Liquidity and Information in Interdealer Markets: A Study of Hot-potato Trading in the European Bond Market

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Abstract

Hot-potato trading is defined by Lyons (1997), as *"the repeated passing of inventory imbalances between dealers"*. This study is an empirical examination of hot potato trading in the German and Danish bond market. A detailed description of the phenonomen is provided and two aspects of hot potato trading is examined in depth. The first analysis concludes, that hot potato trading primarily takes places in liquidity abundant markets and is therefore a clear indication of a well-functioning market as this allows for risk sharing across market participants. Secondly, the estimated price impact of hot potato trades is lower compared to ordinary trades, suggesting that market makers distuinguish between the informational content of the trades.

Keywords: Hot potato trading; market microstructure, bond markets, price information content

JEL classification: E43, G12, G14

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Introduction

Hot-potato trading is defined by Lyons (1997), as *"the repeated passing of inventory imbalances between dealers"*. The behavior reflects that market makers pass around positions among each other until a dealer is willing to put it on its own balance sheet or has an off-setting position. His study was specifically motivated by behavior in the currency market, but such behavior is also observed in the bond market.

This paper is the first to empirically document the extent of hot-potato trading in the bond market. The paper provides detailed information about hot potato trades and examines two aspects of hot potato trading in detail. Firstly, the drivers behind this type of trading is identified in a probit framework - the analysis, in addition to descriptive statistics, suggests that the phenomenon is positively linked with liquidity conditions. Secondly, the price impact is found to be lower for hot potato trades This confirms the results of Lyons (1997) that hot potato trades contains no additional information content about orderflows.

The first analysis suggests, that whilst hot potato trading per definition is liquidity consuming, trading primarily takes places in liquidity abundant conditions. Contrary to what one may expect, hot potato trading is therefore a clear indication of a well-functioning market as this allows for risk sharing across market participants. During the financial crisis a substantial decline in the amount and volume of hot potato trades was observed along side with the deteriorating liquidity conditions.

One of the implications of the theoretical model in Lyons (1997), is that the information content in interdealer trades is reduced. The argument behind this result is that each hot potato trade adds to the noise and makes signal extraction more difficult. However, the result hinges on the assumption that market makers are unable to identify hot potato trades. This is not the case in the data considered in this paper. If market makers can identify hot potato trades, then the price impact should be lower for these trades. This is indeed what is found in our second analysis - the price impact on hot potato trades, after correcting for liquidity conditions and other relevant factors, is lower. Thus confirming the theoretically implications of Lyons (1997).

The data used in this study is government bond market data from MTS Germany and MTS Denmark - the largest interdealer market making platforms for government bonds in Germany and Denmark. The period covered is June 2007 to December 2009 and thus covers the period before to the financial crisis spilled over to bond markets, during the financial crisis and the return to normal market conditions. This gives an unique insight in the functioning of a market.

The objective of the bond market maker is obviously to maximize profits. To achieve this objective, the earning of the bid-ask spread is a well known income, but the market maker typically also holds own positions that exploits the informational value attained from knowing customer flows. To manage own positions, in addition to positions obtained from customer or other dealers, a number of hedging strategies are employed - of which hot potato trading is one option.

The paper is structured as follows. The following section, section 1 reviews the existing literature. In section 2 the data used in this study is discussed and described. In this section a formal empirical definition of hot potato identification and a detailed description on the extent of hot potato trading is given. Finally some time is spent on defining the price impact and various summary statistics about the price impact is provided. An more formal empirical investigation is given in section 3, where two aspects of hot potato trading is considered. Firstly, a probit/logit framework is used to identify the drivers behind hot potato trading in section 3.1. Secondly, the price impact of normal and hot potato trades is analytically compared in a simple regression framework in 3.2. Section 4 offers some concluding remarks.

1 Related literature

The role of the market maker is well established in the market microstructure literature. In his seminal paper, Garman (1976) describes the role of the market maker as to set prices, receive all orders and clear trades. The market maker objective is to set ask and bid prices so to maximize expected profits. Later studies, such as the Glosten and Milgrom (1985) and the Kyle (1985) models, also take into consideration respectively the informational content and the strategic behavior of dealers.

Lyons (1997) studies the particular strategic behavior of hot potato trading in a theoretical context, while this paper is the first to do an empirical analysis of the phenomenon. The risk-averse dealers in Lyons (1997) intermediate customer trades and trade among themselves. The customer trades are not observable, except for the dealer receiving the order, and hence the information content of the trade is also not known to the general market. Furthermore the dealer trades are also not observed by other than the participating dealers. In such a setting, the information content in prices of trades becomes diluted.

The setting studied in this paper distinguishes itself in one small, but important, aspect. Customer trades are still unobserved, as the trading platform studied only is accessed by market makers/dealers. However, dealer trades are observed by all market participants. Assuming that a dealer receives a given customer order and decides to pass this position on to other dealers, a trade is observed on the dealer platform. In this case, one might remark that the dealer simply intermediates the trade to the market. The dealer receiving the position, however, may choose to pass it on - hence starting the game of hot potato trading. The dealers observe another trade with same or similar characteristics to the first trade, i.e. same trade direction. The dealers may therefore infer, that there is a positive probability of it being a hot potato trade. In such a setting it can be expected, that the actual hot potato trades have a lower price impact.

Until recently, however, the hedging activities of the market maker has not been taken into account. Brunnermeier and Pedersen (2005) show that this can have consequences for price setting in their model. When liquidating positions in their model, the trader may experience that liquidity dries out when liquidity is most needed. In their general model, the need to liquidate positions is exogenously given, however one such case where liquidation is needed occur daily, when market makers take on positions from customer flows. If this customer flow is known to other dealers, for instance if the customer has held a competition among say two dealers, the 'losing' dealers may suspect that the winning (unknown) dealer has the need to hedge the position. Hence the hedging activities are a crucial part of the daily work of a market maker.

A recent study by Ejsing and Sihvonen (2009), also based on MTS data, show that differences in market structure between US and German bonds also matters for pricing. The liquidity premium demanded on US on-the-run securities is negligible on German bonds. Whereas trading in the US predominantly takes place in securities, trading takes place in the very liquid German bond futures contract. German liquidity premia is therefore primarily observed on bonds, that are deliverable into futures contracts.

This paper is by far the first to use data from the MTS platform. For instance Cheung, de Jong, and Rindi (2005) use the data to study order effects on macroeconomic announcement days. Another paper studying MTS data is Dunne, Moore, and Portes (2007), which studies the benchmark status of sovereign bonds.

2 Data

We use previously unavailable data from the MTS platform. The MTS platform is a pan-european electronic trading platform for European government bonds. Most major domestic and international financial institutions participate in market making. The platform is the largest electronic platform, see Xtracter, for government bonds in Europe. Most of the bond market trades are done in the OTC market.

The platform is primarily reserved for the interbank customers, with a few exceptions of some very large asset management companies. Two types of dealers participate on the platform, price setters and price takers - the latter typically being the very large asset management companies. The price setters have typically entered into formal arrangements of quoting two-way prices, i.e. a bid and an ask quote, within a predefined bid-ask spread throughout the day. The price takers can only trade at the observed prices set in the market by the price setters.

As this paper examines the behavior of hot potato trades, the behavior of price takers is irrelevant. A price taker can never be the source of a hot potato trade, as this requires them being 'hit' by another trade prior to making the hot potato trade, although it may initiate a hot potato trade. Consequently, this paper only deals with the market makers on the platform.

The information set of the market makers pre-trade includes the 5 best prices at respectively the bid and the ask side - typically with their own quote(s) as a part of those prices. Post-trade, the involved counterparts in a given trade gets the information of the counterpart, with whom they have entered the trade, the price and quantity traded. The remaining participants on the platform are informed of a trade being taken place, the trade price and quantity traded.

Part of the turnover on the MTS platform relates to T-bills, i.e. zero coupon bonds with a maturity less than 1 year, and inflation-linked bonds (German platform only). The T-bills segment of the market is part of the activities on the money market and is likely to have been impacted earlier than the bonds of longer maturities. The inflation-linked bond market appears to be more illiquid compared to conventional government bonds market - including them would give a bias towards a higher price impact in the German market. In order to exclude any impact from money market related activity and from the inflation-linked market, only conventional bonds with a maturity of more than 2 years and less than 12 years is considered in the remainder of the paper.

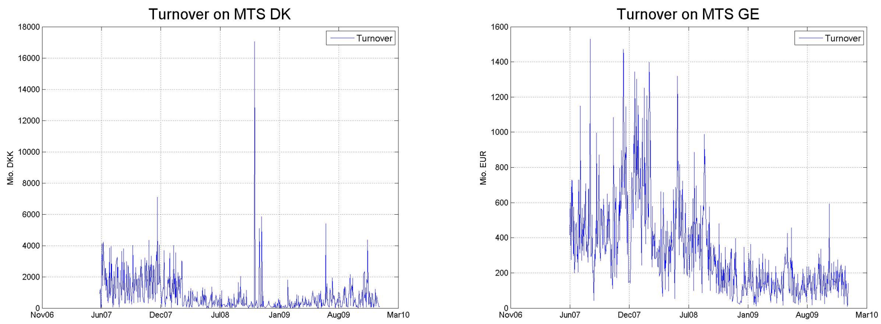

Figure 1: Daily turnover in MTS GE and MTS DK. June 2007 - October 2009.

The data includes all trades done on the Danish and German trading platforms, MTS Deutschland and MTS Denmark from June 2007 to December 2009. The data thus covers a period before the financial crisis spilled over to the bond market, the period with the financial crisis and a pre-crisis/recovery period. The dating of the financial crisis is in part data-driven and in part anecdotal. Figure 1 above shows the turnover in the German market[1], where a substantial drop in turnover took place around

[1] The Danish market exhibits roughly the same behaviour.

March 2008. This also coincides with the Bear Stearns collapse. Hence, the start of the financial crisis on the bond market is in this paper dated the 15th March 2008, as Bear Stearns collapsed on this date.

The recovery of the bond market is somewhat harder to pinpoint. The turnover has been rising modestly in the latter part of 2009, suggesting that market participants are slowly returning to the electronic platforms. We suggest that the financial crisis, albeit not the economic crisis, was over around August 2009. This is confirmed by anecdotal evidence from traders and other market practitioners.

2.1 Identification of Hot Potatoes

The empirical identification of hot potato trades is crucial and the existing literature provides no guidelines on this choice. Some of the characteristics of a hot potato trade are obvious for a given bond. The trade should be done in the same bond and the same side of the market, in addition the price setter should be the initiating part of the hot potato trade.

It is however less simple to identify the time interval that can pass between the first trade and the hot potato trade. In addition, it is also not certain that the amount traded should be same - some market makers may choose to hedge only part of the trade or even pass on a larger quantity. To keep things simple, the following algorithm has been chosen.

Algorithm 1 *A given trade t is considered with characteristics, bond identification(ISIN code), order member (aggressor), proposal member (price setter), order size, quantity and price.*

A hot potato trade is a trade that takes place

i) within the next 30 minutes

ii) in the same bond,

iii) the order member is the proposal member of the prior trade.

Note, this identification is not very strict. Firstly, the algorithm does not require that the amount traded in the hot potato trade is similar to that of the original trade. Hence, some element of position taking may be allowed, i.e. a trader may keep some of the risk from the acquired position on his own balance sheet. Secondly, a time interval of 30 minutes may be considered a relatively long time interval. This time interval however balances on the one hand the reluctance of the trader to keep any risk on his balance sheet, and on the other hand, the search process for off-loading the position to for instance customers or through other trading venues. Using intervals longer than 30 minutes is likely to entail some risk taking and hence not only done for the purpose of hedging.

The impact of imposing a quantity matching restraint and looking at shorter time-intervals is limited. In the following section, some robustness checks are done by imposing these restrictions and especially the time constraint does matter. However, it is primarily an extension of the 30-minute interval that has significant impact. Shortening the window to say 10 minutes has some impact, but not enough to change the overall results.

2.2 Summary statistics

Before we proceed to the analysis of what drives hot potato trading, it is relevant to consider the extent of hot potato trading in the Danish and German market. Over the period June 2007 to December 2009, there was an aggregate turnover of above 200 billion EUR on the German platform and above 500 billion DKK (equivalent to around 75 billion EUR) on the Danish platform. The number of bonds traded on the platform is substantially higher on the German platform, over the considered period, around 85 bonds was traded, where as only around 15 bonds was traded on the Danish platform..

The identification of hot potato trades does reveal some interesting features. Overall turnover, as depicted together with the share of hot potato trades in figure 2, dropped substantially on both platforms dropped substantially around March 2008, especially on the Danish platform. As March 2008 also coincides with the collapse of Bear Stearns, this clearly indicates that the financial crisis hit the bond market somewhat later than the money market. On the German platform, turnover appears to pick up marginally again after March 2008, only to drop again in the wake of the Lehman collapse in September.

	MTS GE (mio. EUR)		MTS DK (mio. DKK)	
	Overall	Hot-Potato	Overall	Hot-Potato
Total turnover	217714.00	13071.50	527639.00	59907.50
Turnover share	-	0.060	-	0.114
No. of trades	31872	1933	10847	1260
Average turnover 1)	335	20	818	93
- Buy initiated	166.63	28.99	559.63	187.90
- Sell initiated	172.49	26.02	495.50	164.65
No. Trades	31872	1933	10847	1260
- Buy initiated	15610	995	6015	680
- Sell initiated	16262	938	4832	580
Average trade size	6.83	6.76	48.64	47.55
- Buy initiated	6.85	6.73	49.50	48.63
- Sell initiated	6.81	6.80	47.58	46.27
No. trading days	649		645	

Table 1: Summary stats for MTS DK and MTS Germany. Data covers the period June 2007 to December 2009. 1) Sum of buy and sell initiated trades is more than average turnover, as some days have zero-trading.

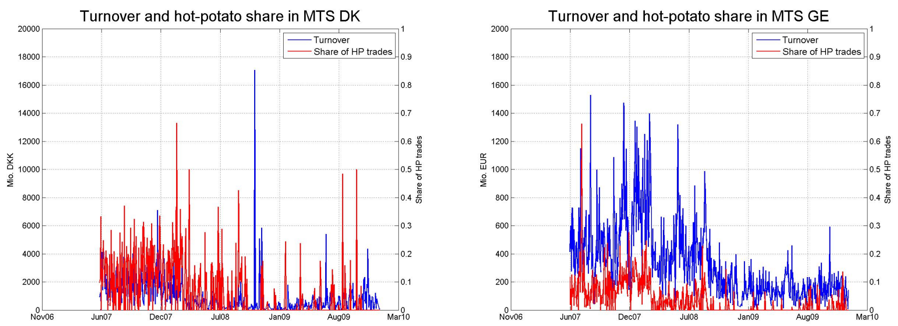

Figure 2: Daily turnover and hot potatoes share of daily turnover in MTS GE and MTS DK. June 2007 - December 2009.

The overall turnover and the share of hot potato trading tends to co-move, see Figure 3. Periods of high turnover tends to be accompanied with a high share of hot potato trading. Over the entire period; hot potato trading is around 11.4% of overall turnover on MTS DK. However, in the first half of the period, June 2007 to March 2008, the share was somewhat higher - around 18% of overall turnover. After that, in line with the decline in turnover, the share decreased to around 3% of overall turnover. For the German platform, the pattern is similar, although less pronounced. A share of around 6% for the entire period, 12% in the first half and 2% in the second half.

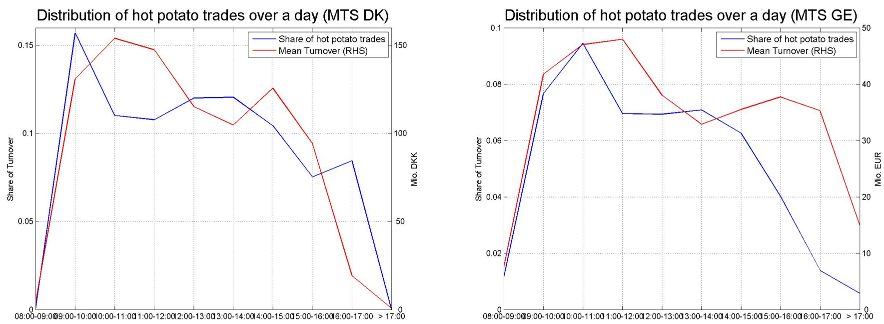

Figure 3: Average turnover and share of hot potato trading in hourly intervals. Averages is calculated on data from June 2007 - December 2009 for respectively the MTS GE and MTS DK trading platform.

When looking within a day, the strong co-movement between volume and the share of hot potato trades is clearly underlined. The average turnover during a day is highest before noon. Around lunch, the turnover drops slightly, probably due to a lunch effect. Average turnover then picks up slightly in the early afternoon and then subsequently fades out. This pattern is similar on both platforms. Similarly the share of hot potato trading follows the same pattern and hence does seem to follow aggregate turnover quite strongly.

The description of hot potatoes is linked with many trades associated to one position in Lyons (1997). This is not the case in the bond market, as most cases of hot potato trading only involves one hot potato trade, see Figure 4. In a few cases, a position is passed around 2 times, but only very rarely more than that. It therefore appears clear, that the bond markets propensity to absorb the risk is somewhat better than in the F/X market. This is probably linked to much better hedging opportunities.

In the F/X market there are few alternative hedging opportunities, where as the bond market offers many. For instance, for hedging a German government bond with $7\frac{1}{2}$ years to maturity can be done by a linear combination of the 5- and 10-year bond futures, by buying another bond with almost similar maturity, such as a German government bond with 7 years to maturity, or by buying bond of similar credit quality, such as a French government bond with $7\frac{1}{2}$ years maturity. Often this will leave some residual risk, for instance the risk stemming from changes in curvature or steepness, however this risk

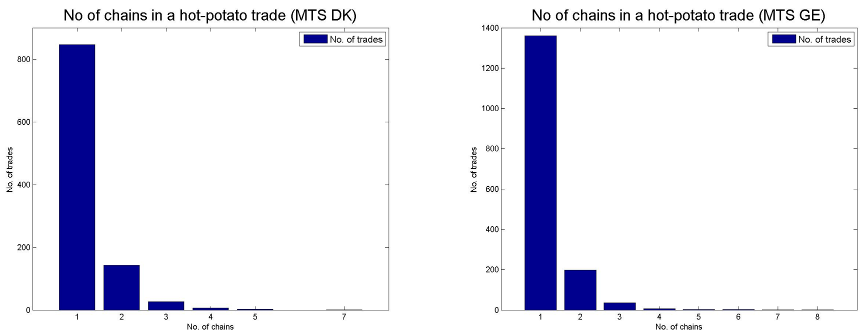

Figure 4: The number of hot potato trades following from an initiating trade on MTS GE and MTS DK over the period June 2007 - December 2009

will be much lower than the full duration and credit risk on the principal.

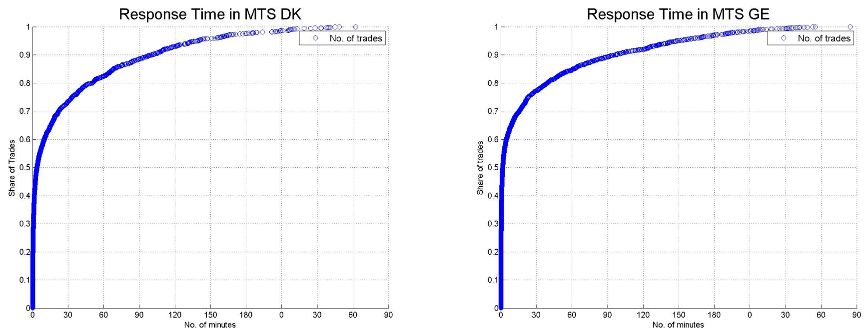

Figure 5: The response time from an initiating trade to the hot potato trade. The data used in this chart differs from the data used elsewhere in this paper, as the 30-minute time constraint is not used in the generation of the data for these charts. The data covers June 2007 - December 2009 on the MTS GE and MTS DK platforms

Figure 5, shows the distribution of time from the original trade to the hot potato trade is entered. This allows us to quantify the effect of the 30 minute time constraint imposed. In order to understand the impact of the time constraint, also trades with hot potato characteristics, but entered after the 30-minute constraint is allowed, although these are not formally considered hot potato trades.

As Figure 5 illustrates, most of hot-potato hedging activities takes places within the first minute. Respectively, 42% and 56% of all identified hot-potato trades on the Danish and German platform. Within 10 minutes, 81% and 87% is identified. The lower share for the Danish market probably reflects the alternative hedging opportunities, i.e. the possibility of using Euro Area government bonds or futures contracts. The chosen interval does seem to catch two different types of hot-potato traders. The first type hedges almost instantaneously, where as the second type awaits the situation, probably trying to off-load the security through different channels - possibly hedging any interest rate risk in futures or other bonds.

There are some trades being entered after the 30 minute interval, but changing the time constraint will only have an marginal impact. The bulk of trades happens within 10 minutes, but to include the second type of hedger, the extension to a 30-minute window has been made.

Another constraint imposed in the identification algorithm was the absence of a quantity matching constraint. Around <X>% has a lower quantity and <y>% has a higher quantity in the Danish market, whereas the shares are <X> and <Y>% in the German market. Therefore, the quantity matching constraint appears to be of little importance.

2.3 Measuring price impact

The measurement of the price impact can be done in several ways. A simple measure entails a comparison with the trade price and the price in the limit order book. I.e. the price impact is simply measured as

$$\begin{aligned} PI_{\Delta}^{Ask} &= P_{t+\Delta} - P_t \\ PI_{\Delta}^{Bid} &= P_t - P_{t+\Delta} \end{aligned}$$

Δ measures the time interval from t. It is necessary to distinguish between bid and ask side entered trades, otherwise the sign would be opposite for trades entered respectively at the bid and ask side.[2] In our case, a 1-second interval after the trade is used. This allows us to measure the immediate impact of the trade on prices and hence gives an indication of the depth of the limit order book. This measure is some times referred to the Kyle λ, following Kyle (1985).

In this section, the perspective is broadened slightly from compared to

[2] In the case of a bid trade at say 100.00, the next bid in the book would be lower, say 99.9. For ask quotes, the next quote in the book would be higher.

the previous section with summary statistics. Instead of focusing solely on the hot potato trade, the price impact of the initiating trade is also considered. One should note that motives behind the initiating trade is primarily unknown, it could for instance stem from hedging of trades in the bond done outside the platform, such as customer trades or position taking. Whatever the reasons, the trade is 'normal', in the sense that it is not hot potato trading. Consequently, the initiating trade gives an indication about the prevailing market conditions in which hot potato trading takes place. The price impact of the actual hot potato trade tells a similar story, however with a subtle difference that the other market makers observe the orderflow of the previous trade (the initiating trade).

This difference in the information set may seem small, but it is vital, as market makers have some indication of it being a hot potato trade. If it can be identified as a hot potato trade, it consequently it brings no new information to the market about orderflows. Market participants is therefore likely to attach a lower weight on its informational value about the orderflow.

The below table shows the average price impact for all non-hot potato trades, hot potato initiating trades and hot potato trades. The price impact of hot potato trades are considerably *lower* than then price impact of an average trade, which does seem to indicate that market participants put lower weight on the informational content of the hot potato trades. However, taking into account prevailing market conditions, as proxied by the price impact of hot potato initiating trades, little difference can be found between hot potato trades and non hot potato trades.

		MTS GE	
	Overall	Hot-Potato	Hot-Potato Initiated
Price Impact (ticks)	5.986	1.737	1.620
		MTS DK	
Price Impact (ticks)	3.597	1.936	1.593

Table 2: Average price impact for the the period June 2007 to December 2009. Price impact is measured as the price change from the trade price to the market price 1 second after trade.

Another measure of price impact, a measure that sums up the accumulated impact of hot potato trades is used. This measure sums the change in the price in ticks from the originating trade and subsequent hot potato trades. The price impact 1 second after trade is used. This gives a measure of whether, price spirals is observed in the market.

	Acc. Price Impact (ticks)	**Avg. no. of Trades**
MTS GE	3.545	2.117
MTS DK	2.8153	2.044

Table 3: Accumulated Price Impact of hot potato trades and average number of trades in a chain. Price impact for the the period June 2007 to December 2009. Price impact is measured as the price change from the trade price to the market price 1 second after trade. Data covers the period June 2007 to December 2009.

The accumulated price impact is lower than an average trade, although the different liquidity conditions are not taken into account. But price spirals do not appear to take place to any noticeable degree.

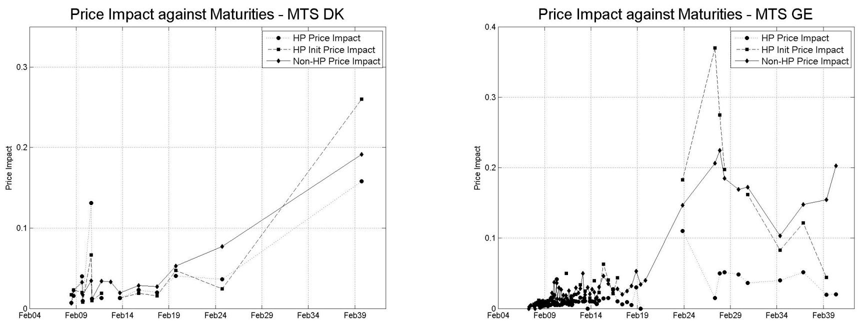

Figure 6: Average price impact on hot potato initiating trades, hot potato trades and other trades plotted against the maturity date on individual bonds. The data covers June 2007 - December 2009 on the MTS GE and MTS DK platforms.

As can be noted from the above Figure 6, the price impact is higher for longer-maturity bonds. This is not surprising, as bid-ask spreads tends to be higher, as measured in ticks, for longer-dated bonds. The higher duration simply entails that prices move more for similar rate movements. Consequently market makers require a higher bid-ask spread to compensate for the higher price volatility in these bonds.

The price impact has been significantly different over the sample. Prior to the crisis, the price impact was very low and the number of normal and hot potato trades was high. During the crisis, the price impact became

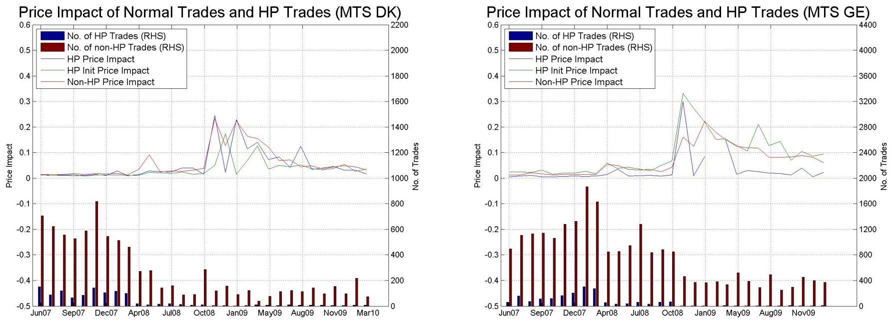

Figure 7: Average monthly price impact on hot potato initiating trades, hot potato trades and other trades and number of trades and hot potato trades. The data covers June 2007 - December 2009 on the MTS GE and MTS DK platforms.

considerably higher and the number of trades fell dramatically. Lately, the price impact has dropped slightly, but remains above pre-crisis levels. Furthermore the number of trades has yet to pick up again.

The summary statistics seem to support that the price impact differ somewhat. The initiating trades generally occur in a liquid market, which indicates that hot potato trading primarily takes place in a liquid market. Furthermore, the price impact of hot potato trades are similar to non hot potato trades, when correcting for prevailing liquidity conditions.

3 Econometric analysis

The purpose of the econometric analysis to underpin the patterns observed above statistically. Firstly we estimate, in a probit/logit framework, the drivers of hot-potato trades. Secondly, we analyze whether the price impact of hot-potato trades differ from the price impact on non-hot-potota related trades. The latter examination goes to the heart of Lyons (1997), as the theoretical model in his paper, predicts that price informativeness is diluted by the presence of hot potato trades. No tests of this has, to our knowledge, been done empirically before.

3.1 Drivers of hot potato trades

In order to estimate the drivers of hot-potato trades, a probit/logit estimation is done, see Wooldridge (2002). That is an estimation of the type:

$$P(Y=1|\mathbf{X}) = \Phi(\beta\mathbf{X}),$$

where X contains a constant (C), a dummy variable indicating if it is a trade done on the ask side (taking the value 1) or a trade done at the bid side (VERB), overall daily turnover on the relevant MTS platform (TURNOVER), daily turnover in the bond (TURNOVER_ISIN), bid-ask spread (BIDASK), the difference between the trade price of the originating trade and the hot potato trade, which typically will be a loss (LOSS) and finally the daily realized volatility[3] calculated from 5-minute intraday prices for the trading day before from the German 2-, 5- and 10-year futures contracts (VOL). The turnover variables is corrected for the hot potato trades, that is the overall daily turnover is calculated without volume from the hot potato trades, in order to gain a measure of non-hot potato related trading activity. The volatility variable is calculated for each trade individually as a maturity weighted average of the relevant futures - for instance, the market volatility for a $3\frac{1}{2}$ year old bond is calculated as a equally weighted average of the 2- and 5-year futures volatility. For bonds with less than 2 years to maturity, the 2-year volatility is used and similarly with bonds with a remaining maturity above 10 years, the 10-year volatility is used.

The selection of observations is non-trivial, as some variables are not available for all observations. Specifically the bid-ask spread and the Kyle λ will not always be available, as there in some periods only is a one-sided market with only a bid or ask quote available. In other periods, there is only a single quote in the market or all quotes are pulled immediately after a trade has occurred, making it impossible to measure the Kyle λ. As this almost per definition occurs in a rather illiquid market, the sample will be biased towards a more liquid sample. For instance trades early and late in the day will typically not enter into the sample. Furthermore, there is a slight bias towards the earlier part of the sample, as markets became more illiquid during the financial crisis and to some extent also after the crisis -

[3] See Andersen, Bollerslev, Diebold, and Labys (2003) for the method used.

at least compared to before the financial crisis. As such, this is not much of a problem, but it does require that the interpretations of the regression results is done with some care, as our results only hold in markets where there is at least a bid and ask quotes and two-layered prices. Hence the results only hold for markets with some minimum requirement to liquidity.

The results from the probit regression is given in the below table. The logit specification did not give very different results in terms of statistical significance, but was quite unable to correctly predict hot potato trades. That is, the prediction rates was almost a 100 per cent for non hot potato trades and 0 for non hot potato trades. The probit specification was more balanced.

	MTS DK	**MTS GE**
Constant	-1.139572***	-1.465926***
	(30.8045)	(28.8213)
Verb	0.003703	-0.064226*
	(0.1068)	(1.9095)
Turnover	0.000052***	0.000395***
	(4.4506)	(9.6111)
Turnover (ISIN)	0.000105***	-0.001328
	(2.7863)	(1.6036)
Bid-ask spread	-0.373340**	-0.134164
	(2.0555)	(0.9830)
Loss	-2.736930***	-5.960814***
	(7.4260)	(8.3061)
Volatility	-0.173859	-1.093807***
	(1.0238)	(4.2756)

Table 4: Probit estimation results. The data covers the period June 2007 - December 2009.

Higher turnover is associated with a higher probability of hot potato trading. Given the summary statistics presented earlier, it is not surprising that overall turnover is a statistically significant variable. Days of higher turnover may be linked to the days of large customer flows - hence the hedging activity is likely to be higher on these days. As hot potato trading is one of the hedging tools available to dealers, it is not surprising to see the higher share of hot potato trading. Smaller flows are more likely to be accommodated into own inventories, but when trading activity continues to be high, the market makers need to hedge their positions.

The daily turnover in the specific bond is also significant on the Danish platform. One explanation to this could be a higher individual risk on Danish bonds, as there are simply fewer issues to choose from. The market makers could hedge their positions in similar maturity bonds, i.e hedge a 9-year bond with a bond with 9 1/4 years left to maturity. The fewer bonds in the Danish market make this a less appealing strategy, as the maturity differences can be some what larger, for instance up to 2-year maturity differences at longer maturities.

Overall market volatility is a significant variable for the German platform. The lack of significance on the Danish platform is not too surprising. Although the Danish market is strongly linked to the German market, the volatility is still taken from the German market, as there is no Danish bond futures contracts. Periods of higher volatility is associated with lower hot potato trading. Market makers appear unwilling to participate in hot potato trading, when the uncertainty is high. Some might argue that this is a spurious relationship, as the high volatility during the financial crisis also coincided with low levels of hot potato trading. However, the result also holds for the pre-crisis period, i.e. before April 2008.

Market makers continuously evaluate the risk and costs of having a position against the potential gains of holding the position. The loss variable, i.e. the immediate amount lost when doing the hot potato trade, is therefore not surprisingly statistically significant on both platforms. The cost of engaging in hot potato trading is an important driver of hot potato trading.

Finally, the bid-ask spread is statistically significant for the Danish platform. It could be expected that periods of high bid-ask spreads might induce traders to hold the position in order to potentially earn the bid-ask spread. However, on the other hand, periods of high bid-ask spreads are typically linked with high uncertainty. As we saw, volatility is statistically significant for the German platform, so there may be a colinearity issue behind the lack of significance on the German platform.

In measuring the predictive power of the model, we use the approach suggested in Cramer (1999)[4], as our sample is very unbalanced. The share of unbalancedness is given by α_{DK} =86% and α_{GE} =93%, which measures respectively the share of Danish and German trades that does not induce hot

[4]The Cramer (1999) only formally covers the logit model, but notes that the method also covers a wider range of binary choice models.

potato trading in our sample. Consequently in the calculation of 'percentage correctly predicted, we use a cut-off value of respectively 14% (100%-86%) and 7% (100%-93%) instead of the usual 50%. This gives the following results:

MTS DK		
	Non-HP Trade	HP Trade
Prob(HP=1|X)<$(1-\alpha_{DK})$	0.403	0.031
Prob(HP=1|X)>$(1-\alpha_{DK})$	0.465	0.101
MTS GE		
	Non-HP Trade	HP Trade
Prob(HP=1|X)<$(1-\alpha_{GE})$	0.482	0.015
Prob(HP=1|X)>$(1-\alpha_{GE})$	0.446	0.057

Table 5: Predictive power of the probit specification. The predictive power is calculated from the estimated coefficients in Table 4.

The prediction rates are not particularly impressive. The German platform has a 'hit ratio' of slightly above 50 per cent, where as the Danish prediction rates are very close to 50 per cent. That is, some drivers behind hot potato trading have been identified.

Anecdotal evidence from traders suggest, that some traders are more likely to enter into this kind of trading, where as others rarely use this hedging tool. Furthermore, market makers face individual risk constraints, which allow a larger risk tolerance in some banks, before they engage into hot potato trading. Therefore individual trader behavior and risk characteristics probably also play a very important role. Nonetheless, the analysis documents, that hot potato trading is driven by rational considerations and is one of many tools in the hedging toolbox.

3.2 Price informativeness on hot potato trades

The real information content lies in the hot potato initiating trade, as this brings new orderflow information to the market. The higher the degree of hot potato trading, i.e. noise trading, the lower the average price informativeness will be according to Lyons (1997).

The claim of the Lyons (1997) model has however, to our knowledge at least, not been put to the test empirically. The task of testing this empirically is however not straightforward. The measure of price informativeness will clearly impact our results. Several measures of price informativeness is available and in order to obtain fairly robust results, we adopt 2 measures.

The first measure is a very simple intraday measure. The price impact at a 1-,10- and 30-minute interval is found, that is the change in price at respectively 1, 10 and 30 minutes after the trade has been entered. If the trade was entered at the bid side, the bid quote 1, 10 and 30-minutes after is used and vice versa with the trade was entered at the ask side of the market. This measure gives a very intuitive and simple measure of price informativeness. If the Lyons hypothesis is true, we would on average observe a difference in the predictive content of hot potato trades and normal trade. In order to correct for the different liquidity conditions, we also calculate the price changes for the hot potato initiating trades. model The hot potato trades does not reveal more information, as this is simply inventories being passed around in the market, hence it is predicted that prices will be less informative, when hot potato trading is taking place.

The second measure takes into account overall market movements. We restrict all bonds to have a maturity between 2 and 12 years and calculate the benchmark return as a weighted average of the 2-year Schatz, 5-year Bobl and 10-year Bund futures contracts, where we use the maturity of the bond to calculate appropriate weights. For instance, the benchmark return of a bond with $7\frac{1}{2}$ year to maturity becomes 0.5xBobl_return+0.5xBund_return. This allows gives a more correct, market-adjusted, return. As in the first measure, we look at the impact at 1, 10 and 30 minutes after trade.

The very widely used PIN measure, see Easley, O'Hara, and Hvidkjær (2002), is however not adopted. The number of transactions in a given bond is normally fairly low, as the trading intensity is typically very low. A typical bond trades only between 0 and 5 times a day, so the PIN measure will be based on very few observations.

The price impact for the normal and hot potato trades differ, see Table 6. The price impact is 6-7 times smaller for hot potato trades, indicating that the price impact is much lower for hot potato trades. The result holds regardless of which of the two measures and the time perspective that is used. The Lyons (1997) intuition does therefore seem to hold.

MTS GE			
	Overall	Hot potato	Hot potato initiated
Absolut Price Change (ticks) - 1 min	0.029	0.021	0.026
Absolut Price Change (ticks) - 10 min	0.028	0.021	0.034
Absolut Price Change (ticks) - 60 min	0.036	0.024	0.059
MTS DK			
Absolut Price Change (ticks) - 1 min	0.036	0.015	0.012
Absolut Price Change (ticks) - 10 min	0.038	0.019	0.015
Absolut Price Change (ticks) - 60 min	0.051	0.019	0.014

Table 6: Price Impact

In order to test this formally, we estimate a regression of the form

$$PI_{d,t+N} = c + \beta_1 \Delta_{d,t} + \beta_2 \lambda_{d,t} + \beta_3 VOL_{d-1} + \beta_4 HP + \beta_5 HP\_init + \beta_6 r_t + \varepsilon_t,$$

where PI_t is the price impact at respectively 1, 10 and 30 minutes.

As documented earlier in this paper, liquidity conditions do appear to play an important role, which must be accounted for. Fleming (September 2003) suggests that the bid-ask spread (Δ) is the best variable to proxy liquidity conditions. Furthermore, the immediate price impact, that is the jump down the limit order book, by some denoted the Kyle Lambda (λ), following Kyle (1985), obviously will also differ from trade to trade - hence another variable that must be controlled for. In addition the weighted return of the German bund futures contract, Bunds, Bobl and Schatz is included, denoted r_t. Finally we need to formally test whether the initiating trades and the actual hot potato trades have a different price impact. This is done by putting in dummy variables indicating respectively, if the trade is a hot potato initiating trade (HP_init) or a hot potato trade (HP). It should not be expected, that the initiating trades have significant impact, as there should be "real" information content in this trades. However, if the Lyons (1997) holds, the dummy variable for hot potato trades should be negative (lower price impact) and significant.

The results are reported in the appendix, see Table 7, 8 and 9. For the German market, across all maturity segments, there are clear indications of a lower price impact of hot potato trades. This is not due to any specific liquidity conditions, as the hot potato initiating trade does not show signs of having lower price impacts. For the Danish market, the results are somewhat more mixed, but still does signs of hot potato trades having a lower impact at shorter maturities. The results hold across different time intervals and is robust to different specifications of the regressions, including the second measure - see Appendix for the results.

4 Concluding remarks

There are clear signs of market makers discriminating between the informativeness of hot potato trades and other trades. This is implicitly in line with Lyons (1997), as he noted that the information carried in hot potato trades is lower. In his model, however, market makers could not differentiate the trades from each other, leading to an average lower price informativeness. In our empirical study, market makers does have the opportunity to distinguish and does indeed seem to differentiate between the trades, as hot potato trades have an average lower price impact.

The current draft has not examined the implications of the crisis to any extent. However, it can be noted, that the level of hot potato trades has dropped substantially during the crisis. This does suggest that liquid markets is a pre-condition for hot potato trades to take place. This was further supported by the probit analysis, where liquidity indicators did indeed come out significantly.

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5 Appendix

	MTS DK			MTS GE		
	2-4 Y	4-8 Y	8-12 Y	2-4 Y	4-8 Y	8-12 Y
Constant	0.0007	0.0015	-0.0021	0.0042***	0.0077***	0.0153***
	(0.5357)	(0.8129)	(-1.0285)	(4.0455)	(5.4419)	(9.1787)
Bid-ask spread	0.1242***	0.0615**	0.1601***	0.0037	0.0738*	-0.0042
	(4.5957)	(2.3943)	(3.6151)	(0.1171)	(1.6529)	(-0.1180)
Kyle λ	0.6280***	0.6672***	0.6852***	0.4632***	0.3604***	0.3947***
	(10.0624)	(16.5726)	(17.9112)	(6.8270)	(9.0343)	(9.9769)
Volatility	0.0606*	0.0159	0.0140**	0.0285*	0.0056	0.0040
	(1.7918)	(1.1047)	(2.1535)	(1.9533)	(0.6139)	(0.6189)
HP trade	-0.0028***	0.0003	-0.0005	-0.0023***	-0.0058***	-0.0113***
	(-2.9015)	(0.3535)	(-0.4338)	(-3.8527)	(-8.0420)	(-7.2151)
HP initiating trade	-0.0010	0.0016	-0.0020	0.0005	-0.0007	-0.0032
	(-1.1435)	(0.8866)	(-1.5230)	(0.3458)	(-0.3534)	(-0.7784)
Returns	0.7947***	0.7080***	0.7973***	0.9402***	0.9407***	0.9037***
	(9.3940)	(11.6147)	(15.2331)	(14.4723)	(19.0657)	(13.9459)
No. Observations	2153	2067	3100	5748	4246	2361
R^2	0.522	0.534	0.527	0.341	0.333	0.393

Table 7: Regression output for price prediction on returns in the 1-minute interval after the trade. The regression run was of the form $PI_{d,t+N} = c + \beta_1 \Delta_{d,t} + \beta_2 \lambda_{d,t} + \beta_3 VOL_{d-1} + \beta_4 HP + \beta_5 HP_{init} + \beta_6 r_t + \varepsilon_t$. The variable HP is a dummy variable indicating whether the trade was a hot potato trade. HP$_{init}$ indicates that the trade is a hot potato initiating trade. Numbers in brackets denote t-statistics. Standard errors are Newey-West corrected standard errors. ***, ** and * respectively denote significance at 1%, 5% and 10% levels.

	MTS DK			MTS GE		
	2-4 Y	4-8 Y	8-12 Y	2-4 Y	4-8 Y	8-12 Y
Constant	0.0045 (1.4779)	0.0046** (2.1260)	0.0027 (1.0394)	0.0061*** (6.1719)	0.0062*** (5.1390)	0.0158*** (8.9331)
Bid-ask spread	0.2536*** (3.0849)	0.0783** (2.1684)	0.1975*** (4.3821)	-0.0343 (-0.9283)	0.0659* (1.6470)	0.0146 (0.3880)
Kyle λ	0.2608*** (2.9604)	0.5650*** (8.0683)	0.4482*** (6.6865)	0.4479*** (8.1971)	0.3819*** (7.9236)	0.3365*** (8.6178)
Volatility	0.0383 (0.8960)	0.0224 (1.3942)	0.0280** (2.3618)	0.0274 (1.4920)	0.0192* (1.9515)	0.0066 (1.0443)
HP trade	-0.0029** (-2.2183)	0.0007 (0.4808)	-0.0019 (-1.1005)	-0.0034*** (-5.4892)	-0.0047*** (-4.3609)	-0.0105*** (-6.0178)
HP initiating trade	-0.0037*** (-2.6479)	0.0033 (1.2999)	-0.0022 (-1.3937)	-0.0028* (-1.6530)	-0.0023 (-1.4525)	-0.0069* (-1.7724)
Returns	0.8219*** (16.2897)	0.9794*** (35.2333)	0.9996*** (40.2043)	1.0380*** (50.5559)	1.0217*** (54.7379)	1.0426*** (45.7985)
No. Observations	2149	2068	3077	5735	4157	2283
R^2	0.425	0.613	0.617	0.601	0.675	0.751

Table 8: Regression output for price prediction on returns in the 10-minute interval after the trade. The regression run was of the form $PI_{d,t+N} = c + \beta_1 \Delta_{d,t} + \beta_2 \lambda_{d,t} + \beta_3 VOL_{d-1} + \beta_4 HP + \beta_5 HP_{init} + \beta_6 r_t + \varepsilon_t$. The variable HP is a dummy variable indicating whether the trade was a hot potato trade. HP_{init} indicates that the trade is a hot potato initiating trade. Numbers in brackets denote t-statistics. Standard errors are Newey-West corrected standard errors. ***, ** and * respectively denote significance at 1%, 5% and 10% levels.

	MTS DK			MTS GE		
	2-4 Y	4-8 Y	8-12 Y	2-4 Y	4-8 Y	8-12 Y
Constant	0.0070***	0.0051***	0.0008	0.0068***	0.0057***	0.0163***
	(2.4072)	(2.6153)	(0.2869)	(6.5133)	(4.2579)	(7.9811)
Bid-ask spread	0.2308***	0.0914**	0.2465***	0.0030	0.1247***	-0.0056
	(3.3243)	(2.2513)	(5.1508)	(0.0591)	(3.1231)	(-0.1169)
Kyle λ	0.3438***	0.5388***	0.5343***	0.4832***	0.3037***	0.3660***
	(4.2199)	(7.6371)	(9.2345)	(11.0346)	(5.5077)	(9.8642)
Volatility	0.0775	0.0582**	0.0376***	-0.0080	0.0256*	0.0080
	(1.2554)	(2.3372)	(2.9266)	(-0.5959)	(1.9001)	(1.1705)
HP trade	-0.0042**	0.0011	-0.0016	-0.0026***	-0.0077***	-0.0077***
	(-2.3559)	(0.6367)	(-0.9281)	(-3.5369)	(-5.7216)	(-3.6210)
HP initiating trade	-0.0046***	0.0036	-0.0028	-0.0011	-0.0014	-0.0008
	(-2.5511)	(1.4271)	(-1.4370)	(-0.6911)	(-0.7982)	(-0.2099)
Returns	0.9386***	0.9534***	1.0047***	1.0572***	1.0381***	1.0804***
	(21.0631)	(34.1797)	(41.5563)	(74.3619)	(68.2108)	(61.9374)
No. Observations	2068	1992	2843	5642	3869	1992
R^2	0.552	0.669	0.677	0.801	0.783	0.837

Table 9: Regression output for price prediction on returns in the 30-minute interval after the trade. The regression run was of the form $PI_{d,t+N} = c + \beta_1 \Delta_{d,t} + \beta_2 \lambda_{d,t} + \beta_3 VOL_{d-1} + \beta_4 HP + \beta_5 HP_{init} + \beta_6 r_t + \varepsilon_t$. The variable HP is a dummy variable indicating whether the trade was a hot potato trade. HP$_{init}$ indicates that the trade is a hot potato initiating trade. Numbers in brackets denote t-statistics. Standard errors are Newey-West corrected standard errors. ***, ** and * respectively denote significance at 1%, 5% and 10% levels.

	MTS DK			MTS GE		
	2-4 Y	4-8 Y	8-12 Y	2-4 Y	4-8 Y	8-12 Y
Constant	0.0007 (0.5267)	0.0013 (0.6785)	-0.0019 (-0.9308)	0.0042*** (4.0652)	0.0077*** (5.4479)	0.0155*** (9.1801)
Bid-ask spread	0.1238*** (4.5340)	0.0627** (2.3661)	0.1561*** (3.5109)	0.0036 (0.1158)	0.0734* (1.6443)	-0.0079 (-0.2214)
Kyle λ	0.6294*** (10.0631)	0.6718*** (16.2169)	0.6850*** (17.6461)	0.4630*** (6.8408)	0.3609*** (9.0404)	0.3951*** (9.9670)
Volatility	0.0598* (1.7663)	0.0177 (1.2018)	0.0149** (2.2964)	0.0284* (1.9504)	0.0057 (0.6283)	0.0043 (0.6633)
HP trade	-0.0029*** (-3.0575)	0.0003 (0.3356)	-0.0007 (-0.5674)	-0.0024*** (-3.8701)	-0.0058*** (-7.9788)	-0.0115*** (-7.1853)
HP initiating trade	-0.0010 (-1.1093)	0.0018 (0.9912)	-0.0022* (-1.7027)	0.0005 (0.3353)	-0.0007 (-0.3398)	-0.0035 (-0.8268)
No. Observations	2153	2067	3099	5748	4246	2361
R^2	0.514	0.507	0.476	0.270	0.232	0.165

Table 10: Regression output for price prediction on market-adjusted returns in the 1-minute interval after the trade. The regression run was of the form $PI_{d,t+N} = c + \beta_1 \Delta_{d,t} + \beta_2 \lambda_{d,t} + \beta_3 VOL_{d-1} + \beta_4 HP + \beta_5 HP_{init} + \varepsilon_t$. The variable HP is a dummy variable indicating whether the trade was a hot potato trade. HP$_{init}$ indicates that the trade is a hot potato initiating trade. Numbers in brackets denote t-statistics. Standard errors are Newey-West corrected standard errors. ***, ** and * respectively denote significance at 1%, 5% and 10% levels.

	MTS DK			MTS GE		
	2-4 Y	4-8 Y	8-12 Y	2-4 Y	4-8 Y	8-12 Y
Constant	0.0043	0.0045**	0.0027	0.0060***	0.0062***	0.0158***
	(1.3881)	(2.1058)	(1.0396)	(6.1156)	(5.0951)	(9.0551)
Bid-ask spread	0.2565***	0.0780**	0.1974***	-0.0338	0.0657*	0.0141
	(3.0719)	(2.1532)	(4.3876)	(-0.9167)	(1.6441)	(0.3755)
Kyle λ	0.2553***	0.5676***	0.4482***	0.4483***	0.3802***	0.3367***
	(2.8528)	(8.0053)	(6.7207)	(8.1905)	(7.8434)	(8.7869)
Volatility	0.0430	0.0227	0.0280**	0.0281	0.0190*	0.0067
	(0.9906)	(1.4066)	(2.3617)	(1.5181)	(1.9247)	(1.0497)
HP trade	-0.0029**	0.0007	-0.0019	-0.0033***	-0.0048***	-0.0101***
	(-2.2099)	(0.4593)	(-1.1004)	(-5.4191)	(-4.3624)	(-5.6078)
HP initiating trade	-0.0036***	0.0033	-0.0022	-0.0028*	-0.0022	-0.0069*
	(-2.4951)	(1.2885)	(-1.3947)	(-1.6345)	(-1.4324)	(-1.7969)
No. Observations	2149	2056	3003	5735	4157	2283
R^2	0.308	0.337	0.285	0.232	0.270	0.142

Table 11: Regression output for price prediction on market-adjusted returns in the 10-minute interval after the trade. The regression run was of the form $PI_{d,t+N} = c + \beta_1\Delta_{d,t} + \beta_2\lambda_{d,t} + \beta_3 VOL_{d-1} + \beta_4 HP + \beta_5 HP_{init} + \varepsilon_t$. The variable HP is a dummy variable indicating whether the trade was a hot potato trade. HP_{init} indicates that the trade is a hot potato initiating trade. Numbers in brackets denote t-statistics. Standard errors are Newey-West corrected standard errors. ***, ** and * respectively denote significance at 1%, 5% and 10% levels.

	MTS DK			MTS GE		
	2-4 Y	4-8 Y	8-12 Y	2-4 Y	4-8 Y	8-12 Y
Constant	0.0068**	0.0051***	0.0008	0.0067***	0.0057***	0.0164***
	(2.3248)	(2.5983)	(0.2891)	(6.4107)	(4.2347)	(8.1026)
Bid-ask spread	0.2301***	0.0889**	0.2465***	0.0044	0.1252***	0.0000
	(3.3029)	(2.2152)	(5.1512)	(0.0877)	(3.1712)	(0.0010)
Kyle λ	0.3433***	0.5434***	0.5340***	0.4837***	0.3048***	0.3588***
	(4.2033)	(7.6177)	(9.3311)	(11.1702)	(5.5130)	(9.7667)
Volatility	0.0848	0.0589**	0.0375***	-0.0061	0.0252*	0.0068
	(1.3580)	(2.3569)	(2.9138)	(-0.4542)	(1.8794)	(1.0187)
HP trade	-0.0044***	0.0010	-0.0016	-0.0025***	-0.0077***	-0.0073***
	(-2.4758)	(0.5866)	(-0.9249)	(-3.2588)	(-5.6922)	(-3.1737)
HP initiating trade	-0.0047***	0.0036	-0.0028	-0.0011	-0.0012	-0.0005
	(-2.5684)	(1.4046)	(-1.4392)	(-0.6837)	(-0.6887)	(-0.1545)
No. Observations	2051	1931	2649	5642	3869	1992
R^2	0.290	0.293	0.308	0.272	0.224	0.125

Table 12: Regression output for price prediction on market-adjusted returns in the 30-minute interval after the trade. The regression run was of the form $PI_{d,t+N} = c + \beta_1\Delta_{d,t} + \beta_2\lambda_{d,t} + \beta_3 VOL_{d-1} + \beta_4 HP + \beta_5 HP_{init} + \varepsilon_t$. The variable HP is a dummy variable indicating whether the trade was a hot potato trade. HP_{init} indicates that the trade is a hot potato initiating trade. Numbers in brackets denote t-statistics. Standard errors are Newey-West corrected standard errors. ***, ** and * respectively denote significance at 1%, 5% and 10% levels.