stocks S. The adjusted R^2s for the second regression model are higher than for the first regression model for the pooled sample and all subsamples.

Table 6 presents regression results for dollar depth. The coefficient of the variable $\log MCAP$ is significantly positive for the pooled sample, Stocks L and Stocks M in the first regression model and for the pooled sample and all the subsamples in the second regression model. This indicates that depth increases with market capitalization. σ has a significantly negative coefficient for the pooled sample, Stocks M (first regression model) and Stocks S (both regression models). The sign of the coefficient for Stocks L is positive but not significant. The coefficient of V is significantly positive for the pooled sample which indicates that higher trading activity is positively related to a deeper order book. Results for the subsamples are not clear as the coefficient is positive for Stocks L and Stocks S but negative for Stocks M, although not significant. The lower panel of Table 6 presents again regression results which include FI as regressor. The coefficient of FI is positive and highly significant at the 1% level for the pooled sample and all the subsamples which indicates that the dollar depth increases with increasing fragmentation for all subsamples. Adjusted R^2s are also higher for the second regression model than for the first one.

So far the regression analysis of the liquidity measures provides strong evidence for increasing market quality in terms of lower spreads and deeper order books related to the fragmentation of trading volume. Furthermore, the inclusion of the fragmentation index yields higher R^2s for all three liquidity measures and all subsamples.

5. Analysis of Trade-Throughs

A trade-through is defined as an order, executed at a price that is worse than the best quoted price, i.e., the stock could have been bought (sold) on another trading venue at a lower (higher) price. In the United States trade-throughs are prohibited for certain financial instruments and trading venues, i.e., best execution is understood as a best price policy. MiFID on the other hand does not regard price as the only dimension of best execution. Other dimensions include execution speed or the probability of execution. Foucault and Menkveld (2008) discuss explanations for trade-throughs like a trade-off between finding the best execution price and monitoring costs for different trading venues or the trade-off between execution price and execution speed. We compare for every one-second interval s the price with the best bid and ask price (BBO) over all trading venues. BBO corresponds to an artificial consolidated tape for the respective stocks. In calculating the BBO prices we follow Hasbrouck (2010) by letting a price on a certain trading venue be valid until it is replaced and by keeping the order of quote changes according to the timestamp (in milliseconds). As we use previous-tick interpolation to allocate trades within the one-second interval, we compare the price of interval s to the best bid and ask prices of interval $s-1$ and s, which ensures that we really capture the trade-throughs. A trade is flagged as trade-through, if either

$$p_s > \max(p_{s-1}^A, p_s^A),$$

or

$$p_s < \min(p_{s-1}^B, p_s^B),$$

where p_s denotes the volume weighted average price of interval s, p_{s-1}^B and p_{s-1}^A denote the best bid and best ask prices among all trading venues of interval $s-1$ and p_s^B and p_s^A of interval s, respectively. Table 7 shows the fraction of trade-throughs in terms of trading volume and the number of trades for the four trading venues.

The average fraction of trade-throughs in terms of trading volume is 10.35%

Table 7 – **Trade-Throughs**

The table shows the fraction of trade-throughs across subsamples and trading venues, where a trade-through is defined as an order executed at a price that is worse than the best quoted price. Panel A shows the analysis for the average daily trading volume (turnover in 1,000 CHF) and Panel B for the average daily number of trades.

Panel A: Average daily trading volume (in 1,000)

	SWX			BS		
	Volume	Trade-Throughs	Fraction	Volume	Trade-Throughs	Fraction
Pooled Sample	2,325,382	236,814	10.35%	85,733	2,502	6.66%
Stocks L	1,846,410	190,416	10.53%	73,229	2,106	6.69%
Stocks M	346,535	35,584	10.30%	10,344	335	6.05%
Stocks S	132,437	10,813	7.78%	2,160	61	4.26%
	CHI			TQ		
	Volume	Trade-Throughs	Fraction	Volume	Trade-Throughs	Fraction
Pooled Sample	348,358	16,711	5.56%	140,633	7,500	5.11%
Stocks L	290,671	13,584	5.61%	119,710	6,488	5.10%
Stocks M	46,948	2,684	5.51%	17,308	835	5.01%
Stocks S	10,739	443	3.86%	3,616	177	4.18%

Panel B: Average daily number of trades

	SWX			BS		
	Trades	Trade-Throughs	Fraction	Trades	Trade-Throughs	Fraction
Pooled Sample	90,431	8,708	10.00%	6,395	195	6.86%
Stocks L	57,170	5,968	10.81%	4,632	143	6.98%
Stocks M	21,515	1,963	9.53%	1,376	41	5.66%
Stocks S	11,746	777	6.79%	387	10	3.87%
	CHI			TQ		
	Trades	Trade-Throughs	Fraction	Trades	Trade-Throughs	Fraction
Pooled Sample	21,690	1,007	5.24%	8,682	411	4.79%
Stocks L	15,692	718	5.37%	6,317	306	4.77%
Stocks M	4,659	240	4.90%	1,826	81	4.68%
Stocks S	1,340	49	3.43%	539	24	4.02%

for the pooled sample on the Swiss exchange and 5.11% − 6.66% for the MTFs. Subsample Stocks S exhibits in general a lower fraction of trade-throughs than the subsamples with larger capitalized stocks. The lower fragmentation of these stocks makes trade-throughs less probable. The fraction of trade-throughs in terms of the number of trades shows similar results with a fraction of trade-throughs of 10.00% for the pooled sample on the Swiss exchange and fractions of 4.79% − 6.86% on the MTFs and with shares of trade-throughs that are higher for the subsamples with higher capitalized stocks. Our estimated ranges for trade-throughs are similar to Storkenmaier and Wagener (2011), but significantly lower than in Foucault and Menkveld (2008). Storkenmaier and Wagener (2011) ascribe this fact to smart order routing which is of higher relevance today, than in the period analyzed by Foucault and Menkveld (2008) (May 2004).

We follow the approach of Storkenmaier and Wagener (2011) and analyze determinants of trade-throughs by means of bivariate logistic regression models. Measures from the consolidation of all trading venues enter as independent variables in the first model. Formally, the model is defined as

$$\begin{aligned} I_{i,s} =& \beta_1 RS^{BBO}_{i,s} + \beta_2 \log D\$^{cum}_{i,s} + \beta_3 \#Shares_{i,s} + \beta_4 \log V^{15}_{i,s} + \\ & \beta_5 (\sigma^{real}_{i,s})^2 + \beta_6 Dir_{i,s} + \beta_7 MI_{i,s} + \beta_8 D_i + \beta_9 D_s + \epsilon_{i,s}, \end{aligned}$$

where $I_{i,s}$ denotes the logarithm of the odds ratio of a trade-through. The relative spread of trade s in stock i measured with the best prevailing bid and offer prices among all trading venues is denoted by $RS^{BBO}_{i,s}$. The logarithm of the cumulative dollar depth over all trading venues is denoted by $logD\$_{i,s}^{cum}$ and the number of shares traded by $\#Shares_{i,s}$. $\log V_{i,s}^{15}$ is the logarithm of the cumulative trading volume over all trading venues within 15 minutes before a trade occurs and $(\sigma_{i,s}^{real})^2$ equals the squared 15 minute log-return of the mid price over all trading venues. The trade direction $Dir_{i,s}$ is set to 1 for a buyer initiated trade and -1 for a seller initiated trade, where we determine trade direction by the algorithm proposed by Lee and Ready (1991). The market impact of trade s in stock i, denoted by $MI_{i,s}$, is calculated as

$$MI_{i,s} = \frac{\left|p_{i,s+5}^{M} - p_{i,s}^{M}\right|}{p_{i,s}^{M}},$$

i.e., as the absolute value of the percentage change of the mid price 5 minutes after the trade. MI is used to measure the price impact of a trade, see for instance Bessembinder and Kaufman (1997), Hasbrouck (2007) or Storkenmaier and Wagener (2011). Company specific fixed effects (D_i) and day specific fixed effects (D_s) are included in the regression model. We define the second regression model as

$$\begin{aligned} I_{i,s} =& \beta_1 RS_{i,s}^{Market} + \beta_2 \log D\$_{i,s}^{Market} + \beta_3 \#Shares_{i,s} + \beta_4 \log V_{i,s}^{15} + \\ & \beta_5 (\sigma_{i,s}^{real})^2 + \beta_6 Dir_{i,s} + \beta_7 MI_{i,s} + \beta_8 D_i + \beta_9 D_s + \epsilon_{i,s}, \end{aligned}$$

i.e., the measures from the consolidation of all trading venues are replaced by the respective measures of the venue where the trade is executed, i.e., $RS_{i,s}^{BBO}$ is replaced by the relative spread of the respective market, denoted by $RS_{i,s}^{Market}$ and $logD\$_{i,s}^{cum}$ is replaced by the dollar depth of the respective market, denoted by $logD\$_{i,s}^{Market}$.

Panel A of Table 8 presents the results for the first regression model without market impact as independent variable. The coefficient of the relative spread is significantly negative for the pooled sample and for two subsamples because the probability of a trade-through increases when the spread between the best bid and ask price among all trading venues decreases. Cumulative dollar depth has a highly significant negative coefficient for the pooled sample and all subsamples.

The coefficients of $\#Shares$, V^{15}, σ^{real} and Dir are all positive and highly significant for the pooled sample. This means that the probability of a trade-through is generally higher for larger trades (higher $\#Shares$), for trades during more active market phases (higher V^{15} and σ^{real}) and for buyer initiated trades (Dir). Significance is confirmed by most of the subsamples. The inclusion of market impact as independent variable leads to the results in Panel B of Table 8. The coefficients of all independent variables and their significance are similar to the results in Panel A for all subsamples. The coefficient of MI is positive and highly significant for the pooled sample and for all subsamples, indicating that the probability of a trade-through is higher for trades which exhibit a higher market impact. Therefore, trade-throughs are mainly caused by informed traders, where execution speed has a higher priority than getting the best price over all trading venues. The robustness of this result is confirmed by the subsamples.

Panel C of Table 8 presents results for the second regression model, where we replace the consolidated liquidity measures by market specific liquidity mea-

Table 8 – **Determinants of Trade-Throughs**

The table shows results from a bivariate logistic regression, where the dependent variable equals the logarithm of the odds ratio of a trade-through. The independent variables include the relative spread according to the best prevailing bid and ask price among all trading venues (RS^{BBO}) or according to the prevailing best bid and ask price of the respective trading venue, where the trade occurs (RS^{Market}). $\log D^{cum}\$$ denotes the logarithm of the cumulative dollar depth over all trading venues and $\log D^{Market}\$$ of the respective trading venue, where the trade occurs. The number of shares traded is denoted by $\#Shares$. The logarithm of the cumulative trading volume over all trading venues within 15 minutes before the trade occurs is denoted by $logV_{15}$. σ^2_{real} is the squared 15 minute log-return of the mid price over all trading venues. Dir equals 1 for a trade initiated from a buyer and -1 for a trade initiated by a seller according to Lee and Ready (1991). Panel B and Panel D additionally include the market impact denoted by MI as independent variable, which is the percentage change of the mid price 5 minutes after the trade. The coefficients of the dummy variables are omitted for brevity.

Panel A: All venues without Market Impact

	Pooled Sample			**Stocks L**			**Stocks M**			**Stocks S**		
	coeff.	t-stat.	sig.	coeff.	t-stat.	sig.	coeff.	t-stat.	sig.	coeff.	t-stat.	sig.
RS^{BBO}	-0.069	-3.46	***	-0.037	-1.74	*	-0.030	-2.73	***	0.027	4.95	***
$\log D\$^{cum}$	-0.812	-37.91	***	-0.967	-29.34	***	-0.870	-21.93	***	-0.855	-13.55	***
$\#Shares$	0.001	51.47	***	0.001	37.57	***	0.002	35.00	***	0.001	27.06	***
$logV_{15}$	0.505	30.18	***	0.698	26.57	***	0.412	13.29	***	0.274	6.70	***
σ^2_{real}	0.108	3.86	***	0.069	1.56		0.368	4.60	***	0.123	2.66	***
Dir	0.495	21.11	***	0.812	19.98	***	0.400	10.36	***	0.255	5.43	***
Cross sections	29			10			10			9		
Observations	62964			28967			21255			12742		

Table continued on next page

Table 8 – continued from previous page

Panel B: All venues with Market Impact

	Pooled Sample			Stocks L			Stocks M			Stocks S		
	coeff.	t-stat.	sig.	coeff.	t-stat.	sig.	coeff.	t-stat.	sig.	coeff.	t-stat.	sig.
RS^{BBO}	-0.071	-3.55	***	-0.039	-1.81	*	-0.031	-2.81	***	0.027	4.91	***
$\log D\$^{cum}$	-0.804	-37.44	***	-0.957	-28.98	***	-0.859	-21.62	***	-0.841	-13.34	***
$\#Shares$	0.001	51.43	***	0.001	37.53	***	0.002	34.83	***	0.001	26.93	***
$logV_{15}$	0.501	29.89	***	0.692	26.32	***	0.407	13.12	***	0.273	6.66	***
σ^2_{real}	0.110	3.91	***	0.071	1.62		0.372	4.63	***	0.123	2.64	***
Dir	0.506	21.40	***	0.822	20.10	***	0.408	10.48	***	0.270	5.69	***
MI	0.005	9.35	***	0.006	5.17	***	0.004	7.30	***	0.032	4.88	***
Cross sections	29			10			10			9		
Observations	62916			28956			21237			12723		

Panel C: Respective market without Market Impact

	Pooled Sample			Stocks L			Stocks M			Stocks S		
	coeff.	t-stat.	sig.	coeff.	t-stat.	sig.	coeff.	t-stat.	sig.	coeff.	t-stat.	sig.
RS^{Market}	0.045	6.38	***	0.036	5.17	***	0.015	5.72	***	0.001	1.92	*
$\log D\$^{Market}$	-0.394	-34.45	***	-0.520	-31.04	***	-0.331	-15.86	***	-0.411	-14.14	***
$\#Shares$	0.001	55.01	***	0.001	41.82	***	0.003	35.03	***	0.002	28.95	***
$logV_{15}$	0.159	12.79	***	0.276	14.99	***	0.089	4.03	***	0.150	4.37	***
σ^2_{real}	0.164	5.58	***	0.077	1.76	*	0.391	5.03	***	0.139	2.83	***
Dir	0.496	21.44	***	0.815	20.14	***	0.405	10.68	***	0.261	5.60	***
Cross sections	29			10			10			9		
Observations	62951			28967			21249			12735		

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Table 8 – continued from previous page

Panel D: Respective market with Market Impact

	Pooled Sample			**Stocks L**			**Stocks M**			**Stocks S**		
	coeff.	t-stat.	sig.	coeff.	t-stat.	sig.	coeff.	t-stat.	sig.	coeff.	t-stat.	sig.
RS^{Market}	0.046	6.41	***	0.036	5.17	***	0.015	5.78	***	0.002	2.15	**
$\log D\$^{Market}$	-0.421	-36.26	***	-0.539	-31.86	***	-0.380	-17.74	***	-0.445	-15.00	***
$\#Shares$	0.001	55.66	***	0.001	42.18	***	0.003	35.61	***	0.002	28.96	***
$logV_{15}$	0.172	13.77	***	0.287	15.56	***	0.110	4.92	***	0.166	4.74	***
σ^2_{real}	0.160	5.43	***	0.075	1.72	*	0.378	4.85	***	0.138	2.81	***
Dir	0.507	21.71	***	0.828	20.26	***	0.415	10.80	***	0.275	5.84	***
MI	0.009	13.57	***	0.013	9.05	***	0.007	9.64	***	0.049	6.67	***
Cross sections	29			10			10			9		
Observations	62916			28956			21237			12723		

***/**/* denotes significance at the 1%/5%/10% level

sures. The relative spread of the respective market where the trade-through occurs is negatively related to the probability of a trade-through. Intuitively, the probability of another trading venue offering a better price increases when the relative spread of a specific market increases. The coefficient of dollar depth on the respective market is also negative and significant, which means that cumulative dollar depth for the whole market and dollar depth on individual markets are negatively related to the probability of a trade-through. The coefficients of $\#Shares$, V^{15}, σ^{real} and Dir are again all positive and highly significant for the pooled sample and robust for the subsamples. The inclusion of the independent variable MI, in Panel D of Table 8, leads to similar results for the coefficients and the significance levels. The coefficient of MI is positive and highly significant at the 1% level for the pooled sample and all subsamples, indicating again a higher probability of a trade-through for trades with higher market impact. The robustness of this relation is again confirmed by the subsamples.

The results of the two regression models provide strong evidence for the hypothesis that trade-throughs are caused by informed market participants for whom execution speed is more relevant than execution price. Therefore, the lack of a rule prohibiting trade-throughs does not necessarily deteriorate market quality. Table 9 presents liquidity measures for trades that are executed at a price within the best prevailing bid and ask price among all trading venues (BBO) and for trade-throughs (tt). Panel A shows the results for all trades, i.e., for the consolidation of trades that were executed on the Swiss exchange or on a MTF. Panel B and Panel C show only results for trades executed on the Swiss exchange and on the MTFs, respectively. We calculate the mean and the median of the relative effective spread RS^{eff} and the market impact MI for ordinary trades and trade-throughs and compare the mean of the two groups of trades with a standard t-test and the medians with a non-parametric Wilcoxon Rank Sum test.

Trade-throughs should exhibit a higher relative effective spread as the execution price of a trade-through lies per definition outside the best prevailing bid and ask prices among all trading venues, whereas the execution price of an ordinary trade lies within. Indeed, Panel A shows that the overall mean relative effective spread is 3 bps higher for trade-throughs than for ordinary trades for the pooled sample and the overall median relative effective spread is 2 bps higher for trade-throughs than for ordinary trades for the pooled sample. These differences are significant at the 1% significance level which confirms that our algorithm identifies trade-throughs.

The results are robust for the subsamples, where the difference is lower for the subsample with higher capitalized stocks. The overall mean market impact is 5 bps higher for trade-throughs than for ordinary trades for the pooled sample and the overall median market impact is 3 bps higher for trade-throughs than for ordinary trades for the pooled sample. These differences are highly significant at the 1% significance level and are confirmed by all three subsamples, where again the differences are larger for subsample Stocks S, i.e., for the stocks with lower market capitalization. This evidence supports the hypothesis that trade-throughs do not express a lack of market quality, but instead are caused by a time over price priority of informed traders.

Table 9 – **Liquidity Measures for Trade-Throughs**

The table shows the relative effective spread RS^{eff} and the market impact MI calculated for trades that are executed within the best prevailing bid and ask price among all trading venues (denoted by BBO) and for trades where the best available price is traded through (denoted by tt). The results for all trades are presented in Panel A, whereas Panel B and Panel C present only results for trades on the Swiss exchange and on the MTFs, respectively. Significance of the difference of the means is tested with a standard t-test and significance of the difference of the medians with a non-parametric Wilcoxon rank sum test.

Panel A: Consolidated Trades

T-test

	Pooled Sample			**Stocks L**			**Stocks M**			**Stocks S**		
	BBO	tt	p-value	BBO	tt	p-value	BBO	tt	p-value	BBO	tt	p-value
RS^{eff}	0.03%	0.06%	***	0.02%	0.03%	***	0.03%	0.06%	***	0.04%	0.10%	***
MI	0.04%	0.09%	***	0.03%	0.06%	***	0.03%	0.09%	***	0.05%	0.14%	***

Wilcoxon Rank Sum Test

	Pooled Sample			**Stocks L**			**Stocks M**			**Stocks S**		
	BBO	tt	p-value	BBO	tt	p-value	BBO	tt	p-value	BBO	tt	p-value
RS^{eff}	0.01%	0.03%	***	0.00%	0.02%	***	0.01%	0.03%	***	0.02%	0.05%	***
MI	0.02%	0.05%	***	0.02%	0.04%	***	0.02%	0.05%	***	0.03%	0.08%	***

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Table 9 – continued from previous page

Panel B: SWX Trades

T-test

	Pooled Sample			**Stocks L**			**Stocks M**			**Stocks S**		
	BBO	tt	p-value	BBO	tt	p-value	BBO	tt	p-value	BBO	tt	p-value
RS^{eff}	0.01%	0.04%	***	0.00%	0.01%	***	0.01%	0.03%	***	0.01%	0.07%	***
MI	0.02%	0.05%	***	0.02%	0.03%	***	0.02%	0.05%	***	0.03%	0.09%	***

Wilcoxon Rank Sum Test

	Pooled Sample			**Stocks L**			**Stocks M**			**Stocks S**		
	BBO	tt	p-value	BBO	tt	p-value	BBO	tt	p-value	BBO	tt	p-value
RS^{eff}	0.00%	0.02%	***	0.00%	0.01%	***	0.00%	0.02%	***	0.01%	0.04%	***
MI	0.02%	0.03%	***	0.01%	0.02%	***	0.02%	0.03%	***	0.02%	0.05%	***

Panel C: MTF Trades

T-test

	Pooled Sample			**Stocks L**			**Stocks M**			**Stocks S**		
	BBO	tt	p-value	BBO	tt	p-value	BBO	tt	p-value	BBO	tt	p-value
RS^{eff}	0.03%	0.06%	***	0.02%	0.04%	***	0.03%	0.07%	***	0.05%	0.11%	***
MI	0.05%	0.11%	***	0.03%	0.08%	***	0.04%	0.11%	***	0.07%	0.17%	***

Wilcoxon Rank Sum Test

	Pooled Sample			**Stocks L**			**Stocks M**			**Stocks S**		
	BBO	tt	p-value	BBO	tt	p-value	BBO	tt	p-value	BBO	tt	p-value
RS^{eff}	0.01%	0.03%	***	0.01%	0.02%	***	0.01%	0.04%	***	0.02%	0.07%	***
MI	0.02%	0.06%	***	0.02%	0.05%	***	0.02%	0.07%	***	0.03%	0.10%	***

***/**/* denotes significance at the 1%/5%/10% level

As Barclay et al. (2003) show, ECNs attract more informed traders. Therefore, we analyze the relative effective spread and the market impact for trade-throughs and ordinary trades for the Swiss exchange and the MTFs separately. If MTFs tend to attract more informed traders and if trade-throughs express a time over price priority of informed traders, we would expect the difference in market impact for trade-throughs against ordinary trades to be higher on MTFs. Indeed, as Panel B and Panel C of Table 9 reveal, the mean market impact for trades on the Swiss exchange is 3 bps higher for trade-throughs than for ordinary trades, but 6 bps higher for trades executed on a MTF. The differences are highly significant. The same holds true for the median market impact which is about 1 bp higher for trade-throughs than for ordinary trades on the Swiss exchange and around 4 bps for trades on MTFs, where all differences are highly significant.

The analysis of the subsamples shows that these differences are stable for different levels of market capitalization. The mean market impact of a trade-through against an ordinary trade is around 4 bps higher if the trade was executed on a MTF against the Swiss exchange for all three subsamples. The same holds true for the differences in the median market impacts for Stocks M and Stocks S, which are around 4bps higher for trades executed on MTFs against trades executed on the Swiss exchange and about 2 bps higher for Stocks L. Overall, the analysis of trades executed on the Swiss exchange and on the MTFs provides evidence for the hypothesis that trade-throughs originate in the time over price priority of informed traders and are, therefore, not necessarily a negative by-product of the fragmentation of liquidity.

6. Conclusion

The implementation of MiFID served as a catalyst for the emergence of MTFs in Europe which lead to an increased fragmentation of liquidity in European equity trading. In contrast to the regulation in the United States MiFID does not include a rule for the prohibition of trade-throughs. It is not clear, if this prevents a virtual consolidation of the markets in Europe, as it is discussed for instance in O'Hara and Ye (2011) for the United States.

We investigate a sample of 29 stocks from companies that are listed on the Swiss exchange and the three MTFs Chi-X, BATS Europe and Turquoise. Several liquidity measures, such as spread and depth measures, are calculated for a long-term sample that covers 20 months. By means of multivariate regression models we determine the long-run effect of fragmentation on market quality and find no evidence for a deterioration of market quality in the aftermath of the implementation of MiFID. In contrast, we find significantly positive effects of the fragmentation on spread and depth measures, which are confirmed by the analysis of different subsamples.

Additionally, we examine determinants of trade-throughs by bivariate logistic regression models and find evidence that trade-throughs are caused by informed traders who consider execution speed as more important than the best available price. The analysis of the market impact, which is larger after a trade-through than after an ordinary trade confirms this result. This difference is even more pronounced for trades that are executed on a MTF. Since previous studies found MTFs to attract more informed traders, this confirms that informed traders cause the trade-throughs. Our study provides evidence that the fragmentation of trading in European equities markets did not deteriorate market quality, although a rule prohibiting trade-throughs is not included in MiFID.

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Part III.
Where does Information Processing in a Fragmented Market Take Place? - Evidence from the Swiss Stock Market after MiFID

Abstract

The implementation of MiFID lead to fragmentation of trading in European equities. We analyze information processing for a sample of Swiss stocks on the Swiss exchange and on Chi-X, the largest multilateral trading facility. According to Hasbrouck information shares, the determination of a leading market is not conclusively possible. By applying an autoregressive conditional intensity (ACI) model that explicitly takes the asynchronous structure of order arrivals into account, we find strong evidence that Chi-X is the leading market in terms of intensity based information shares.

1. Introduction

The implementation of the Markets in Financial Instruments Directive (MiFID) in Europe in 2007 lead to the emergence of several multilateral trading facilities (MTFs). These alternative trading platforms compete with traditional exchanges for trading volume, i.e., for market share. Therefore, the European trading landscape today is similar to the situation in the United States, where the emergence of alternative trading platforms and fragmentation of trading took place over the last decade.

Several studies analyze the effects of fragmentation and come to different conclusions. The two main strands of argumentation in the literature are positive network externalities through consolidated liquidity versus fragmentation leading to higher competition among trading venues. O'Hara and Ye (2011) bring these two strands together with the proposition of a "single virtual market", where different trading venues represent different connections to a virtually consolidated market. However, this argumentation may not be valid for the situation in Europe. Important differences are that under MiFID neither a consolidated tape, nor a trade-through[1] prohibition exist. O'Hara and Ye (2011) argue that this lack of a consolidated tape and a trade-through prohibition could prevent the emergence of a "single virtual market" in Eu-

[1] A trade-through is a trade executed at a price, which is higher (lower) than the best available ask (bid) price among all trading venues. Possible explanations for the occurrence of trade-throughs are investors with a speed over price priority (see Kohler and von Wyss (2012)). Another possible explanation for trade-throughs according to Foucault and Menkveld (2008) is that trade-throughs are caused by investors not using smart order routers to route their trades to the trading venue with the best available price.

rope. An increasing number of studies therefore analyze the implementation of MiFID with a main focus on market quality, e.g., event studies by Foucault and Menkveld (2008), Hengelbrock and Theissen (2009) and Chlistalla and Lutat (2011) and regression analyses by Gresse (2010) and Degryse et al. (2011).

A special aspect in the analysis of fragmented markets is information processing, i.e., how information is incorporated into prices and which trading venue is leading. Two studies that analyze this question in the fragmented European equity market after the implementation of MiFID are Storkenmaier et al. (2012) and Riordan et al. (2011). Storkenmaier et al. (2012) analyze stocks that are traded on the LSE and Chi-X and find for the quote based price discovery higher information shares for Chi-X (58.19%), than for LSE (41.81%), although LSE provides more liquidity. Furthermore, they analyze market reactions of LSE and Chi-X to Thomson Reuters newswire messages and find a shift of information processing towards LSE on days where positive news outweigh. Riordan et al. (2011) also report quote based information shares for Chi-X, which are higher (56.77%) than for LSE (27.63%) or other MTFs, like BATS (11.66%) or Turquoise (3.94%).

Both studies apply Hasbrouck information shares (see Hasbrouck (1995)) for the attribution of information shares to the different trading venues. Although information shares according to Hasbrouck is a widely used concept, there are two main drawbacks. First, information shares require equidistant data and, therefore, do not take the asynchronous nature of intraday data (e.g., order arrivals or order book changes) into account. Second, if there is contemporaneous correlation in the price innovations across different trading venues, the Hasbrouck information share of a market is not uniquely determined, but given in terms of upper and lower bounds. Typically, these bounds cover a wide range, which makes the clear identification of a leading venue impossible. In this article we also apply Hasbrouck information shares, but extend the analysis by using an autoregressive conditional intensity (ACI) model according to Russell (1999) as a new measure. We are, therefore, able to contribute to the literature on information processing after MiFID since, to our best knowledge, this is the first study analyzing directly the intensity processes in the fragmented European markets after MiFID. We analyze information processing on the Swiss exchange and on Chi-X, which is the largest MTF competing with the Swiss exchange[2]. Our contributions are twofold. First, we use a multivariate intensity model which allows us to investigate the research questions in a framework, which lies beyond the scope of previous studies. By modelling the conditional intensities of the order arrivals on the Swiss exchange and Chi-X, we can exploit the duration structure of the effective order arrivals without the loss of information that results from time aggregation. Therefore, we can incorporate typical characteristics of asynchronous order arrivals and we get unbiased point estimates for the information shares of the two trading venues, rather than just upper and lower bounds. Second, we use a new data set, since, to our best knowledge, this is the first study analyzing

[2] According to Fidessa (fragmentation.fidessa.com) the Swiss exchange accounted for 50.48% of total trading volume in 2010, whereas Chi-X accounted for 12.07%. The MTFs Bats Europe, Turquoise and Nasdaq Europe accounted together for 7.37% in the same period.

information processing for Swiss stocks in the fragmented trading landscape after the implementation of MiFID.

Our results suggest that there are significant cross effects between the intensity processes of the trading venues. Furthermore, we provide evidence that Chi-X is the leading market in terms of intensity based information processing irrespective of the market capitalization of the stocks.

The remainder of this paper is organized as follows. The next section presents the two methods that are used to analyze information processing for stocks that are traded on multiple trading venues. In Section 2.1 we present information shares according to Hasbrouck (1995). In Section 2.2 we introduce the ACI model according to Russell (1999). Section 3 exhibits the data and estimation details for the two models. Empirical results are presented and discussed in Section 4. Finally, Section 5 concludes.

2. Measuring Information Processing

2.1. The Hasbrouck Information Shares

Information shares according to Hasbrouck (1995) (HIS) are a widely used measure[3] for the attribution of the share of price discovery to different trading venues. HIS show for different trading venues "who moves first" (see Hasbrouck (1995)). The basic idea is that prices[4] of the same financial instrument on different trading venues are closely-linked and can, therefore, be assumed

[3] See Bingcheng and Zivot (2010).

[4] The model is applicable to different types of prices, such as bid or ask prices, midquote prices or transaction prices.

to be cointegrated, i.e., a linear combination of the prices is stationary. We follow in the presentation of the model Hasbrouck (1995), Hasbrouck (2002) and Storkenmaier and Wagener (2011).

If p_t^{SWX} denotes the price on the Swiss exchange in period t and p_t^{CHI} denotes the price on Chi-X in the same period for the same financial instrument, then the price vector $p_t = (p_t^{\text{SWX}}, p_t^{\text{CHI}})'$ is driven by a common random walk component r_t, i.e.,

$$p_t = r_t + (\epsilon_t^{\text{SWX}}, \epsilon_t^{\text{CHI}})', \tag{2.1}$$

with

$$r_t = r_{t-1} + u_t, \tag{2.2}$$

where u_t are uncorrelated with $\mathbf{E}(u_t) = 0$ and $\mathbf{E}(u_t^2) = \sigma_u^2$. Based on the cointegration relation there exists a representation as bivariate vector error correction model (VECM) for the price vector p_t, which is given as follows

$$\Delta p_t = p_t - p_{t-1} = \alpha\beta' p_{t-1} + \Gamma_1 \Delta p_{t-1} + \Gamma_2 \Delta p_{t-2} + \cdots + \Gamma_T \Delta p_{t-T} + \epsilon_t. \tag{2.3}$$

The vector β defines the cointegration relation between the two prices and vector α shows how fast prices adjust to deviations from the underlying equilibrium price process. $\Gamma_i, i \in \{1, \ldots, T\}$ denote parameter matrices associated with the i^{th} lag of Δp_t. ϵ_t has zero mean and variance Σ_ϵ. With $Var(\epsilon_t) = \Sigma_\epsilon$, the variance of the random walk component of the price process p_t can be expressed as

$$\sigma_u^2 = \xi \Sigma_\epsilon \xi', \tag{2.4}$$

where ξ denotes the row vector[5] of long run impacts of innovations ϵ_t. As can be seen from Equation 2.4, both markets contribute to the variance of the random walk component. If Σ_ϵ is diagonal, i.e., the innovations ϵ_t exhibit no correlation, the contribution of each market's innovation to the random walk innovation is given by

$$S^k = \frac{\xi_k^2 \Sigma_{\epsilon_{kk}}}{\xi \Sigma_\epsilon \xi'}, \tag{2.5}$$

where S^k is defined as market k's information share, ξ_k denotes the k^{th} element of ξ and $\Sigma_{\epsilon_{kk}}$ denotes the k^{th} diagonal element of Σ_ϵ.

As price innovations across markets are typically not uncorrelated, two suggestions are given in Hasbrouck (1995) to minimize correlation and limit the information shares. First, shorter time intervals for price aggregation are proposed. As markets will typically react sequentially to events with one market adjusting faster than the other, price aggregation over long time spans will make the adjustment of the leading market and the reaction of the other market look contemporaneous. This effect can be minimized by shortening the observation intervals. In this paper we follow Hasbrouck (2003) and use one-second sampling intervals. Second, upper and lower bounds for the information shares can be calculated as

$$HIS^k = \frac{([\xi C]_k)^2}{\xi \Sigma_\epsilon \xi'}, \tag{2.6}$$

[5] ξ can be calculated as common row vector of $\beta_\perp \left[\alpha'_\perp \left(I_n - \sum_{i=1}^{T} \Gamma_i\right) \beta_\perp\right]^{-1} \alpha'_\perp$, where $\perp$ denotes the orthogonal complement and I_n denotes a n-dimensional identity matrix. See Johansen (1991), Engle and Granger (1987) and Kehrle and Peter (2011).

where C denotes the lower triangular matrix resulting from the Cholesky factorization of Σ_ϵ. The lower triangular structure of C leads to a hierarchy among the trading venues which results in maximized information shares for the first and minimized information shares for the second trading venue. Hasbrouck (1995) suggests to permute Σ_ϵ and ξ to get an upper (lower) bound for HIS^k, denoted by HIS_{up} (HIS_{low}), by setting market k as first (last) market. The mean of the upper and lower bound for HIS is then taken as the measure for the information share of market k, i.e.,

$$HIS^k = \frac{HIS^k_{up} + HIS^k_{low}}{2}. \tag{2.7}$$

There are two major drawbacks of HIS. As discussed above and stated in Hasbrouck (1995), upper and lower bounds for HIS have to be calculated because of contemporaneous correlation among price innovations. These bounds can diverge considerably[6], which makes the determination of a leading market in terms of information processing very difficult[7]. Moreover, the upper and lower bound do not present statistical confidence bounds and taking the mean does not result in a statistically meaningful point estimate.

The second and major drawback is that the calculation of HIS requires equidistant data, i.e., for the calculation of information shares a time aggregation is necessary. This time aggregation over equidistant intervals (typically over a one-second or one-minute interval) leads to a loss of information as

[6] See Booth et al. (2002), Hupperets and Menkveld (2002) and Kehrle and Peter (2011), who show not only the estimates of HIS, but also estimates of HIS_{up} and HIS_{low}.

[7] See Grammig and Peter (2011).

the irregular structure of the arrival of price changes cannot be taken into account. This problem is even more pronounced with the recent emergence of high frequency trading, which lead to a considerable increase[8] in electronic messages (for instance quote changes).

2.2. The Autoregressive Conditional Intensity Model

Russell (1999) proposes a model which focuses on the intensities of the price processes of different trading venues. Several authors applied this model on different research questions. Kehrle and Peter (2011) analyze the price discovery of US-listed Canadian stocks with the home market. Bauwens and Hautsch (2006) present a generalization of Russell's model with a latent factor that jointly influences the individual intensities. Hall and Hautsch (2006, 2007) analyze the intensity processes of order arrivals and order book changes for a sample of five stocks on the Australian stock exchange. All authors emphasize the flexibility of the approach, as it does not require equidistant data, but can be applied on asynchronous data.

Let K denote the number of different trading venues and $N^k(t)$ be the counting process associated with the k^{th} point process, i.e., $N^k(t)$ equals the number of k-type events up to time t. We define the point process $\{t_i^k\}_{i=1}^{n^k}$ as the sequence of changes of the quoted prices on the Swiss exchange (k = SWX) and on Chi-X (k = CHI). The pooled point process $\{t_i\}_{i=1}^{n}$ is simply the combination of the individual k-type point processes and is associated with the counting process $N(t)$. The arrival times of the pooled process and

[8] See Hendershott et al. (2011).

therefore of the individual k-type events are assumed to be distinct, i.e., $0 < t_1 < t_2 < \cdots < t_n$. $\mathfrak{F}_t$ denotes the filtration of the pooled process and $\lambda^k(t, \mathfrak{F}_t)$ the intensity of the k-type point process, i.e.,

$$\lambda^k(t, \mathfrak{F}_t) = \lim_{\Delta \to 0} \frac{\mathbb{P}\left\{N^k(t+\Delta) - N^k(t) > 0, N^{k'}(t+\Delta) - N^{k'}(t) = 0 \mid \mathfrak{F}_t\right\}}{\Delta}, \tag{2.8}$$

where $k \neq k'$. This means $\lambda^{\text{SWX}}(t, \mathfrak{F}_t)$ and $\lambda^{\text{CHI}}(t, \mathfrak{F}_t)$ are the instantaneous probabilities at time t of a change in the order book of the Swiss exchange and Chi-X, respectively.

In the extended ACI model of Russell (1999) the conditional intensity function of process k can be written as

$$\lambda^k(t, \mathfrak{F}_t) = \lambda_0^k \psi_t^k \phi_t^k, \tag{2.9}$$

where λ_0^k denotes a baseline intensity function, ψ_t^k equals the actual intensity process and ϕ_t^k captures seasonal effects. The pooled bivariate intensity process $\psi_t = (\psi_t^{\text{SWX}}, \psi_t^{\text{CHI}})'$ itself is parametrized as

$$\psi_t = \exp\left(\tilde{\psi}_{N(t)} + z'_{N(t)}\mu^k\right), \tag{2.10}$$

where $\tilde{\psi}_i$ is a vector autoregressive moving average (VARMA) process, $z = (z_1, z_2, \ldots, z_n)'$ denotes a vector of explanatory variables for market characteristics and μ^k is the coefficient vector of z. Hall and Hautsch (2006, 2007) show the importance of the incorporation of the current state of the market in the modeling of the intensity processes. Moreover, they show a significant improvement of the goodness of fit of the model. The VARMA process $\tilde{\psi}_i$ is given by

$$\tilde{\psi}_i = \sum_{k \in \{\text{SWX},\text{CHI}\}} (a^k \epsilon_{i-1}^k + B\tilde{\psi}_{i-1}) y_{i-1}^k, \qquad (2.11)$$

where a^k are (2×1) coefficient vectors and B denotes a (2×2) coefficient matrix. y_i^k are variables, indicating where the i^{th} event occurred, i.e., $y_i^{\text{SWX}} = 1$ if the i^{th} event occurred on the Swiss exchange and zero otherwise and $y_i^{\text{CHI}} = 1$ if the i^{th} event occurred on Chi-X and zero otherwise. Due to the autoregressive structure of the intensity process the model is called an autoregressive conditional intensity (ACI) model. In the terminology of Russell (1999), Equation 2.11 determines an ACI(1,1) model as it contains one autoregressive and one moving average component. Extending the model to a higher order ACI(p,q) model is done straightforward by including the respective number of lags of ϵ_i^k and $\tilde{\psi}_i$. The vectors $a^k = (a_1^k, a_2^k)', k \in \{\text{SWX}, \text{CHI}\}$ measure the impact of innovations of the point process of market k, ϵ_i^k, on the intensity process of the Swiss exchange by a_1^k and on the intensity process of Chi-X by a_2^k. It is therefore clear that the k-type intensity process ψ_t^k and the k-type conditional intensity function $\lambda^k(t, \mathfrak{F}_t)$ are not only influenced by k-type innovations, but also by innovations of the other point process, i.e., by quote changes of the other trading venue.

The off-diagonal elements of the autoregressive coefficient matrix B are set to zero following Russell (1999), Bauwens and Hautsch (2006) and Kehrle and

Peter (2011), which makes

$$B = \begin{pmatrix} b^{\text{SWX}} & 0 \\ 0 & b^{\text{CHI}} \end{pmatrix}$$

a diagonal matrix and Equation 2.11 a diagonal ACI(1,1) model[9]. This restriction implies that only the vectors a^k cause cross effects of an innovation on the intensity of the other point process.

The innovation in Equation 2.11 is based on the compensator, which is given by

$$\Lambda^k(t_{i-1}^k, t_i^k) = \int_{t_{i-1}^k}^{t_i^k} \lambda^k(u, \mathfrak{F}_u)du = \sum_j \int_{\tilde{t}_j}^{\tilde{t}_{j+1}} \lambda^k(u, \mathfrak{F}_u)du, \tag{2.12}$$

i.e., by the piecewise integration of the conditional k-type intensity $\lambda^k(t, \mathfrak{F}_t)$ over all inter-event intervals $[\tilde{t}_j, \tilde{t}_{j+1}]$ with $t_{i-1}^k < \tilde{t}_j < \tilde{t}_{j+1} \leq t_i^k$. As in Equation 2.11 innovations of both point processes have an impact on the conditional k-type intensity $\lambda^k(t, \mathfrak{F}_t)$, the k-type compensator $\Lambda^k(t_{i-1}^k, t_i^k)$ also depends on the cross effects of the other point process.

According to the multivariate random time change theorem[10] the processes $\Lambda^k(0, t_i^k), i = 1, \ldots, n^k, k \in \{\text{SWX}, \text{CHI}\}$ are Poisson processes with unit intensity. As increments of a Poisson process, $\Lambda^k(t_{i-1}^k, t_i^k)$ are iid standard exponentially distributed. We follow Russell (1999) and define the innovations

[9] See the terminology used by Russell (1999). In the remainder of this paper the term ACI model is used as synonym for a diagonal ACI(1,1) model.

[10] See also Bowsher (2007), Bauwens and Hautsch (2006) and Brown and Nair (1988).

in the VARMA process by

$$\epsilon_i^k = 1 - \Lambda^k(t_{i-1}^k, t_i^k). \tag{2.13}$$

The compensator $\Lambda^k(t_{i-1}^k, t_i^k)$ expresses the expected number of events within the interval $[t_{i-1}^k, t_i^k]$. Hence, a positive innovation term ϵ_i^k implies that the arrival rate was underestimated and a negative innovation term implies an overestimation of the arrival rate. As can be seen from Equation 2.11, an underestimation of the arrival rate ($\epsilon_i^k > 0$) leads to an increase in the intensity process ψ_t^k and the k-type conditional intensity function $\lambda^k(t, \mathfrak{F}_t)$ and an overestimation ($\epsilon_i^k < 0$) to a decrease. As stated in Bauwens and Hautsch (2006), according to the definition the innovation term depends only on the time between past events and on past intensities, which eases computation.

The log-likelihood function of the ACI model can be expressed in terms of the intensity function solely (see Bauwens and Hautsch (2006) and Karr (1991)). For the bivariate point process the log-likelihood function $\log L(\theta)$ is given by

$$\log L(\theta) = \sum_{k \in \{\text{SWX,CHI}\}} \sum_{i=1}^{n} \left(-\Lambda^k(t_{i-1}, t_i) + y_i^k \log \lambda^k(t_i, \mathfrak{F}_{t_i}) \right), \tag{2.14}$$

where θ denotes the vector of the model parameters. We follow Kehrle and Peter (2011) and apply robust estimators[11] for the standard errors of the components of θ. These robust estimators for the standard errors are consistent

[11] The robust variance-covariance matrix of the components of θ is calculated following Kehrle and Peter (2011) as $\Sigma_{\tilde{\theta}} = H^{-1}\mathbf{E}\left[\left(\frac{\delta \log L}{\delta\theta}\right)\left(\frac{\delta \log L}{\delta\theta}\right)\right]H^{-1}$, where H denotes the estimator of the Hessian matrix.

with quasi-maximum likelihood estimators for θ in case of a misspecification of the model.

The empirical distribution of the residuals of the estimated innovations $\tilde{\epsilon}_i^k = \Lambda^k(t_{i-1}^k, t_i^k)$ is then compared to the theoretical distribution iid Exp(1) for testing the model specification. We follow previous studies (e.g., Russell (1999), Bauwens and Hautsch (2006), Kehrle and Peter (2011) and Hall and Hautsch (2006, 2007)) and report summary statistics of the series of estimated residuals and a Ljung-Box Test with 20 lags (LB_{20}) for autocorrelation. Additionally, a test for overdispersion is applied, which follows Engle and Russell (1998), who propose the test statistic $OD^k = \sqrt{\frac{n^k}{8(\sigma_{\tilde{\epsilon}}^k)^2}}$, where n^k denotes the number of k-type residuals and $(\sigma_{\tilde{\epsilon}}^k)^2$ the empirical variance. OD^k is asymptotically standard normally distributed under the null hypothesis ($\tilde{\epsilon}_i^k \sim \text{Exp}(1)$).

As we are particularly interested in the cross effects of the intensity processes of the two markets, we follow Kehrle and Peter (2011) and calculate intensity based information shares for the two trading venues ($IIS^k, k \in \{\text{SWX, CHI}\}$) based on the respective impulse response functions. We define the intensity based information share as

$$IIS^{\text{SWX}} = \frac{\frac{\left|a_2^{\text{SWX}}\right|}{\left|a_2^{\text{CHI}}\right|}}{\frac{\left|a_1^{\text{CHI}}\right|}{\left|a_1^{\text{SWX}}\right|} + \frac{\left|a_2^{\text{SWX}}\right|}{\left|a_2^{\text{CHI}}\right|}} \qquad \text{and} \qquad IIS^{\text{CHI}} = \frac{\frac{\left|a_1^{\text{CHI}}\right|}{\left|a_1^{\text{SWX}}\right|}}{\frac{\left|a_1^{\text{CHI}}\right|}{\left|a_1^{\text{SWX}}\right|} + \frac{\left|a_2^{\text{SWX}}\right|}{\left|a_2^{\text{CHI}}\right|}}, \tag{2.15}$$

which is the ratio of the absolute impact[12] of a cross effect (e.g., $\left|a_2^{\text{SWX}}\right|$

[12]In contrast to the definition of IIS in Kehrle and Peter (2011), we take the absolute values of a^k for the calculation of IIS, as we do not discard negative values for the

denotes the absolute impact of an innovation shock at Swiss exchange on Chi-X's intensity) relative to the absolute impact of a shock in the same market (e.g., $\left|a_2^{\mathrm{CHI}}\right|$ denotes the absolute impact of an innovation shock at Chi-X on Chi-X's intensity). This measure is then standardized by $\frac{\left|a_1^{\mathrm{CHI}}\right|}{\left|a_1^{\mathrm{SWX}}\right|} + \frac{\left|a_2^{\mathrm{SWX}}\right|}{\left|a_2^{\mathrm{CHI}}\right|}$ to lie between zero and one. Higher values of IIS^{SWX} indicate that shocks in the point process of the Swiss exchange have a relatively larger absolute effect on Chi-X's intensity process and vice versa. The delta method is applied to calculate standard errors of IIS^{SWX} and IIS^{CHI}.

3. Data and Estimation

We use quote data from the Thomson Reuters Tick History database for 28 Swiss stocks which are traded on the Swiss exchange and on Chi-X. Table 1 gives the company names and ticker symbols of the stocks in our sample.
The quote data contains changes in the limit order book of the Swiss exchange and Chi-X on the best bid and ask level and is timestamped to the millisecond.

3.1. Estimation of Hasbrouck Information Shares

For the calculation of Hasbrouck Information Shares we build one-second snapshots[13] of historical order books containing the best bid and ask price.

coefficients a^k, i.e., we allow a shock in one market to have a negative impact on the intensity of another market.

[13] One second sampling intervals are also used by Hasbrouck (2003), Hendershott and Jones (2005) and Tse et al. (2006).

Table 1 – Final Sample

The table shows the 28 companies contained in our final sample. The sample consists of Swiss stocks that are listed on the Swiss exchange and on Chi-X. MCAP denotes the average daily market capitalization in billion Swiss francs over the first quarter 2010. The full sample is divided into two subsamples, denoted by Stocks L and Stocks S.

Company	Symbol	MCAP	Subsample
Nestle	NESN	188.2	Stocks L
Novartis	NOVN	150.9	
Roche	ROG	125.5	
Credit Suisse	CSGN	59.8	
UBS	UBSN	56.0	
ABB	ABBN	48.9	
Zurich Financial Services	ZURN	36.6	
Syngenta	SYNN	26.9	
Holcim	HOLN	24.9	
Swisscom	SCMN	19.9	
Richemont	CFR	19.7	
Swiss Re	RUKN	18.1	
Synthes	SYST	15.8	
Kuehne + Nagel	KNIN	12.3	
SGS	SGSN	11.0	Stocks S
Adecco	ADEN	10.9	
Swatch Group I	UHR	9.3	
Givaudan	GIVN	7.7	
Geberit	GEBN	7.7	
Actelion	ATLN	6.7	
Baloise	BALN	4.6	
Swiss Life Holding	SLHN	4.4	
Lonza	LONN	4.3	
Nobel Biocare	NOBN	3.8	
Logitech	LOGN	3.4	
Clariant	CLN	2.8	
Petroplus	PPHN	1.6	
OC Oerlikon	OERL	0.5	

Based on the series of midprices[14] the VECM model according to Equation 2.3 is estimated with $T = 300$ lags, i.e., with a memory of 5 minutes. As for every lag i a (2×2) matrix Γ_i has to be estimated, the model includes roughly $2 \times 2 \times 300 = 1,200$ coefficients. In order to reduce the complexity we follow Hasbrouck (2003) and use quadratic distributed lags over lags $1 - 10$, $11 - 20$ and $21 - 30$ and constant coefficients over lags $31 - 60$, $61 - 120$ and $121 - 300$. Upper (HIS_{up}) and lower (HIS_{low}) bounds for the information shares are calculated on a daily basis and HIS is set to the arithmetic mean of the bounds, i.e.,

$$HIS^k = \frac{HIS^k_{up} + HIS^k_{low}}{2}, k \in \{\text{SWX, CHI}\}. \tag{3.1}$$

3.2. Estimation of Intensity Based ACI Model

For the determination of the intensity processes we build point processes for the two trading venues based on the interarrival times between two consecutive quote changes, denoted by $\tau^k_i = t^k_i - t^k_{i-1}$, where $k = \text{SWX}$ denotes a quote change in the limit order book of the Swiss exchange and $k = \text{CHI}$ in the limit order book of Chi-X. The two series of individual interarrival times are then combined to the pooled series of interarrival times denoted by τ_i. Subsequently, overnight spells and quote changes before 9:30am (CET) and after 4:30pm (CET) are removed to eliminate any disturbances from opening and closing and, as the simultaneous arrival of two quote changes is not

[14] Erroneous quotes are filtered by applying a rule that discards all midprices, where the deviation between the prices exceeds 5%.

permitted in the model, quote changes with the same timestamp are skipped. Furthermore, we use price marks[15] for the thinning of the processes following Engle and Russell (1997), Bauwens and Hautsch (2006) and Kehrle and Peter (2011). First, we calculate the mean midquote change per day. Second, we retain quote changes of the individual series of interarrival times of the two venues where the absolute cumulative price change exceeds the threshold of 50 times the mean midquote change per day, which is consistent with previous studies[16]. With the thinned processes, we can disentangle information driven price changes from pure noise.

Following Kehrle and Peter (2011) we use polynomial and trigonometric time functions according to Eubank and Speckman (1990) for the adjustment of intraday patterns of the pooled process. The interarrival times of the pooled process (τ_i) are regressed on polynomial and trigonometric time functions according to the following regression equation

$$\tau_i = \beta_0 + \sum_{j=1}^{d} \beta_j^p t_i^j + \sum_{j=1}^{\delta} [\beta_j^c \cos(jt_i) + \beta_j^s \sin(jt_i)] + \epsilon_i. \tag{3.2}$$

We select the number of polynomial (d) and trigonometric (δ) regressors as the combination that minimizes the generalized cross-validation criteria GCV

15 Price marks are information that is observed simultaneously with the arrival of a price change, e.g., the change in the midquotes.

16 The chosen threshold leads to a median threshold of 0.06 Swiss Francs, which lies between the average thresholds used by Kehrle and Peter (2011) and Bauwens and Hautsch (2006). Hall and Hautsch (2006) use a thinning algorithm based on the order volume which skips 94.3% of all observations in their initial sample.

given by

$$GCV = \frac{nRSS}{(n - 2\delta - d - 1)^2}, \tag{3.3}$$

where RSS is the residual sum of squares, n the number of observations and GCV is evaluated for $d \in \{1, \ldots, 5\}$ and $\delta \in \{1, \ldots, 5\}$. Figure 1 shows a typical intraday pattern of interarrival times, which follows a ∩-shape, i.e., the time periods between two consecutive price changes are lower at the beginning and the end of the trading day and exhibit a maximum around noon.

Additionally any linear trend, which would indicate a general increase or decrease in interarrival times due to a generally decreasing or increasing market activity, is removed. The series of the adjusted pooled process of interarrival times is then calculated by the division of the interarrival times of the pooled process (τ_i) by the typical intraday pattern (ϕ_i), which results from Equation 3.2, i.e.,

$$\tilde{\tau}_i = \frac{\tau_i}{\phi_i}. \tag{3.4}$$

Based on the adjusted interarrival times $\tilde{\tau}_i$ the ACI(1,1) model in Equation 2.11 is estimated by the maximization of the log-likelihood function given by Equation 2.14 with the BHHH[17] algorithm and numerical derivatives[18].

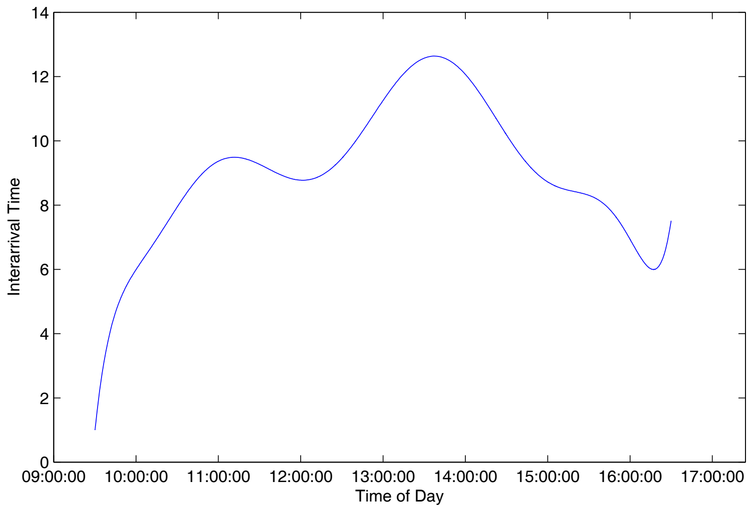
The baseline intensity function λ_0^k in Equation 2.9 is modeled in dependence of a baseline intensity specific to the trading venue and the backward recurrence time associated with the point process of the trading venue. In detail, we follow Bauwens and Hautsch (2006) and Hall and Hautsch (2007) and model

[17]See Berndt et al. (1974).

[18]See also Engle and Russell (1997) and Russell (1999)

Figure 1 – Typical Intraday Pattern of Interarrival Times

The figure shows the estimated diurnal pattern for interarrival times of the pooled process for a randomly chosen stock (BALN) between 9:30am (CET) and 4:30pm (CET). The time series of estimated interarrival times is normalized to 1 at 9:30am (CET). We estimate the diurnal pattern of interarrival times τ_i with a combination of polynomial and trigonometric time functions $\tau_i = \beta_0 + \sum_{j=1}^{d} \beta_j^p t_i^j + \sum_{j=1}^{\delta} [\beta_j^c \cos(jt_i) + \beta_j^s \sin(jt_i)] + \epsilon_i$, where the number of polynomial (d) and trigonometric (δ) regressors are selected as the combination that minimizes the generalized cross-validation criteria $GCV = \frac{nRSS}{(n-2\delta-d-1)^2}$. RSS denotes the residual sum of squares and n the number of observations. GCV is evaluated for $d \in \{1, \ldots, 5\}$ and $\delta \in \{1, \ldots, 5\}$.



λ_0^k as a Burr-type hazard function, i.e.,

$$\lambda_0^k(t) = \exp(\omega^k) \frac{U^k(t)^{\gamma_1^k - 1}}{1 + \gamma_2^k U^k(t)^{\gamma_1^k}}, \tag{3.5}$$

where $U^k(t)$ denotes the backward recurrence time at time t of the k^{th} point process, i.e., in Equation 3.5 $U^k(t)$ is given and ω^k, γ_1^k and γ_2^k have to be estimated. We restrict the baseline intensity function λ_0^k of process k to depend only on its own backward recurrence time[19]. Therefore, we can ensure that cross effects are captured by the vectors a^k solely.

For the incorporation of the current state of the market by vector z, the current liquidity, we follow Hall and Hautsch (2006) and include the relative spread of the respective market (RS^k), the logarithm of the cumulated volume of the bid and ask side of the respective market (BV^k, AV^k), the cumulated midquote price change (MQ_{15}^k) and the volatility (VOL_{15}^k) over the last 15 minutes, $k \in$ {SWX, CHI}. This choice of variables reflects the multi-dimensionality of liquidity[20].

[19] Bauwens and Hautsch (2006) propose a parameterization that includes also the backward recurrence time of the other $k-1$ processes. However, in the numerical estimation they restrict the Burr-type hazard functions to depend on the backward recurrence time of the own process solely.

[20] Liquidity is understood as multi-dimensional concept and, therefore, multiple measures are used for capturing different dimensions of liquidity. See Chordia et al. (2000) and Chordia et al. (2001).

4. Empirical Results

We present descriptive statistics for the series of adjusted order book changes for the Swiss exchange and Chi-X in Table 2.

The average number of midquote price changes Q per stock for the Pooled Sample during the sample period January 1 to March 31, 2010 is $1,542$ for the Swiss exchange and $1,379$ for Chi-X with mean price durations of 35 and 56 minutes, respectively. Bauwens and Hautsch (2006) report mean price durations in the range of $12-20$ minutes for their sample of five highly liquid NYSE stocks, which is comparable to our findings for the first quartile of subsample Stocks L where we find average price durations in the range of $13-29$ minutes. Overall, the number of midquote price changes is higher on the Swiss exchange and for the stocks in subsample Stocks L, where this difference is significant for the Swiss exchange.

4.1. Empirical Results from HIS

Table 3 shows the average daily HIS per stock for the Pooled Sample and for the subsamples Stocks L and Stocks S.

The mean information share of the Swiss exchange for the Pooled Sample equals 53.25%, which would indicate that the Swiss exchange has a higher information share than Chi-X. However, the median information share of the Swiss exchange is 48.16%, which is slightly below 50%. The problem of clearly identifying the leading venue in terms of the information share arises with the consideration of the upper and lower bounds of HIS. Figure 2 shows

Table 2 – **Descriptive Statistics**

The table shows descriptive statistics of the number of quote revisions Q and interarrival times τ in seconds for the thinned process of order arrivals for the Swiss exchange (SWX) and Chi-X (CHI). For the thinning process mean midquote changes per day are calculated and quote changes are retained where the absolute cumulative price change exceeds 50 times the mean midquote change per day. Panel A covers the Pooled Sample and Panel B and Panel C the subsamples Stocks L and Stocks S, respectively. The mean, median, first and third quartile are given over the sample period January 1 to March 31, 2010. Panel D presents the differences in the means and medians between subsamples Stocks L and Stocks S, together with p-values for significant differences between the means and medians, respectively.

Panel A: Pooled Sample				
	Q^{SWX}	Q^{CHI}	τ^{SWX}	τ^{CHI}
Mean	1,542	1,379	2,081	3,337
Median	1,223	1,179	1,687	2,942
Q75	1,925	1,587	2,827	4,423
Q25	830	574	1,016	2,010
Panel B: Stocks L				
	Q^{SWX}	Q^{CHI}	τ^{SWX}	τ^{CHI}
Mean	1,997	1,785	2,017	3,405
Median	1,864	1,511	1,054	2,603
Q75	2,924	2,007	3,272	4,931
Q25	982	561	805	1,741
Panel C: Stocks S				
	Q^{SWX}	Q^{CHI}	τ^{SWX}	τ^{CHI}
Mean	1,087	973	2,145	3,270
Median	1,049	1,139	2,068	2,942
Q75	1,308	1,249	2,819	4,353
Q25	823	587	1,491	2,474
Panel D: Diff. Stocks L - Stocks S				
	Q^{SWX}	Q^{CHI}	τ^{SWX}	τ^{CHI}
Mean	910	812	-128	135
p-value	0.02	0.11	0.82	0.84
Median	815	372	-1,014	-339
p-value	0.06	0.18	0.12	0.60

Table 3 – Hasbrouck Information Shares

The table shows the average daily mean, median, first and third quartile of the Hasbrouck information shares (HIS) together with the upper and lower bounds (HIS_{up} and HIS_{low}) for the Swiss exchange (SWX) and for Chi-X (CHI) over the sample period January 1 to March 31, 2010. Panel A covers the Pooled Sample and Panel B and Panel C the subsamples Stocks L and Stocks S, respectively. The information shares are calculated as daily means of the upper and lower bound.

Panel A: Pooled Sample						
	HIS^{SWX}	HIS^{CHI}	HIS_{up}^{SWX}	HIS_{up}^{CHI}	HIS_{low}^{SWX}	HIS_{low}^{CHI}
Mean	53.25%	46.75%	66.04%	59.53%	40.47%	33.96%
Median	48.16%	51.84%	63.94%	67.55%	32.45%	36.06%
Q75	67.62%	63.50%	77.49%	81.23%	58.80%	45.87%
Q25	36.50%	32.38%	54.13%	41.20%	18.77%	22.51%
Panel B: Stocks L						
	HIS^{SWX}	HIS^{CHI}	HIS_{up}^{SWX}	HIS_{up}^{CHI}	HIS_{low}^{SWX}	HIS_{low}^{CHI}
Mean	44.12%	55.88%	60.33%	72.08%	27.92%	39.67%
Median	41.34%	58.66%	58.87%	75.92%	24.08%	41.13%
Q75	51.65%	67.23%	68.21%	85.44%	35.74%	49.10%
Q25	32.77%	48.35%	50.90%	64.26%	14.56%	31.79%
Panel C: Stocks S						
	HIS^{SWX}	HIS^{CHI}	HIS_{up}^{SWX}	HIS_{up}^{CHI}	HIS_{low}^{SWX}	HIS_{low}^{CHI}
Mean	62.38%	37.62%	71.74%	46.98%	53.02%	28.26%
Median	60.92%	39.08%	71.96%	49.07%	50.93%	28.04%
Q75	81.86%	55.73%	86.46%	71.10%	78.18%	41.15%
Q25	44.27%	18.14%	58.85%	21.82%	28.90%	13.54%

the estimated HIS together with the upper and lower bounds HIS_{up} and HIS_{low}, respectively.

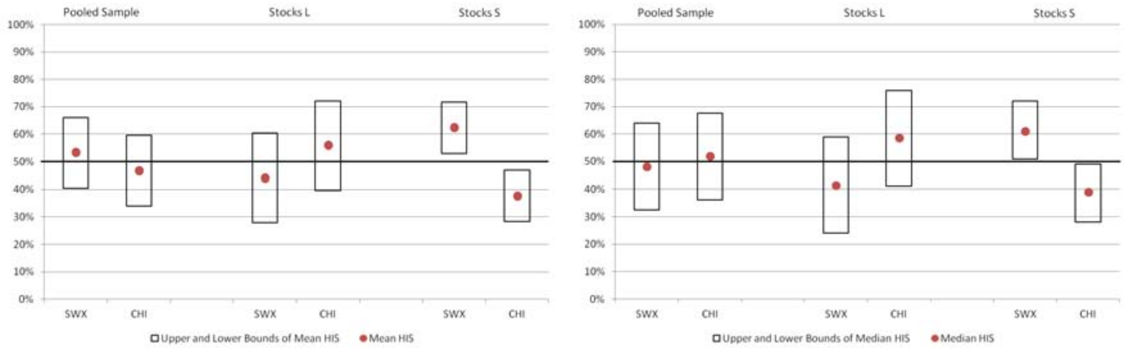
As already stated, HIS^{SWX} and HIS^{CHI} are calculated as mean of the respective upper and lower bounds HIS_{up} and HIS_{low}. This means that for the Pooled Sample the information share of the Swiss exchange lies between 40.47% (HIS_{low}^{SWX}) and 66.04% (HIS_{up}^{SWX}) and the information share of Chi-X between 33.96% (HIS_{low}^{CHI}) and 59.53% (HIS_{up}^{CHI}), respectively. No trading venue has an information share which lies clearly above or below 50%, which makes the identification of the leading trading venue for the Pooled Sample impossible.

The same holds true for subsample Stocks L. Although the mean and the median information share of Chi-X are larger than 50%, according to the upper and lower bounds, a clear identification of the leading venue is not possible as the mean of HIS_{low}^{SWX} lies with 27.92% below 50% and the mean of HIS_{up}^{SWX} with 60.33% above 50%.

For subsample S the mean and median information share is higher for the Swiss exchange than for Chi-X with a mean information share of 62.38% and a median information share of 60.92% for the Swiss exchange. For this subsample the range between upper and lower bounds of HIS are disjoint, which allows the identification of the Swiss exchange as trading venue "who moves first".

Overall, the question which trading venue is actually leading in terms of Hasbrouck information shares cannot be answered conclusively. For the large caps some evidence is found that Chi-X is the leading market, which would confirm

Figure 2 – **Upper and Lower Bounds of Hasbrouck Information Shares**
The figure shows estimated mean (left panel) and median (right panel) Hasbrouck information shares (HIS) for the Pooled Sample and the two subsamples Stocks L and Stocks S over the sample period January 1 to March 31, 2010. The range between the upper and lower bounds for the Swiss exchange (SWX) and Chi-X (CHI) is presented as rectangle. The arithmetic mean of the respective upper and lower bound is denoted by a red dot.



the results of Storkenmaier and Wagener (2011) and Riordan et al. (2011). However, upper and lower bounds of HIS do not allow a clear identification of the leading venue. For the small caps evidence suggests that the Swiss exchange is the leading market.

4.2. Empirical Results from ACI Model

We present the estimation results for the bivariate ACI(1,1) model outlined in Section 2.2 in Table 4. Estimation is done by the maximization[21] of the log-likelihood function given in Equation 2.14.

As can be seen from Table 4, the estimates of a_1^{SWX} and a_2^{CHI} are positive for all stocks, which indicates positive autocorrelation in the intensities of the two trading venues. The coefficients are significantly positive for 64% and 71% of the stocks in the Pooled Sample, for 71% and 79% of the stocks in subsample Stocks L and for 57% and 64% of the stocks in subsample Stocks S. An underestimation of the intensity on the Swiss exchange ($\epsilon_i^{\text{SWX}} > 0$), therefore, leads to an increase in the Swiss exchange's intensity and the same holds true for Chi-X where an underestimation of the intensity ($\epsilon_i^{\text{CHI}} > 0$) also increases Chi-X's intensity.

The coefficients a_2^{SWX} and a_1^{CHI} are positive and significant for the majority of the stocks of the Pooled Sample, which means that there are significant spillover effects between the different intensity processes[22]. Furthermore, the

[21] Maximization is performed without constraints for ω^k and a^k. b^k are constraint to lie between 0 and 1 to ensure stationarity of the VARMA process defined in Equation 2.11. γ^k are constraint to be positive.

[22] Similar findings are documented in other studies using the ACI model, e.g., Kehrle and Peter (2011), Bauwens and Hautsch (2006) and Hall and Hautsch (2006, 2007).

Table 4 – **ACI Parameters**

The table shows the mean, median, first and third quartile of the estimated parameters from an autoregressive conditional intensity (ACI) model for the intensity of order book changes of the Swiss exchange (SWX) and Chi-X (CHI). Panel A covers stocks from the Pooled Sample and Panel B and Panel C stocks from the subsamples Stocks L and Stocks S, respectively. The numbers of positive (negative) estimates are given by pos. (neg.) and the fraction of significant estimates based on a significance level of 95% by sig. The intensity process of trading venue k is parametrized as $\lambda^k(t, \mathfrak{F}_t) = \lambda_0^k \psi_t^k \phi_t^k$, where $k \in \{\text{SWX}, \text{CHI}\}$. λ_0^k is a baseline intensity function, ψ_t^k is the actual intensity process and ϕ_t^k captures the diurnal seasonality. The intensity process ψ_t is parametrized as $\psi_t = \exp(\tilde{\psi}_{N(t)} + z'_{N(t)}\mu^k)$, where z is a vector of state variables and $\tilde{\psi}_i$ is modelled as the VARMA process $\tilde{\psi}_i = \sum_{k\in\{\text{SWX,CHI}\}}(a^k \epsilon_{i-1}^k + B\tilde{\psi}_{i-1})y_{i-1}^k$. y_{i-1}^k is an indicator variable, denoting where the last order book change occurred. Vector $a^k = (a_1^k, a_2^k)'$ and matrix B denote the parameters of the VARMA process, where B is modeled as a diagonal matrix whose diagonal elements are given by b^{SWX} and b^{CHI}. γ and ω denote the parameters of the Burr-type hazard functions given by $\lambda_0^k(t) = \exp(\omega^k)(U^k(t)^{\gamma_1^k - 1})/(1 + \gamma_2^k U^k(t)^{\gamma_1^k})$. $U^k(t)$ is the backward recurrence time at time t of the k^{th} point process. Robust standard errors are calculated based on the outer products of gradients and the inverse of the estimated Hessian matrix.

Panel A: Pooled Sample

	a_1^{SWX}	a_2^{SWX}	a_1^{CHI}	a_2^{CHI}	b^{SWX}	b^{CHI}	γ_1^{SWX}	γ_1^{CHI}	γ_2^{SWX}	γ_2^{CHI}	ω^{SWX}	ω^{CHI}
Mean	0.306	0.116	0.008	0.606	0.906	0.890	1.420	1.243	4.963	1.024	0.565	6.020
Median	0.304	0.089	0.111	0.434	0.960	0.972	1.477	1.211	3.098	0.469	1.186	5.732
Q75	0.405	0.165	0.154	0.496	0.982	0.988	1.590	1.325	5.353	1.613	2.120	7.754
Q25	0.214	0.037	0.065	0.357	0.907	0.907	1.223	1.121	1.594	0.010	-0.421	4.217
pos.	28	25	26	28	28	28	28	28	28	28	20	27
neg.	0	3	2	0	0	0	0	0	0	0	8	1
sig.	64.3%	53.6%	53.6%	71.4%	71.4%	67.9%	78.6%	75.0%	92.9%	67.9%	92.9%	96.4%

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Table 4 – continued from previous page

Panel B: Stocks L

	a_1^{SWX}	a_2^{SWX}	a_1^{CHI}	a_2^{CHI}	b^{SWX}	b^{CHI}	γ_1^{SWX}	γ_1^{CHI}	γ_2^{SWX}	γ_2^{CHI}	ω^{SWX}	ω^{CHI}
Mean	0.299	0.127	-0.082	0.577	0.874	0.935	1.518	1.316	7.023	1.078	0.021	5.959
Median	0.303	0.113	0.124	0.445	0.968	0.971	1.531	1.325	4.425	0.394	0.720	5.975
Q75	0.409	0.178	0.179	0.495	0.989	0.985	1.692	1.465	9.064	1.620	1.941	7.908
Q25	0.209	0.034	0.075	0.393	0.894	0.949	1.286	1.167	1.758	0.050	-1.182	3.931
pos.	14	12	12	14	13	14	14	14	14	14	9	13
neg.	0	2	2	0	0	0	0	0	0	0	5	1
sig.	71.4%	64.3%	71.4%	78.6%	71.4%	78.6%	78.6%	78.6%	100.0%	78.6%	92.9%	100.0%

Panel C: Stocks S

	a_1^{SWX}	a_2^{SWX}	a_1^{CHI}	a_2^{CHI}	b^{SWX}	b^{CHI}	γ_1^{SWX}	γ_1^{CHI}	γ_2^{SWX}	γ_2^{CHI}	ω^{SWX}	ω^{CHI}
Mean	0.313	0.104	0.098	0.636	0.938	0.844	1.323	1.171	2.902	0.970	1.109	6.080
Median	0.309	0.064	0.098	0.384	0.951	0.978	1.402	1.202	2.645	0.657	1.728	5.557
Q75	0.399	0.112	0.142	0.698	0.981	0.990	1.517	1.220	3.740	1.607	2.498	7.503
Q25	0.219	0.039	0.056	0.196	0.909	0.875	1.081	1.104	1.250	0.008	0.286	4.502
pos.	14	13	14	14	14	14	14	14	14	14	11	14
neg.	0	1	0	0	0	0	0	0	0	0	3	0
sig.	57.1%	42.9%	35.7%	64.3%	71.4%	57.1%	78.6%	71.4%	85.7%	57.1%	92.9%	92.9%

first quartiles for both coefficients are positive. For subsample Stocks L the mean of the coefficient a_1^{CHI} is negative, however, the median and the first quartile are positive. The coefficients are significant for 64% and 71% of the stocks in subsample Stocks L. This means that an intensity shock on one trading venue directly affects the intensity on the other trading venue, e.g., an underestimation of the Swiss exchange's intensity ($\epsilon_i^{\text{SWX}} > 0$) leads to an increase of the intensity on Chi-X and vice versa.

The persistence of innovation shocks, measured with the coefficients b^{SWX} and b^{CHI}, is high and significant for the majority of the stocks. The mean of b^{SWX}, which measures the persistence of the innovation shocks on the Swiss exchange, equals 0.906 for the Pooled Sample and 0.874 and 0.938 for Stocks L and Stocks S, respectively. For Chi-X the persistence is similar with $b^{\text{CHI}} = 0.890$ for the Pooled Sample and 0.935 and 0.844 for Stocks L and Stocks S, respectively. These findings are consistent with findings from other authors (e.g., Engle and Russell (1998) and Kehrle and Peter (2011)).

The baseline intensity functions show rather stable coefficients γ_1^k for the dependence on the backward recurrence time $U^k(t)$, where both Burr-type hazard functions have a positive but decreasing slope, which means that the baseline intensity $\lambda_0^k(t)$ increases between two k-type events. These findings correspond to the results of Bauwens and Hautsch (2006), who estimate very similar coefficients γ_1^k for their backward recurrence functions. There is considerable cross-sectional variability in the coefficients ω^k, which reflects the variability in the baseline intensity functions among the different stocks.

We control for the current state of the market and liquidity situation by incorporating the five state variables relative spread (RS^k), logarithm of the cumulated volume of the bid and ask side (BV^k, AV^k), cumulated midquote price change (MQ^k_{15}) and volatility (VOL^k_{15}) over the last 15 minutes, $k \in \{\text{SWX, CHI}\}$. Table 5 shows the estimation results for the impact of the state variables.

The coefficient of RS^k is negative and significant for the majority of the stocks for the Swiss exchange and positive for Chi-X. The coefficients for the cumulated depth on the other hand are positive and predominantly significant for the Swiss exchange and negative for Chi-X. This means high liquidity on the Swiss exchange increases intensity on the Swiss exchange while high liquidity on Chi-X is associated with decreasing intensity on Chi-X.

The coefficients of the cumulated midquote price change over the last 15 minutes are negative for both trading venues and both subsamples meaning that a recent increase of the midquote price is associated with a decrease of the intensity of the two trading venues. This corresponds to the findings of Hall and Hautsch (2006) who find evidence that positive midquote returns decrease the overall intensity on the ask side of the order book, while increasing the intensity of the bid side of the order book. A possible reason for the net negative effect of recent midquote returns and intensity, which is also discussed in Hall and Hautsch (2006), could be liquidity considerations which lead to an overall decrease of the intensity of order book changes after a significant midquote change.

Findings for recent volatility are mixed for the different stocks and subsamples. Overall, the median coefficients for VOL_{15} tend to be positive (e.g., for

Table 5 – **State Variables**
The table shows the mean, median, first and third quartile of the coefficients of the state variables from the bivariate autoregressive conditional intensity (ACI) model for the intensity of order book changes of the Swiss exchange (SWX) and Chi-X (CHI) over the sample period January 1 to March 31, 2010. Panel A covers stocks from the Pooled Sample and Panel B and Panel C stocks from the subsamples Stocks L and Stocks S, respectively. The fraction of significant estimates based on a significance level of 95% is denoted by sig. The intensity process of trading venue k is parametrized as $\lambda^k(t, \mathfrak{F}_t) = \lambda_0^k \psi_t^k \phi_t^k$, $k \in \{\text{SWX}, \text{CHI}\}$. λ_0^k is a baseline intensity function, ψ_t^k is the actual intensity process and ϕ_t^k captures the diurnal seasonality. The intensity process $\psi_t = (\psi_t^{\text{SWX}}, \psi_t^{\text{CHI}})'$ is parametrized as $\psi_t = \exp(\tilde{\psi}_{N(t)} + z'_{N(t)}\mu^k)$, where $\tilde{\psi}_i$ is modelled as the vector autoregressive moving average process $\tilde{\psi}_i = \sum_{k \in \{\text{SWX},\text{CHI}\}} (a^k \epsilon_{i-1}^k + B\tilde{\psi}_{i-1}) y_{i-1}^k$. y_{i-1}^k is an indicator variable, denoting where the last order book change occurred. The vector of state variables z includes the variables relative spread (RS^k), the logarithm of the cumulated volume of the bid and ask side (BV^k, AV^k), the cumulated midquote price change (MQ_{15}^k) and the volatility (VOL_{15}^k) over the last 15 minutes, $k \in \{\text{SWX, CHI}\}$. All variables are calculated immediately before the order book change occurs. Robust standard errors are calculated based on the outer products of gradients and the inverse of the estimated Hessian matrix.

Panel A: Pooled Sample

	RS^{SWX}	BV^{SWX}	AV^{SWX}	MQ_{15}^{SWX}	VOL_{15}^{SWX}	RS^{CHI}	BV^{CHI}	AV^{CHI}	MQ_{15}^{CHI}	VOL_{15}^{CHI}
Mean	-236.753	0.133	0.121	-0.143	8.041	149.955	-0.210	-0.202	-0.169	-46.292
Median	-250.711	0.123	0.129	-0.077	-2.113	56.706	-0.196	-0.192	-0.080	1.430
Q75	-118.227	0.165	0.159	0.009	11.631	133.509	-0.171	-0.162	0.005	4.690
Q25	-308.261	0.087	0.077	-0.298	-11.122	27.995	-0.240	-0.224	-0.220	-0.152
sig.	96.4%	60.7%	67.9%	71.4%	92.9%	92.9%	60.7%	64.3%	60.7%	85.7%

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Table 5 – continued from previous page

Panel B: Stocks L										
	RS^{SWX}	BV^{SWX}	AV^{SWX}	MQ_{15}^{SWX}	VOL_{15}^{SWX}	RS^{CHI}	BV^{CHI}	AV^{CHI}	MQ_{15}^{CHI}	VOL_{15}^{CHI}
Mean	-252.333	0.125	0.118	-0.039	45.290	243.840	-0.193	-0.189	-0.082	-96.985
Median	-224.511	0.116	0.119	-0.104	1.596	115.517	-0.177	-0.182	-0.130	0.755
Q75	-103.256	0.148	0.155	0.115	29.148	326.025	-0.168	-0.148	-0.036	10.477
Q25	-407.329	0.092	0.076	-0.254	-5.218	46.600	-0.212	-0.217	-0.231	-25.921
sig.	100.0%	71.4%	71.4%	78.6%	92.9%	100.0%	64.3%	71.4%	64.3%	78.6%
Panel C: Stocks S										
	RS^{SWX}	BV^{SWX}	AV^{SWX}	MQ_{15}^{SWX}	VOL_{15}^{SWX}	RS^{CHI}	BV^{CHI}	AV^{CHI}	MQ_{15}^{CHI}	VOL_{15}^{CHI}
Mean	-221.173	0.140	0.123	-0.248	-29.208	56.070	-0.227	-0.216	-0.255	4.401
Median	-251.061	0.130	0.140	-0.035	-7.184	47.809	-0.219	-0.203	-0.060	1.883
Q75	-133.198	0.170	0.160	0.002	-0.439	60.771	-0.175	-0.176	0.013	3.162
Q25	-281.559	0.081	0.078	-0.535	-36.531	27.265	-0.244	-0.228	-0.210	0.344
sig.	92.9%	50.0%	64.3%	64.3%	92.9%	85.7%	57.1%	57.1%	57.1%	92.9%

Chi-X in the Pooled Sample and in subsample Stocks S and for both trading venues for subsample Stocks L). This is consistent with findings from Hall and Hautsch (2006, 2007) who also find positive relations between past volatility and intensity processes.

Hall and Hautsch (2007) show that including state variables that describe the current state of the market significantly improves residual diagnostics, which are displayed in Table 6 for the three subsamples.

If the model is correctly specified, the residuals $\tilde{\epsilon}$ should follow an iid Exp(1) distribution, i.e., the mean of the empirical residuals and their standard deviation should be equal to 1. Table 6 shows summary and test statistics for the empirical residuals of the Pooled Sample and for the two subsamples. The mean and median of $\tilde{\epsilon}_i^k$ are close to 1 for the Swiss exchange and Chi-X for both subsamples. The average standard deviation of the residuals $\sigma_{\tilde{\epsilon}}$ is 0.76 and 0.75 for the Swiss exchange and for Chi-X, respectively, which indicates that the residuals are slightly underdispersed. This is consistent with the test statistic for overdispersion OD^k, which is negative and indicates an underdispersion. As proxy for the iid property, we present two test statistics for autocorrelation, namely the first order autocorrelation coefficients AC_1^k and the Ljung-Box test statistic LB_{20}^k. While AC_1^k should be close to zero, the critical value for LB_{20}^k equals 37.57 on a 99% confidence level. Both test statistics indicate that the residuals exhibit some autocorrelation, where the degree of autocorrelation for the residuals Chi-X is smaller with a mean AC_1^{CHI} of 0.01 and a mean LB_{20}^{CHI} of 36.70. The results from the residual diagnostics are consistent for the full sample and the two subsamples. Overall, the model

Table 6 – **Residual Diagnostics**

The intensity of the order book changes of the Swiss exchange (SWX) and Chi-X (CHI) over the sample period January 1 to March 31, 2010 is parametrized as $\lambda^k(t,\mathfrak{F}_t) = \lambda_0^k \psi_t^k \phi_t^k$, $k \in \{\text{SWX}, \text{CHI}\}$. λ_0^k is a baseline intensity function, ψ_t^k is the actual intensity process and ϕ_t^k captures the diurnal seasonality. The compensator is defined as piecewise integration of the conditional k-type intensity $\lambda^k(t,\mathfrak{F}_t)$ over all inter-event intervals $[\tilde{t}_j, \tilde{t}_{j+1}]$ with $t_{i-1}^k < \tilde{t}_j < \tilde{t}_{j+1} \leq t_i^k$, i.e., $\Lambda^k(t_{i-1}^k, t_i^k) = \int_{t_{i-1}^k}^{t_i^k} \lambda^k(u,\mathfrak{F}_u)du = \sum_j \int_{\tilde{t}_j}^{\tilde{t}_{j+1}} \lambda^k(u,\mathfrak{F}_u)du$. The residuals ϵ_i^k are calculated as $\epsilon_i^k = 1 - \Lambda^k(t_{i-1}^k, t_i^k)$. The table shows the mean, median, first and third quartile of the estimated residuals and test statistics for the residuals of the ACI model. $\tilde{\epsilon}^{\text{k}}$ denotes the mean of the estimated k-type residuals and $\sigma_{\tilde{\epsilon}}^{\text{k}}$ the standard deviation of the k-type residuals. OD^{k} denotes the test statistic for overdispersion for the k-type residuals given by $OD^k = \sqrt{\frac{n^k}{8(\sigma_{\tilde{\epsilon}}^k)^2}}$, where n^k denotes the number of k-type residuals. AC_1^{k} and LB_{20}^{k} are tests for autocorrelation, where AC_1^{k} denotes the first order autocorrelation coefficient and LB_{20}^{k} the Ljung-Box test statistic for 20 residuals.

Panel A: Pooled Sample

	$\tilde{\epsilon}^{\text{SWX}}$	$\tilde{\epsilon}^{\text{CHI}}$	$\sigma_{\tilde{\epsilon}}^{\text{SWX}}$	$\sigma_{\tilde{\epsilon}}^{\text{CHI}}$	OD^{SWX}	OD^{CHI}	AC_1^{SWX}	AC_1^{CHI}	LB_{20}^{SWX}	LB_{20}^{CHI}
Mean	0.98	0.83	0.76	0.75	-5.53	-4.87	0.05	0.01	41.77	36.70
Median	0.98	0.86	0.74	0.76	-5.27	-4.62	0.05	0.02	35.18	25.31
Q75	1.00	0.90	0.80	0.79	-4.40	-3.54	0.07	0.05	54.49	38.19
Q25	0.95	0.83	0.70	0.71	-6.66	-6.25	0.02	-0.01	28.85	20.13

Table continued on next page

Table 6 – continued from previous page

Panel B: Stocks L										
	$\tilde{\epsilon}^{\text{SWX}}$	$\tilde{\epsilon}^{\text{CHI}}$	$\sigma_{\tilde{\epsilon}}^{\text{SWX}}$	$\sigma_{\tilde{\epsilon}}^{\text{CHI}}$	OD^{SWX}	OD^{CHI}	AC_1^{SWX}	AC_1^{CHI}	LB_{20}^{SWX}	LB_{20}^{CHI}
Mean	0.99	0.83	0.75	0.72	-6.52	-6.08	0.05	0.02	49.24	41.61
Median	0.98	0.86	0.73	0.75	-6.45	-5.96	0.05	0.02	50.05	25.92
Q75	1.00	0.88	0.76	0.77	-4.53	-4.56	0.06	0.05	61.08	39.74
Q25	0.96	0.85	0.70	0.72	-8.22	-6.95	0.02	-0.01	32.52	18.28
Panel C: Stocks S										
	$\tilde{\epsilon}^{\text{SWX}}$	$\tilde{\epsilon}^{\text{CHI}}$	$\sigma_{\tilde{\epsilon}}^{\text{SWX}}$	$\sigma_{\tilde{\epsilon}}^{\text{CHI}}$	OD^{SWX}	OD^{CHI}	AC_1^{SWX}	AC_1^{CHI}	LB_{20}^{SWX}	LB_{20}^{CHI}
Mean	0.98	0.83	0.77	0.79	-4.53	-3.66	0.05	0.00	34.30	31.80
Median	0.99	0.88	0.75	0.79	-4.93	-4.05	0.06	0.02	31.48	25.03
Q75	1.00	0.90	0.80	0.89	-4.34	-2.55	0.07	0.07	36.54	36.63
Q25	0.93	0.82	0.69	0.70	-5.45	-4.69	0.02	-0.02	27.90	22.24

fit is comparable to previous studies using autoregressive conditional intensity models, e.g., Hall and Hautsch (2006, 2007) and Kehrle and Peter (2011). Based on the estimated ACI(1,1) model we calculate intensity based information shares for the Pooled Sample and the two subsamples. Table 7 gives the results.

The intensity based information share for Chi-X equals 63.4% in terms of the mean and 66.4% in terms of the median which means that for the Pooled Sample Chi-X is the leading market in terms of the intensity based information share. The lead of Chi-X is highly significant for 42.9% of the Pooled Sample, whereas the lead of the Swiss exchange is only significant for 3.6% of the stocks. These findings are supported by the analysis of the two subsamples. For Stocks L the mean of IIS^{CHI} equals 62.4% and for 57.1% of the stocks in subsample Stocks L the lead of Chi-X is highly significant. The same holds true for subsample Stocks S with a mean IIS^{CHI} of 64.4%. However, the lead of Chi-X is only significant at the 1% level for 28.6% of the stocks. There is no stock in subsample Stocks S for which the Swiss exchange is significantly leading at the 1% or 5% level.

Overall, we find strong evidence that Chi-X is the leading market in terms of the intensity based information shares, which, in contrast to the Hasbrouck information shares, take the effective duration structure of the order book changes into account. Although the first quartiles of IIS^{CHI} lie below 50% for the Pooled Sample and subsample Stocks L, the mean estimates, which in case of the intensity based information shares are point estimates for the true values, lie well above the 50% threshold and are confirmed by respective significance tests.

Table 7 – Intensity Based Information Shares

The table shows intensity based information shares $IIS^{\text{SWX}} = \frac{\frac{|a_2^{\text{SWX}}|}{|a_2^{\text{CHI}}|}}{\frac{|a_1^{\text{CHI}}|}{|a_1^{\text{SWX}}|}+\frac{|a_2^{\text{SWX}}|}{|a_2^{\text{CHI}}|}}$ and $IIS^{\text{CHI}} = \frac{\frac{|a_1^{\text{CHI}}|}{|a_1^{\text{SWX}}|}}{\frac{|a_1^{\text{CHI}}|}{|a_1^{\text{SWX}}|}+\frac{|a_2^{\text{SWX}}|}{|a_2^{\text{CHI}}|}}$, where the parameters a_1^k and a_2^k, $k \in \{\text{SWX}, \text{CHI}\}$, are estimates from the bivariate autoregressive conditional intensity (ACI) model for the intensity of order book changes of the Swiss exchange (SWX) and Chi-X (CHI) over the sample period January 1 to March 31, 2010. Panel A covers stocks from the Pooled Sample and Panel B and Panel C stocks from the subsamples Stocks L and Stocks S, respectively. Lead 95% and Lead 99% denote the fraction of stocks in the respective subsamples, where the intensity based information share of one market is significantly higher than 50% with a confidence level of 95% and 99%, respectively.

Panel A: Pooled Sample		
	IIS^{SWX}	IIS^{CHI}
Mean	36.6%	63.4%
Median	33.6%	66.4%
Q75	52.8%	83.7%
Q25	16.3%	47.2%
Lead 95%	7.1%	46.4%
Lead 99%	3.6%	42.9%
Panel B: Stocks L		
	IIS^{SWX}	IIS^{CHI}
Mean	37.6%	62.4%
Median	42.1%	57.9%
Q75	57.3%	84.0%
Q25	16.0%	42.7%
Lead 95%	14.3%	57.1%
Lead 99%	7.1%	57.1%
Panel C: Stocks S		
	IIS^{SWX}	IIS^{CHI}
Mean	35.6%	64.4%
Median	31.1%	68.9%
Q75	44.6%	83.3%
Q25	16.7%	55.4%
Lead 95%	0.0%	35.7%
Lead 99%	0.0%	28.6%

The findings from the analysis of the intensity based information shares confirm our findings from the Hasbrouck information shares for subsample Stocks L, which suggested that Chi-X is the leading trading venue. The intensity based information shares also confirm the lead of Chi-X for the second subsample Stocks S, where Hasbrouck information shares suggested a lead of the Swiss exchange. Overall, by taking the effective duration structure into account we calculated unbiased point estimates for the information share, which suggest that Chi-X is the leading market in terms of intensity based information processing irrespective of the market capitalization of the stocks.

5. Conclusion

The exchange landscape in Europe changed fundamentally with the implementation of MiFID in 2007. The emergence of several MTFs lead to a fragmentation of trading in European equities. A key question when a stock is traded in a fragmented market is, where information is processed, i.e., which trading venue is leading in incorporating new information.

Previous studies analyzed information processing after MiFID with the well known Hasbrouck information shares. We also apply Hasbrouck information shares with inconclusive results. Evidence suggests that Chi-X is the leading trading venue for larger stocks, whereas for smaller stocks the Swiss exchange is still leading. However, overall the clear identification of the leading venue according to Hasbrouck information shares is not possible. This finding stems from the fact that Hasbrouck information shares do not result in a point estimate of the information shares, but rather in upper and lower bounds, which differ significantly.

In this article a new method for the analysis of information processing is used by the calculation of intensity based information shares. By applying an autoregressive conditional intensity model, we calculate intensity based information shares, which take the effective irregular duration structure of order book changes into account. Furthermore, the autoregressive intensity model allows to calculate statistically meaningful point estimates for the information shares of the respective trading venues.

We find significant cross effects between the intensity processes of the Swiss exchange and Chi-X. Furthermore, we provide evidence that Chi-X is the leading market in terms of intensity based information processing irrespective of the market capitalization of the stocks.

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Curriculum Vitae

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Education

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