Applications of Financial High-Frequency Data

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Contents

Preface

With the hand-in of this thesis, I have now finished my Ph.D. studies at the University of Copenhagen and Danmarks Nationalbank. The thesis consists of three essays which can be read independently, involving applications of high-frequency data,. The two first papers follow a paper, Andersson, Overby, and Sebestyén (2009), that was started before the ph.d. at my stay in the ECB during 2004/2005, published during my ph.d. and involve the use of macroeconomic announcements. The third paper will hopefully be the first in a series of more classic market microstructure papers using a unique data set from the interdealer bond trading platform MTS.

1.1 Structure of the thesis

The first essay, "*Extracting Market Expectations on Macroeconomic Announcements from Bond Prices*", looks at what happens just prior to a macroeconomic release coming to the market. A larger literature has described the impact of macroeconomic announcements, but not much attention has been given on the price movements prior to a macroeconomic release. In this essay we develop a simple market microstructure model, which links price movements prior to release in US and Euro Area bond markets with expectation adjustments about the upcoming release. This is tested and some signs of price adjustments are found and some predictability in whether the release surprises negatively or positively is found.

The second essay, "*Asymmetric Responses in Bond Risk Premia to News*", also considers macroeconomic announcements, but the focus is on the response in the bond risk premia. Previous papers has used affine term structure models to extract risk premia. This approach becomes prohibitively slow and uncertain, when using intraday data. As an alternative to this, we propose a different approach, where we use changes in the monetary policy path up to 12 months as a proxy for the fundamental response in the yield curve. As a result of this identification scheme, we find that the larger absolute response to positive news is linked with an asymmetric risk premia response.

The third and final essay, "*Liquidity and Information in Interdealer Markets: A Study of Hot-potato Trading in the European Bond Market*", looks at a particular form of hedging behavior, namely hot potato trading. Hot potato trading typically takes place in markets with mandatory price setting, such as market maker arrangements, where market makers pass on unwanted positions to other market makers. The paper is the first to provide an empirical examination of the issue. A detailed description of the phenomenon is provided based on data from the German and Danish bond market, 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 distinguish between the informational content of the trades.

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It goes without saying, that all remaining errors are mine and that the views expressed in this thesis not necessarily reflect the views of Danmarks Nationalbank.

Essay 1

Extracting Market Expectations on Macroeconomic Announcements from Bond Prices

Abstract

Event studies measuring the impact of macroenomic announcements rely on surveys as a measure of market expectations. However, these survey measures are noisy indicators of actual market expectations as they are collected with a time lag and not among actual market participants. Based upon a Hellwig (1980) type market microstructure model, a market-based survey measure is proposed that takes into account orderflow/price movements prior to release in order to capture changes in market expectations. The model is tested on US and German 10-year bond futures contracts for 6 US and 2 German macroeconomic announcements and confirms the presence of expectation adjustments for the most important releases. Furthermore, the market-based survey measure captures the directionality of the surprise better than the standard Bloomberg survey measure.

Keywords: Macroeconomic announcements; price formation; market microstructure

JEL classification: E43, E44, G14

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Introduction

There are significant market price movements following the release of macroeconomic announcements across most major asset markets, where prices adjust to reflect the unanticipated news component in these releases. The use of accurate measures for market expectations, which per definition measure the anticipated news component, is therefore crucial in any study exploring the market impact of macroeconomic releases. The existing literature on macroeconomic announcements has traditionally measured the surprise content of a given release as the difference between the actual release and published survey expectations. However, these survey expectations are not perfect.

Gauging market expectations by static survey measures does seem prone to induce measurement errors for the unanticipated news component for at least two reasons. Firstly, the survey expectations are typically polled over several days before the announcement. Secondly, the typical respondents are the research units in the investment banks and other researchers, but rarely actual traders. Hence, any new information may not have been taken into account by all respondents and the expectation may differ between traders, who set the price, and market analysts. Consequently, the lack of survey expectations that are dynamically updated and conducted among actual traders may lead to differences between actual market expectations and survey measures.

This paper adopts a market-based expectation measure which is based on a theoretical market microstructure model. The model indicates that the information contained in the orderflow prior to release of macroeconomic announcements should be taken into account. Specifically, if financial market prices reflect additional information beyond what is contained in survey expectations, this is likely to be reflected in price movements prior to releases. These price movements may reflect expectation adjustments taking place.

The theoretical model allows a formalization of the linkages between price movements prior to and after announcement. In addition, two important testable implications of the theoretical model are derived. Firstly, it proposes a direct test of whether an expectations adjustment does take place. Secondly, a market-based expectation measure can be derived which can be compared with the survey measures.

The empirical evidence presented in this paper confirms that expectations adjustments are actually taking place. The price movements prior to release are statistically significant for the most important releases, i.e. the price movements do contain information about the upcoming release. In the US, announcements of non-farm payroll and the ISM manufacturing survey and in Germany, the IFO and ZEW indicators tend to experience significant price movements prior to release - indicating the presence of expectations adjustments. The fact that expectations adjustments can only be confirmed for the most important releases suggests that the costs related to information search therefore must exceed a minimum gain. The information search and active position taking thereby only appears to take place for the announcements with the highest profit potential.

The market-based expectation measure does not give lower forecast errors, but captures the directionality better. The market-based measure has some success of predicting the sign of the surprise component of the release. Hence, adopting a market-based measure appears to give more noisy measures, as these tend to over- and undershoot more often. The market-based measure nonetheless allows for dynamic updating of expectations among actual traders. All in all, the market-based measure outperforms static survey measures as directionality is captured somewhat better.

The structure of the paper is as follows. Section 2.1 takes a look at the related literature. In section 2.2, a standard theoretical market microstructure model along the lines of Hellwig (1980) explains how prices and expectations around macroeconomic announcements interact in a theoretical setting. Section 2.3 examines the issue empirically. Specifically section 2.3.1 discusses the data and the considerations about formulating a test that builds on the theoretical framework in section 2.2. Section 2.3.2 tests whether market prices contain information about the expectations of upcoming macroeconomic announcements. This is done in a standard event study model. In section 2.3.3 a measure for market-adjusted expectations for the macroeconomic announcements is derived and forecast errors are compared with standard survey expectation measures. Section 2.4 concludes.

2.1 Related literature

The event studies on macroeconomic releases, such as Andersen and Bollerslev (1997), Andersen, Bollerslev, Diebold, and Vega (2003) and Fleming and Remolona (1999), all find significant market reactions to macroeconomic releases. However, as Rigobon and Sack (2006) note, the response coefficients appear rather small and only to a lesser extent explain the market movements around releases. This suggests that other factors around releases are at play.

Rigobon and Sack (2006) explain this by poor survey quality data, which can be attributed to issues such as time lag and surveys being analyst expectations rather than market participant expectations. In addition they note that the "true" macroeconomic news in a given release is not necessarily given by actual releases, as actual releases are noisy signals of the underlying news.

The explanation of Rigobon and Sack (2006) is in part examined by Campbell and Sharpe (2007) who show that behavioral biases may exist in surveys. Specifically they show that surveys are centered around the actual release of the previous month and that this anchoring bias in some cases results in sizable forecast errors. Hence, they confirm the poor survey quality.

Gürkaynak and Wolfers (2007) consider improved expectation measures. They use the market for macroeconomic derivatives to derive measures of market expectations and show that macroeconomic derivatives provide more accurate estimates of actual market outcomes. This also confirms the apparent shortcomings of existing survey measures.

A more theoretically appealing approach is given in Hautsch and Hess (2007) and Hautsch, Hess, and Müller (2007). They find that the price impact is significantly stronger with higher-precision information, as predicted by Bayesian learning models, on applications on US employment announcements. They show this by including a richer information set and hence improve the differing value/precision of the individual release. Consequently, they show that additional information beyond the actual release probably also plays an important role.

In a similar Bayesian spirit Andersson, Ejsing, and von Landesberger (2007) use the information content of previously announced, but related releases, extracted through Kalman filtering, to derive more precise expectation measures. They consequently show the importance of learning from previous releases.

This paper also implements a Bayesian motivated approach by adopting a standard market microstructure approach. However, the approach differs in one important aspect. Instead of using a richer information set, for instance from similar announcements, this paper uses the information contained in prices.

2.2 Model

The interaction between price movements before and after announcement releases can be illustrated in a standard market microstructure model, in which prices reflect information conveyed by the trade actions of informed investors. The model is specified to resemble the typical econometric set-up used in macroeconomic event studies. Consequently the empirical results later in this paper can be directly linked to the theoretical model implications.

The chosen specification originates from Hellwig (1980), the exact implementation is however based on Vives (2008). Some modifications have been introduced to the model in order to better capture the pricing mechanics surrounding macroeconomic releases.

The model builds on market efficiency principles as the trade actions of investors in part or fully reveal their private information. However, the model departs from the majority of market microstructure models in one crucial assumption. The market expectations of the outcome of the macroeconomic release are based on a linear updating rule instead of using the conventional approach of conditional expectations. This implies that the expectations of the market participants may not be fully rational, but capture noise in their expectation formation. The use of a plausible linear updating rule for expectations introduces correlation between market expectations and the actual realization of the macroeconomic release.

We consider a two-period model with a single risky asset and a riskless and interest free borrowing/lending asset, with rational investors and noise traders. There is a continuum of investors indexed in the interval $i \in [0, 1]$ with CARA-type utility functions, $U(\pi_i) = -\exp^{-\rho\pi_i}$, that participate in the market together with noise traders.

The investors utility is a function of profits, $\pi_i = (p_t - p_{t-1})x_i$, which naturally depends on prices p_{t-1} and p_t in respectively the first period, $t-1$, and the second period, t, in addition to their position in the risky asset x_i. As usual, $\rho > 0$ is the constant risk aversion coefficient. The noise traders demand a stochastic amount u of the risky asset, where $u \sim N(0, 1/\tau_u)$.

In the first period, $t-1$, the outcome of some event ζ is realized, for our purposes a macroeconomic release, but not made publicly available before period t. We assume $\zeta \sim N(\bar{v}, 1/\tau_\zeta)$, where we may informally call $\bar{v}$ the survey expectation which is the a priori or unconditional expectation about the event. $1/\tau_\zeta$ is a measure of the uncertainty related to the outcome.

All investors receive private signals about the outcome of the event ζ at time $t-1$. Their signal, $s_i = \zeta + \varepsilon_i$ is a noisy measure of the actual outcome of ζ as $\varepsilon_i \sim N(0, 1/\tau_\varepsilon)$. τ_ε measures the precision of the signal. Based on the unconditional expectation and their private signals, the investors optimize their utility and thereby make their investment decision x_i.

At period t, the realization of ζ is announced and prices are determined. The pricing dynamic in this model is assumed to be given by

$$p_t = \alpha(\zeta - \tilde{v}). \tag{2.1}$$

The price depends on the non-anticipated information from the event ζ multiplied by some coefficient α - in macroeconomic event studies this coefficient is denoted the price impact coefficient. The anticipated information/market expectation is denoted by $\tilde{v}$, which may differ from the survey expectation $\bar{v}$. Note we have normalized prices of the intrinsic value of the asset to be 0 and solely let the price depend on the outcome of the event and market expectations. Prices can therefore be interpreted as returns, which will be done later in the empirical part.

The market expectation, $\tilde{v}$, is formulated in the form

$$\tilde{v} = \bar{v} + \beta(\zeta - \bar{v}). \tag{2.2}$$

The chosen specification of expectations is crucial for understanding the model. It states that market expectations are based on the survey expectation $\bar{v}$, but at the same time allows market expectations to be correlated with the actual outcome with some coefficient β.

Consider two extreme cases. Firstly, the case of $\beta = 0$ captures the case when the survey expectation includes all available information in the market, as we then obtain $\tilde{v} = \bar{v}$. Secondly, $\beta = 1$ captures the case of perfect forecast abilities as $\tilde{v} = \zeta$. It therefore seems reasonable to impose the restriction of $0 < \beta < 1$, which we will use later.

The specification, however, introduces the possibility of non-rationality in the expectation formation, as $\tilde{v}$ is not necessarily the conditional expectation of ζ. Nonetheless, the specification appears to be suited for capturing the market expectation as it seems to crudely capture the uncertainties related to the expectation formation process. The specification for the market expectation therefore appears to be a plausible approximation.

Finally we impose that aggregate supply should equal aggregate demand for the risky asset in a market clearing condition:

$$X = \int_0^1 x_i di + u = 0. \tag{2.3}$$

Theorem 1 *Given the model above, there is a unique Bayesian linear equilibrium characterized by conditions:*

$$(i)\ x_i = ap_{t-1} + b\left(s_i - \bar{v}\right),$$

$$(ii)\ p_{t-1} = \tfrac{1}{a}\left(b(\zeta - \bar{v}) + u\right).$$

where $a = \frac{\rho^{-1}\left(\tau_\zeta + b^2\tau_u + \tau_\varepsilon\right)}{1+\rho^{-2}\alpha^2(1-\beta)^2\tau_\varepsilon\tau_u}$ *and* $b = \rho^{-1}\alpha(1-\beta)\tau_\varepsilon$.

Proof. See appendix. ■

The theorem gives an explicit solution for the price dynamics at period $t-1$. This can be used to find the pricing dynamics after the announcement, i.e. at period t. To see this, note that (ii) from Theorem 1 can be re-written as

$$\zeta - \bar{v} = \frac{1}{b}\left(ap_{t-1} - u\right).$$

Inserting this into (2.2) gives

$$\tilde{v} = \bar{v} + \beta \frac{1}{b} \left(a p_{t-1} - u \right). \tag{2.4}$$

Finally substitute this into (2.1) to obtain

$$p_t = \alpha \left(\zeta - \bar{v} \right) - \frac{\alpha\beta}{b} \left(a p_{t-1} - u \right). \tag{2.5}$$

This shows that the pricing dynamics following the announcement are determined by two factors. Firstly, there is an impact from the deviation from the survey expectation. Secondly, there is a component related to the updating of expectations, which is revealed through prices, but blurred by the noise trading shock. Hence, the second term capture the market impact of investors, as prices change to reflect their expectations.

The model has some testable implications, which will be considered in the following section. For this use, the following lemma is useful.

Lemma 2 *For $\alpha < 0$ and $0 < \beta < 1$ then $a > 0$ and $b < 0$.*
Proof. *See appendix.* ■

The assumption of $\alpha < 0$ in Lemma 2 is consistent with empirical observations from the bond market, as documented later in this paper. For instance a stronger-than-expected GDP report is likely to make market participants revise up their expectations for future growth and induce higher bond yields, thereby causing negative bond market returns. For $\alpha < 0$, we observe that $b < 0$ and $a > 0$, hence the expectation adjustment term, the second term in (2.5), is negative as $-\frac{\alpha\beta a}{b} < 0$.

The negative expectation adjustment term implies a negative relationship between prices after and before the announcement of ζ, when adjusting for the impact of the surprise. For instance, in the case of a better-than-expected outcome compared to survey expectations, that is $\zeta - \bar{v} > 0$, we should observe decreasing prices prior to release, i.e. $p_{t-1} < 0$, in anticipation of this outcome. The implication of a negative relationship between prices before and after release, when adjusting for the surprise as measured by the deviation from the survey expectation, is testable. This is done in the following section.

2.3 Econometric framework

Two important implications can be drawn from the model, which is important to our empirical study. Firstly, a negative and significant coefficient on the price change prior to the release of a given macroeconomic announcement in a regression along the lines of (2.5) is consistent with the hypothesis of expectation adjustments. Secondly, by including price movements prior to release in order to capture expectation adjustments, a market based measure of market expectations for upcoming macroeconomic releases can be derived. Using high-frequency futures contract data from US and Euro Area long-term bond markets, a standard event study model built upon (2.5) is implemented.

The theoretical model does, however, leave two important answers unsolved, even if the implications of the model are taken at face value. Firstly, the length of the intraday periods to be used are not indicated. In this paper the 5-minute return after release of the announcement and the 10-, 15-, 30- and 60-minute intervals prior to release are considered. The 5-minute interval after release has in previous studies, as for instance Andersen, Bollerslev, Diebold, and Vega (2003), been found to be adequate for measuring the market reaction.

The chosen 10-, 15-, 30- and 60-minute intervals prior to release capture the period in which private information is disseminated into prices. The considered intervals may be considered relatively short windows, but, using longer windows implies the risk of incorporating the impact from other events. Furthermore, it is plausible that only investors with superior information or forecasting skills, who are so to speak, placing their bets on a specific outcome, are likely to trade shortly prior to announcement and the price impact is likely to be largest in this relatively short interval. Therefore, it is on the one hand very likely that some investors have put on positions prior to the considered time interval, which are not incorporated into the considered priceflow, but on the other hand, those actually putting on a position are likely to have information and give a clear signal. The chosen interval size is therefore a trade-off between having a clear signal and extracting most possible information.

Secondly, it must be kept in mind that it is a well-known fact in the literature that high-frequency return series are negatively correlated. Roll (1984) shows that the bid-ask bounce may induce this behavior. Therefore, the negative correlation may not only arise from the re-pricing of market expectations but also from the bid-ask bounce. The empirical implementation therefore has to disentangle the effects from market microstructure noise and re-pricing of market expectations. In order to separately identify the re-pricing of market expectations I compare return dynamics around announcements with those in the absence of announcements. In the final part of the paper, a market-based expectation measure is derived, based on the estimations of the event study model. Forecast errors of the market based expectation measure are compared with standard survey measures.

2.3.1 Data

Data from US and German bond markets are used, as bond market data appear to be most receptive to economic news. In principle, data from the equity market and the foreign exchange markets could be used as well. However, as regards the equity market, macroeconomic news may have an ambiguous effect on equity prices and the impact of macroeconomic news may therefore not be obvious. For instance, a better-than-expected GDP report may, on the one hand, lead to more positive growth prospects for companies. On the other hand, this also induces higher bond yields, which lowers the net present value of companies future cash flows and increases the borrowing costs of companies. Similarly, but less restrictive, is the impact on foreign exchange markets, where some sort of ambiguity may also exist. A strong US number is likely to have the opposite effect compared to a strong euro area release on the EURUSD exchange rate. As we consider both US and German macroeconomic announcements, the analysis is restricted to bond markets.

We use bond market futures data which has the fastest price discovery and most liquidity, see for instance Upper and Werner (2006). The data set consists of prices on leading bond futures contracts in the US and the euro area at 10-year maturities. The data is provided by TickData Inc and covers the period July 2003 - March 2008.

The macroeconomic data predominantly covers important US macroeconomic releases, see for instance the selection by Bartolini, Goldberg, and Sacarny (2008), and in addition to two important German survey indicators, which are found to have importance for euro area bond market developments in Andersson, Overby, and Sebestyén (2009). We use the following eight monthly macroeconomic announcements: US non-farm payroll, US CPI (MoM), US industrial production, US ISM manufacturing confidence, US ISM non-manufacturing confidence, US Retail Sales, GE IFO business sentiment indicator and GE ZEW indicator.[1] The announcement data, both the actual release and survey expectations, is collected from Bloomberg.

2.3.2 Testing for pre-announcement market reactions

The theoretical model implies that expectation adjustments should be tested in a regression of the form:

$$r_t = \hat{\gamma} r_{t-1} + \hat{\alpha}(\zeta - \bar{v}) + \varepsilon_t, \tag{2.6}$$

where r_t is returns after the announcement, ζ is the announcement, and $\bar{v}$ is the survey-based market expectation, i.e. $\zeta - \bar{v}$ measures the surprise content of the announcement. Significance of the $\hat{\gamma}$ parameter hence indicates that some expectation adjustment does take place, as market movements prior to release has information content. It is not possible to identify the parameters of the theoretical model, hence we do not perform a structural estimation. Compared to the theoretical model, the $\hat{\gamma}$ parameter corresponds to $\frac{\alpha\beta}{b}a$, where we can only identify α.

One possibility is to adopt the approach of Andersen, Bollerslev, Diebold, and Vega (2003)[2] where all intraday returns, not only those around macroeconomic announcements, are modelled. Their approach is very suited for capturing intraday volatility patterns. However, as we are not particularly interested in intraday

[1] Originally a slightly larger set of releases was considered. However, the GDP Advance and the Chicago PMI releases were not included in the final results. The GDP Advance is only released quarterly and hence only 18 observations were available in the considered sample. Chicago PMI is according to market participants made available to subscribers prior to release, which also appears to be confirmed in the data, as most of the market reaction appears to take place prior to release.

[2] For adoptions of their approach, see for instance Andersson, Overby, and Sebestyén (2009) for an application on German bond market data, Sebestyén (2006) on money market announcements and Fatum and Pedersen (2009) for measuring the impact of F/X interventions.

volatility patterns, we utilize that macroeconomic announcements are announced at pre-specified times, for instance 08.30 EST, and only examine returns on announcement and non-announcement days around the release time.[3]

The event study approach is more simplistic, but still accounts for structural patterns around release time on non-announcement days, for instance induced by market microstructure noise. The regressions are performed individually for each announcement for 4 different return intervals prior to release, i.e. 10-, 15-, 30- and 60-minute returns. The length of the return after release is, as earlier mentioned, kept constant at 5 minutes.

The conditional mean regression for each of the 8 macroeconomic announcements, denoted by k =CPI, Industrial Production, ISM manufacturing Survey, ISM non-manufacturing Survey Non Farm Payroll, Retail Sales, IFO and ZEW, is specified as

$$r_t = \alpha_0 + \gamma_k \tilde{r}^N_{t-1} + \gamma^{EA}_k D_k \tilde{r}^N_{t-1} + \alpha^{MA}_k (\zeta^k_t - \bar{v}^k_t) + \varepsilon_t, \tag{2.7}$$

where the 5-minute bond return after release[4], r_t, is regressed on a *constant*; the lagged N =10-, 15-, 30- and 60-*minute return* $\tilde{r}^N_{t-1}$; the *return prior to announcements* as D_k is a dummy taking the value 1 when announcement k is released in order to account for expectation adjustments and the *surprise* $\zeta^k_t - \bar{v}^k_t$ of the considered announcement. This specification allows us to disentangle the effects of the bid-ask bounce, which is accounted for by γ_k, as this coefficient will be estimated on information from all days, i.e. both announcement and non-announcement days.

It is well known that volatility in financial returns is time-varying and increases around macroeconomic announcements. To account for these effects, a conditional volatility equation is fitted as well. The conditional volatility equation is specified with a GARCH(1,1) process amended with a dummy indicating whether an announcement took place.[5]

[3]In order to exclude the impact from other announcements, days with other announcements than the 8 announcements considered in this paper are also removed. In addition, two days with FOMC intermeeting rate cuts are removed.

[4]Returns are calculated from 1 minute before release to 4 minutes after release. This is to avoid discrepancies in the time measurement between the announcement and price data.

[5]The GARCH specification is unusual, as the daily volatility only relates to the volatility

$$\sigma_t^2 = \beta_o + \beta \varepsilon_{t-1}^2 + \beta_2 \sigma_{t-1}^2 + \beta_3 D_k. \tag{2.8}$$

In the conditional mean equation, γ_k measures the microstructure noise from the previous period, γ_k^{EA} measures the expectation adjustment and α_k^{MA} measures the contemporaneous impact coefficient. Hence a negative and significant γ_k^{EA} coefficient is supportive of some sort of expectation adjustment taking place.

The results are shown in the tables below for the German Bunds and the T-note futures contracts. For brevity only the test results for γ_k^{EA} are shown. The full estimation results for the two markets and 8 announcements are given in Appendix A.

Several features can be noted from Tables 1 and 2. The results show that for some macroeconomic releases, we do observe a statistical significant market adjustment prior to release. Hence the hypothesis of price movements signalling true market expectations appears to be well supported for some, but not all macroeconomic announcements. There are significantly negative γ_k^{EA} parameters for non-farm payroll and ISM Management and the German ZEW indicator from the US and German bond market data, and also for the IFO indicator in the German data. In addition, the coefficients are generally negative, albeit insignificantly, for most other releases. All in all, financial prices therefore do exhibit signs of expectations adjustment prior to the release of macroeconomic releases.

The strongest signs of expectations adjustment appears in the 10- and 15-minute intervals. The γ_k^{EA} coefficients tend to decrease, when extending the event window, which appears to suggest that the closer the release is, the more likely the trades are to reflect some information about the upcoming release. Extending the prior return window seems to decrease the release-related trading and introduces more noise.

The magnitude of the coefficients also deserves some attention, as these suggest that some sort of price reversal is taking place. The significant coefficients are mostly statistically indistinguishable from -1, which suggests that any prior price movements are simply reversed subsequently after the release, when taking into

around the announcement time, such as 08.30 EST. Other volatility specifications have been attempted, such as a constant volatility with a dummy for announcement days. Results are robust to this specification.

	γ_k^{EA}			
	10-minute	15-minute	30-minute	60-minute
CPI	0.3693	-0.4279	-0.3825	0.2963
	(0.4412)	*(0.4250)*	*(0.3953)*	*(0.2826)*
Ind. Prod.	-0.0349	-0.1360	0.0591	0.0102
	(0.1709)	*(0.1121)*	*(0.0955)*	*(0.0572)*
ISM Man.	-0.6535*	-0.1544	-0.6139***	-0.1454
	(0.3599)	*(0.3279)*	*(0.1739)*	*(0.1873)*
ISM Non-Man.	-0.1192	-0.1012	-0.0879	-0.1187
	(0.2421)	*(0.2315)*	*(0.1154)*	*(0.1006)*
Non-farm payroll	-1.4065***	-1.1396***	-1.0712***	-0.8921***
	(0.2347)	*(0.2160)*	*(0.2068)*	*(0.2883)*
Retail Sales	-0.1255	-0.2270	-0.0076	-0.0104
	(0.5921)	*(0.4425)*	*(0.3061)*	*(0.2152)*
IFO (GE)	-1.2399***	-0.9802**	-0.7288**	-0.4900**
	(0.4349)	*(0.4093)*	*(0.3200)*	*(0.2127)*
ZEW (GE)	-0.4829***	-0.4685***	-0.2450	-0.0773
	(0.1660)	*(0.1453)*	*(0.1426)*	*(0.1000)*

Table 2.1: Test of expectations adjustments taking place prior to release for 8 macroeconomic announcements based on the German Bunds futures contract. The table shows the γ^{EA} parameter for each of the announcements, estimated using N=10-, 15-, 30- and 60-minute return intervals prior to announcement on the German Bunds futures contract. The hypothesis of expectations adjustments corresponds to a significantly negative γ^{EA} parameter in the conditional mean, which is estimated for each announcement as $r_t = a_0 + \gamma_k \tilde{r}_{t-1} + \gamma_k^{EA} D_k \tilde{r}_{t-1} + \alpha_k^{MA}(\zeta_t^k - v_t^k) + u_t$. r_t is the 5-minute return after release of the announcement, $\tilde{r}_{t-1}$ is the N-minute return before release and $(\zeta_t^k - v_t^k)$ is the surprise of the announcement. Full estimation results can be found in the appendix. Bollerslev-Wooldridge robust standard errors are reported in parentheses. *, ** and *** denote significance at respectively the 10%, 5% and 1% level.

the account the information conveyed to the market by the surprise. The impact of the expectations adjustment in some sense disappears, as the market response becomes lower (higher) when the surprise is in (out of) line with the prior price movement. For instance an increase in prices prior to release suggests a weaker macroeconimic announcement than suggested by survey expectations, which when realised causes the surprise to have a lower market impact. Such an effect may cause the omitted-variables bias suggested in Rigobon and Sack (2006).

Interestingly enough, the announcements that do exhibit signs of expectation adjustments, are the announcements for which market reactions, on average, tend to be the largest. Hence it may be hypothesized that market participants only engage in active position taking around the announcements which are likely to

	γ_k^{EA}			
	10-minute	15-minute	30-minute	60-minute
CPI	-0.2616	-0.6163	-0.4011	0.1158
	(0.6697)	*(0.5647)*	*(0.3623)*	*(0.2070)*
Ind. Prod.	-0.0319	-0.0486	0.1052	0.0431
	(0.1820)	*(0.1354)*	*(0.0946)*	*(0.0490)*
ISM Man.	-1.0313***	-0.7215***	-0.3541	-0.1406
	(0.3331)	*(0.0910)*	*(0.2097)*	*(0.1900)*
ISM Non-Man.	-0.0968	-0.0906	-0.2284*	-0.2136
	(0.2742)	*(0.1740)*	*(0.1198)*	*(0.1189)*
Non-farm payroll	-1.1739***	-1.1696***	-1.1798***	-1.0858***
	(0.3150)	*(0.3019)*	*(0.2611)*	*(0.3897)*
Retail Sales	-0.7940	-0.7075	-0.3478	-0.4403
	(0.5991)	*(0.5346)*	*(0.3564)*	*(0.2952)*
IFO (GE)	-0.3600	-0.0301	-0.1152	-0.0475
	(0.2219)	*(0.1654)*	*(0.1390)*	*(0.0742)*
ZEW (GE)	-0.4217***	-0.1979	-0.0490	-0.0273
	(0.1427)	*(0.1121)*	*(0.0860)*	*(0.0569)*

Table 2.2: Test of expectations adjustments taking place prior to release for 8 macroeconomic announcements based on the US T-note futures contract. The table shows the γ^{EA} parameter for each of the announcements, estimated using N=10-, 15-, 30- and 60-minute return intervals prior to announcement on the US T-note futures contract. The hypothesis of expectations adjustments corresponds to a significantly negative γ^{EA} parameter in the conditional mean, which is estimated for each announcement as $r_t = a_0 + \gamma_k \tilde{r}_{t-1} + \gamma_k^{EA} D_k \tilde{r}_{t-1} + \alpha_k^{MA}(\zeta_t^k - v_t^k) + u_t$. r_t is the 5-minute return after release of the announcement, $\tilde{r}_{t-1}$ is the N-minute return before release and $(\zeta_t^k - v_t^k)$ is the surprise of the announcement. Full estimation results can be found in the appendix. Bollerslev-Wooldridge robust standard errors are reported in parentheses. *, ** and *** denote significance at respectively the 10%, 5% and 1% level.

produce the largest price fluctuations, i.e. where the outcome of successful position taking is likely to lead to the biggest profits. It therefore appears that the costs related to forming independent expectations, such as information search, has to exceed some minimum gain.

Finally and not surprisingly, the information contained in bond prices on German announcements appears to be largest in the German bond market. However, the conclusion does not hold for US announcements. The information contained in US announcements, at least in terms of significance, appear to be almost the same in the German bond market data. This probably reflects the high importance of US announcements on German bond markets as discussed in Andersson, Overby, and Sebestyén (2009).

2.3.3 Extracting expectations

At least for some announcements there appear to be adjustments to market expectations. Obviously the adjusted market expectations are not directly observable, but it is possible to extract a market-adjusted expectation measure.

By re-arranging our conditional mean specification (2.7) we obtain

$$r_t = \alpha_0 + \gamma_k r_{t-1} + \alpha_k^{MA}\left(\zeta_t^k - \left(\bar{v}_t^k - \frac{\gamma_k^{EA}}{\alpha_k^{MA}} D_k r_{t-1}\right)\right) + \varepsilon_t, \qquad (2.9)$$

which gives an estimator for the market-adjusted expectation for announcement k at time t, $v_{market,t}^k = \bar{v}_t^k - \frac{\gamma_k^{EA}}{\alpha_k^{MA}} D_k r_{t-1}$. Note that this estimator corresponds to our theoretical estimate of the market-adjusted expectation, as $\frac{\gamma_k^{EA}}{\alpha_k^{MA}}$ is the empirical counterpart of $\frac{a\beta}{b}$ in (2.4) and hence appears a natural estimator for actual market expectations.

In order to compare the performance of respectively the market adjusted expectations measure, v_{market}^k, the standard Bloomberg survey expectations is compared in terms of its forecast error. The forecast error is measured as the absolute forecast deviation for the n announcements, i.e.

$$FE_k = \frac{1}{n} \sum_{t=1}^{n} \left|\zeta_t^k - v_t^k\right|$$

for announcement k with n announcements using respectively $v_t^k = v_{market,t}^k$ and $v_t^k = \bar{v}_t^k$ for the market-adjusted expectation and the Bloomberg survey. The forecasts errors are shown in Table 3.

A bit disappointingly the forecast errors in Table 3 show no convincing outperformance over the traditional Bloomberg survey measure. If there is any tendency in Table 3, then the forecast errors are either similar or even higher for most US announcements. Not even the variables, which came out significant in our earlier test, exhibit any meaningful outperformance. Both the ISM Management Survey and the very important non-farm payroll release fare slightly worse. For the German releases, the market expectation measure fare slightly better, at least based on the German bond market data. Therefore, at first glance, the information of the informed traders does appear limited.

	Bloomberg	Bunds				T-notes			
		10-minute	15-minute	30-minute	60-minute	10-minute	15-minute	30-minute	60-minute
CPI	0.0010	0.0034	0.0011	0.0011	0.0015	0.0011	0.0012	0.0011	0.0011
Ind. Prod.	0.0025	0.0025	0.0027	0.0026	0.0025	0.0025	0.0025	0.0026	0.0026
ISM Man.	1.4373	1.5418	1.4334	**1.6753**	1.4342	**1.6975**	**1.5356**	1.4822	1.4822
ISM Non-Man.	2.5093	2.5047	2.5021	2.5239	2.5424	2.4851	2.4957	2.4936	2.4936
Non-farm payroll	**61.5283**	**62.9793**	**63.9185**	**64.5375**	**64.8844**	**61.1402**	**61.6214**	**62.3499**	**62.3499**
Retail Sales	0.0032	0.0032	0.0032	0.0032	0.0032	0.0035	0.0035	0.0031	0.0031
IFO (GE)	0.9179	**0.8576**	**0.9071**	**0.9205**	**0.9260**	0.9158	0.9085	0.9347	0.9347
ZEW (GE)	6.4667	**6.2163**	**6.1792**	6.2832	6.3615	**6.9133**	6.3695	6.2566	6.2566

Table 2.3: Forecast errors of the market-adjusted expectation and Bloomberg survey measures. The forecast error is measured as the absolute average forecast deviation.

	Bunds				T-notes			
	10-minute	15-minute	30-minute	60-minute	10-minute	15-minute	30-minute	60-minute
CPI	0.43	0.38	0.42	0.26	0.41	0.36	0.40	0.33
Ind. Prod.	0.41	0.44	0.49	0.33	0.51	0.48	0.43	0.35
ISM Man.	0.49	0.52	**0.48**	0.53	**0.54**	**0.60**	0.58	0.54
ISM Non-Man.	0.48	0.48	0.50	0.44	0.55	0.46	0.53	0.51
Non-farm Payroll	**0.53**	**0.57**	**0.49**	**0.53**	**0.52**	**0.54**	**0.50**	**0.50**
Retail Sales	0.45	0.55	0.26	0.33	0.51	0.53	0.60	0.63
IFO (GE)	**0.60**	**0.52**	**0.54**	**0.57**	0.55	0.49	0.42	0.42
ZEW (GE)	**0.54**	**0.60**	0.57	0.61	**0.53**	0.54	0.55	0.64

Table 2.4: Hit ratio of the market-adjusted expectation and Bloomberg survey measures. The hit ratio is defined as the share of sucessful hits, i.e. better directional forecasts than the Bloomberg survey measure.

However, the objective of the market investor is not, perhaps a bit surprisingly, to obtain low forecast errors. The investor is rather concerned about getting the directionality in the surprise correctly, i.e. whether the given release was above or below consensus. As noted earlier a positive surprise is linked with negative returns and vice versa for negative surprises. Hence having made a larger forecast error is not important, as long as the investor captured whether the release was above or below consensus. In other words, the success or hit ratio for the forecast is of interest.

The hit ratio is measured as

$$H = \frac{1}{n}\sum_{i=1}^{n}\left(\mathbf{1}_{\left\{\left(\bar{v}_i^k - v_{market,i}^k\right)>0 \wedge \left(\zeta_i^k - \bar{v}_i^k\right)<0\right\}} + \mathbf{1}_{\left\{\left(\bar{v}_i^k - v_{marke,it}^k\right)<0 \wedge \left(\zeta_i^k - \bar{v}_i^k\right)>0\right\}}\right)$$

The hit ratio consequently counts the total share of 'hits', i.e. where the market-adjusted expectation measure indicated a higher or similar release compared to the Bloomberg measure and the release actually surprised positively and similarly where the expectation measure indicated a lower number and the release surprised negatively, out of the total number of announcements. The results of this is reported in Table 4.

The results in Table 4 show that the hit-ratio is above 50 per cent in almost all cases where we previously found signs of expectations adjustments. The forecast error may be higher, but the market on average gets the directionality of their forecast correctly. Therefore, as seen from the perspective of an investor, their forecasting skills are above average.

It appears that the market-adjusted expectation measure often tends to under- or overshoot, even though the directionality more often is correct. Therefore market participants' forecasting skills appear better than the Bloomberg measure, but with a strong tendency to under- or overshoot

2.4 Concluding remarks

There are clear indications from the analysis that markets adjust prices prior to releases, in the sense of an expectations adjustment. The chosen approach of using information from price movements at 10-, 15-, 30- and 60-minute intervals prior to release to supplement existing survey measures therefore appears justified. Markets appear to adjust prices to reflect true market expectations and the market-based measure therefore appears superior compared to static survey measures.

The estimations are theoretically underpinned and offer a simple solution for obtaining improved expectation measures. The paper therefore demonstrates the soundness of a market microstructure based approach and demonstrates an economically justified method of extracting information. The approach is rather general and may be extended to improve survey measures to for instances market expectations about earnings releases in equity markets.

The econometric analysis suggests four important implications. Firstly, the analysis, as could be expected, that domestic markets contain most information about domestic releases, although US releases do appear to impact German/European bond markets almost in equal effect. This result does confirm the worldwide importance of US announcements.

Secondly, announcements that have the highest market impact are also those that exhibit the strongest degree of expectations adjustment. It therefore appears that investors do demand some sort of minimum return in order to engage in individual information collection.

Thirdly, measures of expectation adjustment increase in precision as the announcement gets closer. The precision of the expectations adjustment therefore appears the highest relatively close to the announcement, as those trades entered at that time do appear to have the highest information content about the upcoming release.

Finally, the forecast errors of the market-adjusted expectation measure is not improved, but it does appear to be somewhat better at capturing the directionality of the surprise, i.e. whether the release surprises positively or negatively. Consequently, the market-adjusted measure does seem to outperform standard survey measures.

Appendix: Proof of Theorem 1

Proof of Theorem 1

We assume that the informed investors follow a linear strategy of the type $X = -ap_{t-1} + b(s_i - \bar{v})$. We then insert the linear strategy in the market clearing condition (2.3) and solve for p_{t-1} and obtain

$$p_{t-1} = \frac{1}{a}\left(b(\zeta - \bar{v}) + u\right), \tag{2.10}$$

where we have used that $\int_0^\omega s_i di = \zeta$. This gives us (ii).

Optimizing the investor's CARA utility function with respect to x_i, gives

$$x_i = \rho^{-1}\frac{\mathrm{E}[p_t|p_{t-1}, s_i] - p_{t-1}}{\mathrm{Var}[p_t|p_{t-1}, s_i]}. \tag{2.11}$$

We define $\hat{p}_{t-1} = \frac{a}{b}p_{t-1} + \bar{v}$, hence $\hat{p}_{t-1} = \zeta + \frac{1}{b}u$. We now note that

$$E[p_t|p_{t-1}, s_i] = E[p_t|\hat{p}_{t-1}, s_i].$$

Inserting the expression in (2.10) and the expression for $\hat{p}_{t-1}$ we obtain

$$\begin{aligned} E[p_t|\hat{p}_{t-1}, s_i] &= E[\alpha(1-\beta)(\zeta - \bar{v})|\zeta + \frac{1}{b}u, \zeta + \varepsilon_i] \\ &= \alpha(1-\beta)\left(E[\zeta|\zeta + \frac{1}{b}u, \zeta + \varepsilon_i] - \bar{v}\right) \\ &= \alpha(1-\beta)\left(\frac{\tau_\zeta\bar{v} + b^2\tau_u\hat{p}_{t-1} + \tau_\varepsilon s_i}{\tau_\zeta + b^2\tau_u + \tau_\varepsilon} - \bar{v}\right) \end{aligned}$$

In the final line we use Bayes formula. Then we substitute the expression for $\hat{p}_{t-1}$ and find that

$$\begin{aligned} E[p_t|p_{t-1}, s_i] &= \alpha(1-\beta)\frac{\tau_\zeta\bar{v} + b^2\tau_u\left(\frac{a}{b}p_{t-1} + \bar{v}\right) + \tau_\varepsilon s_i - \left(\tau_\zeta + b^2\tau_u + \tau_\varepsilon\right)\bar{v}}{\tau_\zeta + b^2\tau_u + \tau_\varepsilon} \\ &= \alpha(1-\beta)\frac{\left(\tau_\zeta + b^2\tau_u\right)\bar{v} + ab\tau_u p_{t-1} + \tau_\varepsilon s_i - \left(\tau_\zeta + b^2\tau_u + \tau_\varepsilon\right)\bar{v}}{\tau_\zeta + b^2\tau_u + \tau_\varepsilon} \\ &= \alpha(1-\beta)\frac{ab\tau_u p_{t-1} + \tau_\varepsilon(s_i - \bar{v})}{\tau_\zeta + b^2\tau_u + \tau_\varepsilon} \end{aligned}$$

Similarly we find that $Var[p_t|p_{t-1}] = \tau_\zeta + b^2\tau_u + \tau_\varepsilon$.

Inserting these expressions into (2.11) gives us

$$\begin{aligned} x_i &= \rho^{-1}\left(\tau_\zeta + b^2\tau_u + \tau_\varepsilon\right)^{-1}\left(\alpha(1-\beta)\frac{ab\tau_u p_{t-1} + \tau_\varepsilon(s_i - \bar{v})}{\tau_\zeta + b^2\tau_u + \tau_\varepsilon} - p_{t-1}\right) \\ &= \rho^{-1}\left(\alpha(1-\beta)\left(ab\tau_u p_{t-1} + \tau_\varepsilon(s_i - \bar{v})\right) - \left(\tau_\zeta + b^2\tau_u + \tau_\varepsilon\right)p_{t-1}\right) \end{aligned}$$

This indicates directly that $b = \rho^{-1}\alpha(1-\beta)\tau_\varepsilon$. It also follows that for $\rho > 0$, $0 < \beta < 1$, $\alpha < 0$ and positive variance $\tau_\varepsilon > 0$ we obtain $b < 0$.

In addition we get

$$a = -\rho^{-1}\left(\alpha(1-\beta)ab\tau_u - \left(\tau_\zeta + b^2\tau_u + \tau_\varepsilon\right)\right)$$

which, using the expression for b, can be re-arranged to

$$a = \frac{\rho^{-1}\left(\tau_\zeta + b^2\tau_u + \tau_\varepsilon\right)}{1 + \rho^{-2}\alpha^2(1-\beta)^2\tau_\varepsilon\tau_u}$$

Again noting that for $\rho > 0$ and positive variances $\tau_\varepsilon, \tau_\zeta, \tau_u > 0$, we obtain $a > 0$. The expressions of a and b gives us (i), which concludes the proof. ∎

2.5 Appendix: Tables

	CPI	**Ind. Prod**	**ISM Man.**	**ISM Non-Man.**	**Non Farm Payroll**	**Retail Sales**	**IFO (GE)**	**ZEW (GE)**
	Conditional Mean Equation							
α_0	0.0056	-0.0311	0.2409**	0.1853	-0.0027	-0.0646	-0.0558	0.1467**
	(0.0558)	*(0.0728)*	*(0.1135)*	*(0.1128)*	*(0.0880)*	*(0.0884)*	*(0.0630)*	*(0.0626)*
γ	-0.0643*	-0.0280	-0.0448	-0.0390	-0.0525	-0.0530	-0.0303	-0.0841***
	(0.0345)	*(0.0264)*	*(0.0331)*	*(0.0337)*	*(0.0356)*	*(0.0317)*	*(0.0283)*	*(0.0333)*
γ^{EA}	0.3693	-0.0349	-0.6535*	-0.1192	-1.4065***	-0.1255	-1.2399***	-0.4829***
	(0.4412)	*(0.1709)*	*(0.3599)*	*(0.2421)*	*(0.2347)*	*(0.5921)*	*(0.4349)*	*(0.1660)*
α^{MA}	-257.6143	-720.7528***	-2.8229***	-1.1666***	-0.2776***	-915.8615***	-6.4119***	-0.6343***
	(908.0982)	*(207.2484)*	*(0.3760)*	*(0.1875)*	*(0.0225)*	*(157.5098)*	*(0.8698)*	*(0.0625)*
	Conditional Volatility Equation							
β_0	4.8212***	3.4030	10.0485***	3.8737***	4.8007***	7.8104***	4.5878***	-0.2137***
	(0.0859)	*(2.0433)*	*(1.3768)*	*(1.3291)*	*(0.3837)*	*(1.3703)*	*(0.3557)*	*(0.0428)*
β_1	-0.0084***	-0.0122	-0.0214**	0.0124	0.0017	-0.0256	0.0202	-0.0139***
	(0.0011)	*(0.0072)*	*(0.0099)*	*(0.0267)*	*(0.0037)*	*(0.0340)*	*(0.0179)*	*(0.0036)*
β_2	-0.0075	0.4508	-0.0311	0.5745***	-0.0091*	0.5285***	-0.0194	1.0027***
	(0.0045)	*(0.3256)*	*(0.1072)*	*(0.1295)*	*(0.0047)*	*(0.0975)*	*(0.0254)*	*(0.0038)*
β_3	87.1949***	10.2789***	22.9786***	2.6741	202.9726***	1.3006	37.6372***	5.2421***
	(14.8918)	*(3.0917)*	*(7.3220)*	*(2.6323)*	*(39.0083)*	*(12.5883)*	*(8.6485)*	*(0.7393)*
R^2	0.0126	0.0321	0.1694	0.1058	0.6618	0.1306	0.2624	0.1828
No. observations	642	1214	770	773	641	643	1188	1113
No. announcements	54	55	51	54	53	55	56	57

Table 2.5: Estimation results for 8 macroeconomic announcements on the German Bunds futures contract using 10-minute prior return intervals. The conditional mean is for each announcement estimated as $r_t = a_0 + \gamma_k \tilde{r}_{t-1} + \gamma_k^{EA} D_k \tilde{r}_{t-1} + \alpha_k^{MA}(\zeta_t^k - v_t^k) + u_t$, where r_t is the 5-minute return after release of the announcement, $\tilde{r}_{t-1}$ is the 10-minute return before release and $(\zeta_t^k - v_t^k)$ is the surprise of the announcement. The conditional volatility is specified as a GARCH(1,1) augmented with a dummy indicating whether the announcement was released in this period, i.e. $\sigma_t^2 = \beta_0 + \beta_1 u_{t-1}^2 + \beta_2 \sigma_{t-1}^2 + \beta_3 D_k$. The hypothesis of expectations adjustments corresponds to a significantly negative γ^{EA} parameter. Bollerslev-Wooldridge robust standard errors are reported in parentheses. *, ** and *** denote significance at respectively the 10%, 5% and 1% level.

	CPI	**Ind. Prod**	**ISM Man.**	**ISM Non-Man.**	**Non Farm Payroll**	**Retail Sales**	**IFO (GE)**	**ZEW (GE)**
				Conditional Mean Equation				
α_0	-0.3222**	0.0260	0.1683	0.2183	-0.3301**	-0.3330**	0.0070	0.0515
	(0.1360)	*(0.0956)*	*(0.1326)*	*(0.1448)*	*(0.1375)*	*(0.1356)*	*(0.0457)*	*(0.0492)*
γ	-0.0775**	-0.0023	-0.0324	-0.0347	-0.0739**	-0.0782**	-0.0800***	-0.0989**
	(0.0345)	*(0.0319)*	*(0.0194)*	*(0.0325)*	*(0.0348)*	*(0.0351)*	*(0.0279)*	*(0.0491)*
γ^{EA}	-0.2616	-0.0319	-1.0313***	-0.0968	-1.1739***	-0.7940	-0.3600	-0.4217***
	(0.6697)	*(0.1820)*	*(0.3331)*	*(0.2742)*	*(0.3150)*	*(0.5991)*	*(0.2219)*	*(0.1427)*
α^{MA}	-3616.0765*	-1171.9525***	-5.0946***	-2.0009***	-0.5708***	-1711.0849***	-2.1351***	-0.1906***
	(1876.9629)	*(298.2464)*	*(0.7414)*	*(0.3342)*	*(0.0475)*	*(290.8816)*	*(0.3045)*	*(0.0284)*
				Conditional Volatility Equation				
β_0	11.0772***	8.3167***	16.3734***	12.5829**	10.9715***	11.4274***	2.5351***	0.0689
	(0.9475)	*(1.3931)*	*(6.2062)*	*(5.9910)*	*(0.9908)*	*(1.1046)*	*(0.2896)*	*(0.0454)*
β_1	-0.0035***	0.0490	-0.0514***	-0.0139	-0.0015***	0.0080	0.0661*	0.0119*
	(0.0004)	*(0.0436)*	*(0.0000)*	*(0.0097)*	*(0.0002)*	*(0.0071)*	*(0.0346)*	*(0.0063)*
β_2	-0.0055**	0.1353	0.5120***	0.2064	-0.0021	-0.0391***	-0.0745	0.9580***
	(0.0024)	*(0.1181)*	*(0.1902)*	*(0.3363)*	*(0.0033)*	*(0.0146)*	*(0.0791)*	*(0.0152)*
β_3	343.8409***	24.9723***	0.0584	16.3152**	735.0327***	143.5962***	5.3551***	0.0633
	(59.6559)	*(7.7233)*	*(10.8867)*	*(6.9129)*	*(145.9443)*	*(32.4008)*	*(1.9463)*	*(0.4237)*
R^2	0.0448	0.0451	0.3029	0.1392	0.6776	0.2204	0.0989	0.0711
No. observations	614	1216	768	769	614	615	1167	1092
No. announcements	54	55	53	54	54	55	53	57

Table 2.6: Estimation results for 8 macroeconomic announcements on the US T-note futures contract using 10-minute prior return intervals. The conditional mean is for each announcement estimated as $r_t = a_0 + \gamma_k \tilde{r}_{t-1} + \gamma_k^{EA} D_k \tilde{r}_{t-1} + \alpha_k^{MA}(\zeta_t^k - v_t^k) + u_t$, where r_t is the 5-minute return after release of the announcement, $\tilde{r}_{t-1}$ is the 10-minute return before release and $(\zeta_t^k - v_t^k)$ is the surprise of the announcement. The conditional volatility is specified as a GARCH(1,1) augmented with a dummy indicating whether the announcement was released in this period, i.e. $\sigma_t^2 = \beta_0 + \beta_1 u_{t-1}^2 + \beta_2 \sigma_{t-1}^2 + \beta_3 D_k$. The hypothesis of expectations adjustments corresponds to a significantly negative γ^{EA} parameter. Bollerslev-Wooldridge robust standard errors are reported in parentheses. *, ** and *** denote significance at respectively the 10%, 5% and 1% level.

	CPI	Ind. Prod	ISM Man.	ISM Non-Man.	Non Farm Payroll	Retail Sales	IFO (GE)	ZEW (GE)
				Conditional Mean Equation				
α_0	0.0064	-0.0324	0.2424**	0.1881	-0.0047	-0.0564	-0.0568	0.0788
	(0.0879)	*(0.0730)*	*(0.1136)*	*(0.1129)*	*(0.0875)*	*(0.0774)*	*(0.0634)*	*(0.0731)*
γ	-0.0475	-0.0294	-0.0397	-0.0362	-0.0476	-0.0426	-0.0206	-0.0546
	(0.0304)	*(0.0198)*	*(0.0257)*	*(0.0259)*	*(0.0303)*	*(0.0268)*	*(0.0229)*	*(0.0358)*
γ^{EA}	-0.4279	-0.1360	-0.1544	-0.1012	-1.1396***	-0.2270	-0.9802**	-0.4685***
	(0.4250)	*(0.1121)*	*(0.3279)*	*(0.2315)*	*(0.2160)*	*(0.4425)*	*(0.4093)*	*(0.1453)*
α^{MA}	-1751.7417*	-718.9266***	-2.8307***	-1.1693***	-0.2750***	-937.5165***	-5.9279***	-0.6364***
	(960.2399)	*(210.7684)*	*(0.4270)*	*(0.1908)*	*(0.0238)*	*(157.8492)*	*(0.8226)*	*(0.0696)*
				Conditional Volatility Equation				
β_0	4.8090***	3.3646	9.8719***	3.6984***	4.8098***	7.8372***	4.5906***	5.3403
	(0.3990)	*(2.0819)*	*(1.3656)*	*(1.2529)*	*(0.3832)*	*(0.7139)*	*(0.3538)*	*(3.6684)*
β_1	-0.0047***	-0.0121	-0.0156*	0.0088	0.0022	-0.0270	0.0200	0.0061
	(0.0014)	*(0.0070)*	*(0.0078)*	*(0.0259)*	*(0.0032)*	*(0.0300)*	*(0.0164)*	*(0.0155)*
β_2	-0.0094	0.4566	-0.0217	0.5962***	-0.0096**	0.5329***	-0.0195	0.0604
	(0.0087)	*(0.3322)*	*(0.1049)*	*(0.1232)*	*(0.0043)*	*(0.0294)*	*(0.0239)*	*(0.5508)*
β_3	82.6484***	9.8425***	24.9901***	2.5236	213.7197***	1.6734	39.5522***	4.1787
	(15.1201)	*(3.0286)*	*(8.9077)*	*(2.5823)*	*(40.7970)*	*(12.0343)*	*(9.3535)*	*(2.4063)*
R^2	0.0565	0.0368	0.1605	0.1047	0.6476	0.1323	0.2517	0.1901
No. observations	642	1214	770	773	641	643	1188	1113
No. announcements	54	55	51	54	53	55	56	57

Table 2.7: Estimation results for 8 macroeconomic announcements on the German Bunds futures contract using 15-minute prior return intervals. The conditional mean is for each announcement estimated as $r_t = a_0 + \gamma_k \tilde{r}_{t-1} + \gamma_k^{EA} D_k \tilde{r}_{t-1} + \alpha_k^{MA}(\zeta_t^k - v_t^k) + u_t$, where r_t is the 5-minute return after release of the announcement, $\tilde{r}_{t-1}$ is the 15-minute return before release and $(\zeta_t^k - v_t^k)$ is the surprise of the announcement. The conditional volatility is specified as a GARCH(1,1) augmented with a dummy indicating whether the announcement was released in this period, i.e. $\sigma_t^2 = \beta_0 + \beta_1 u_{t-1}^2 + \beta_2 \sigma_{t-1}^2 + \beta_3 D_k$. The hypothesis of expectations adjustments corresponds to a significantly negative γ^{EA} parameter. Bollerslev-Wooldridge robust standard errors are reported in parentheses. *, ** and *** denote significance at respectively the 10%, 5% and 1% level.

	CPI	Ind. Prod	ISM Man.	ISM Non-Man.	Non Farm Payroll	Retail Sales	IFO (GE)	ZEW (GE)
				Conditional Mean Equation				
α_0	-0.2677*	0.0233	0.2068	0.1347	-0.3155**	-0.3174**	0.0020	0.0469
	(0.1455)	*(0.0956)*	*(0.2940)*	*(0.1441)*	*(0.1374)*	*(0.1353)*	*(0.0455)*	*(0.0493)*
γ	-0.0445	0.0074	-0.0191	-0.0162	-0.0467	-0.0487	-0.0632***	-0.0732*
	(0.0311)	*(0.0243)*	*(0.0483)*	*(0.0276)*	*(0.0298)*	*(0.0298)*	*(0.0217)*	*(0.0373)*
γ^{EA}	-0.6163	-0.0486	-0.7215***	-0.0906	-1.1696***	-0.7075	-0.0301	-0.1979
	(0.5647)	*(0.1354)*	*(0.0910)*	*(0.1740)*	*(0.3019)*	*(0.5346)*	*(0.1654)*	*(0.1121)*
α^{MA}	-3449.0707*	-1182.8037***	-5.2897***	-1.7052***	-0.5645***	-1705.0143***	-2.0801***	-0.1945***
	(1878.9832)	*(302.5574)*	*(0.2068)*	*(0.2737)*	*(0.0494)*	*(287.1291)*	*(0.2932)*	*(0.0339)*
				Conditional Volatility Equation				
β_0	8.6139***	7.8639***	17.8663	1.0889**	11.0231***	11.3476***	2.5940***	0.0644
	(1.0311)	*(1.3993)*	*(13.0423)*	*(0.4483)*	*(0.9763)*	*(1.0752)*	*(0.2610)*	*(0.0415)*
β_1	-0.0126***	0.0586	-0.0346***	-0.0037	-0.0013***	0.0135	0.0844**	0.0091
	(0.0048)	*(0.0461)*	*(0.0042)*	*(0.0096)*	*(0.0002)*	*(0.0081)*	*(0.0363)*	*(0.0053)*
β_2	0.1381***	0.1689	0.5279	0.9361***	-0.0024	-0.0387***	-0.1084	0.9631***
	(0.0347)	*(0.1223)*	*(0.3584)*	*(0.0128)*	*(0.0035)*	*(0.0143)*	*(0.0605)*	*(0.0128)*
β_3	166.2344***	23.9756***	4.5358	-0.7908	732.4490***	149.7454***	6.4610***	0.0491
	(66.3032)	*(7.6243)*	*(283.8911)*	*(4.2869)*	*(146.9193)*	*(32.8855)*	*(2.2425)*	*(0.4192)*
R^2	0.0585	0.0447	0.2652	0.1310	0.6784	0.2024	0.0862	0.0605
No. observations	614	1216	768	769	614	615	1167	1092
No. announcements	54	55	53	54	54	55	53	57

Table 2.8: Estimation results for 8 macroeconomic announcements on the US T-note futures contract using 15-minute prior return intervals. The conditional mean is for each announcement estimated as $r_t = a_0 + \gamma_k \tilde{r}_{t-1} + \gamma_k^{EA} D_k \tilde{r}_{t-1} + \alpha_k^{MA}(\zeta_t^k - v_t^k) + u_t$, where r_t is the 5-minute return after release of the announcement, $\tilde{r}_{t-1}$ is the 15-minute return before release and $(\zeta_t^k - v_t^k)$ is the surprise of the announcement. The conditional volatility is specified as a GARCH(1,1) augmented with a dummy indicating whether the announcement was released in this period, i.e. $\sigma_t^2 = \beta_0 + \beta_1 u_{t-1}^2 + \beta_2 \sigma_{t-1}^2 + \beta_3 D_k$. The hypothesis of expectations adjustments corresponds to a significantly negative γ^{EA} parameter. Bollerslev-Wooldridge robust standard errors are reported in parentheses. *, ** and *** denote significance at respectively the 10%, 5% and 1% level.

	CPI	Ind. Prod	ISM Man.	ISM Non-Man.	Non Farm Payroll	Retail Sales	IFO (GE)	ZEW (GE)
				Conditional Mean Equation				
α_0	-0.0050	-0.0282	0.2549**	0.1910	-0.0148	-0.0198	-0.0611	0.0920
	(0.0870)	*(0.0728)*	*(0.1128)*	*(0.1135)*	*(0.0864)*	*(0.0862)*	*(0.0642)*	*(0.0733)*
γ	-0.0537***	-0.0163	0.0018	0.0113	-0.0576***	-0.0530***	0.0110	-0.0560**
	(0.0194)	*(0.0149)*	*(0.0192)*	*(0.0198)*	*(0.0196)*	*(0.0193)*	*(0.0162)*	*(0.0239)*
γ^{EA}	-0.3825	0.0591	-0.6139***	-0.0879	-1.0712***	-0.0076	-0.7288**	-0.2450
	(0.3953)	*(0.0955)*	*(0.1739)*	*(0.1154)*	*(0.2068)*	*(0.3061)*	*(0.3200)*	*(0.1426)*
α^{MA}	-1830.8131*	-721.6998***	-2.7624***	-1.1522***	-0.2704***	-917.4630***	-5.9981***	-0.6107***
	(1015.0247)	*(202.2936)*	*(0.3656)*	*(0.1841)*	*(0.0235)*	*(159.7674)*	*(0.8913)*	*(0.0734)*
				Conditional Volatility Equation				
β_0	4.7680***	3.4521	10.4041***	4.2119***	4.7867***	4.7442***	4.5991***	6.1897***
	(0.3987)	*(2.0818)*	*(1.2235)*	*(1.5638)*	*(0.3823)*	*(0.4073)*	*(0.3450)*	*(2.3878)*
β_1	-0.0043	-0.0119	-0.0343***	0.0219	0.0023	0.0180	0.0087	0.0116
	(0.0036)	*(0.0075)*	*(0.0043)*	*(0.0290)*	*(0.0035)*	*(0.0154)*	*(0.0129)*	*(0.0191)*
β_2	-0.0093	0.4431	-0.0436	0.5301***	-0.0106**	-0.0328	-0.0098	-0.0911
	(0.0121)	*(0.3320)*	*(0.0776)*	*(0.1513)*	*(0.0043)*	*(0.0226)*	*(0.0252)*	*(0.2957)*
β_3	83.2351***	10.2518***	21.0016***	2.9588	202.1111***	54.7979***	41.7450***	6.3199**
	(15.1281)	*(3.0986)*	*(5.9698)*	*(2.7008)*	*(37.6313)*	*(14.0681)*	*(9.9364)*	*(2.5453)*
R^2	0.0557	0.0329	0.1759	0.1032	0.6636	0.1320	0.2387	0.1863
No. observations	642	1214	770	773	641	643	1188	1113
No. announcements	54	55	51	54	53	55	56	57

Table 2.9: Estimation results for 8 macroeconomic announcements on the German Bunds futures contract using 30-minute prior return intervals. The conditional mean is for each announcement estimated as $r_t = a_0 + \gamma_k \tilde{r}_{t-1} + \gamma_k^{EA} D_k \tilde{r}_{t-1} + \alpha_k^{MA}(\zeta_t^k - v_t^k) + u_t$, where r_t is the 5-minute return after release of the announcement, $\tilde{r}_{t-1}$ is the 30-minute return before release and $(\zeta_t^k - v_t^k)$ is the surprise of the announcement. The conditional volatility is specified as a GARCH(1,1) augmented with a dummy indicating whether the announcement was released in this period, i.e. $\sigma_t^2 = \beta_0 + \beta_1 u_{t-1}^2 + \beta_2 \sigma_{t-1}^2 + \beta_3 D_k$. The hypothesis of expectations adjustments corresponds to a significantly negative γ^{EA} parameter. Bollerslev-Wooldridge robust standard errors are reported in parentheses. *, ** and *** denote significance at respectively the 10%, 5% and 1% level.

	CPI	Ind. Prod	ISM Man.	ISM Non-Man.	Non Farm Payroll	Retail Sales	IFO (GE)	ZEW (GE)
				Conditional Mean Equation				
α_0	0.1806	0.0276	0.2546	0.2157	-0.3621***	-0.3344**	0.0085	0.0457
	(0.2841)	*(0.0955)*	*(0.1444)*	*(0.1450)*	*(0.1431)*	*(0.1341)*	*(0.0456)*	*(0.0493)*
γ	0.1272***	0.0031	0.0295	0.0305	-0.0415	-0.0503**	-0.0436***	-0.0494*
	(0.0327)	*(0.0170)*	*(0.0172)*	*(0.0182)*	*(0.0244)*	*(0.0234)*	*(0.0164)*	*(0.0259)*
γ^{EA}	-0.4011	0.1052	-0.3541	-0.2284*	-1.1798***	-0.3478	-0.1152	-0.0490
	(0.3623)	*(0.0946)*	*(0.2097)*	*(0.1198)*	*(0.2611)*	*(0.3564)*	*(0.1390)*	*(0.0860)*
α^{MA}	-3552.9254*	-1115.8091***	-5.0865***	-1.9964***	-0.5488***	-1843.4857***	-2.0351***	-0.1901***
	(1939.7674)	*(284.2825)*	*(0.8241)*	*(0.3468)*	*(0.0246)*	*(332.0452)*	*(0.2886)*	*(0.0337)*
				Conditional Volatility Equation				
β_0	20.7506***	8.0850***	17.1444***	12.0408**	9.2602***	11.3334***	2.5539***	0.0722
	(7.3170)	*(1.4043)*	*(2.4976)*	*(5.9964)*	*(1.3945)*	*(1.0758)*	*(0.2639)*	*(0.0429)*
β_1	-0.0234	0.0535	-0.0066**	-0.0138	-0.0132***	0.0073	0.0877**	0.0094
	(0.0264)	*(0.0452)*	*(0.0028)*	*(0.0099)*	*(0.0001)*	*(0.0083)*	*(0.0373)*	*(0.0055)*
β_2	0.5665***	0.1528	-0.0585	0.2399	0.1566**	-0.0342**	-0.0963	0.9603***
	(0.1854)	*(0.1219)*	*(0.0663)*	*(0.3445)*	*(0.0781)*	*(0.0143)*	*(0.0634)*	*(0.0135)*
β_3	4.7611	23.9480***	0.8051**	13.7698**	258.2338*	154.8171***	5.9851***	0.0322
	(59.1599)	*(7.7169)*	*(0.3486)*	*(6.4911)*	*(136.6992)*	*(30.9845)*	*(2.1288)*	*(0.4194)*
R^2	0.0302	0.0480	0.2529	0.1413	0.6858	0.1878	0.0896	0.0535
No. observations	614	1216	768	769	614	615	1167	1092
No. announcements	54	55	53	54	54	55	53	57

Table 2.10: Estimation results for 8 macroeconomic announcements on the US T-note futures contract using 30-minute prior return intervals. The conditional mean is for each announcement estimated as $r_t = a_0 + \gamma_k \tilde{r}_{t-1} + \gamma_k^{EA} D_k \tilde{r}_{t-1} + \alpha_k^{MA}(\zeta_t^k - v_t^k) + u_t$, where r_t is the 5-minute return after release of the announcement, $\tilde{r}_{t-1}$ is the 30-minute return before release and $(\zeta_t^k - v_t^k)$ is the surprise of the announcement. The conditional volatility is specified as a GARCH(1,1) augmented with a dummy indicating whether the announcement was released in this period, i.e. $\sigma_t^2 = \beta_0 + \beta_1 u_{t-1}^2 + \beta_2 \sigma_{t-1}^2 + \beta_3 D_k$. The hypothesis of expectations adjustments corresponds to a significantly negative γ^{EA} parameter. Bollerslev-Wooldridge robust standard errors are reported in parentheses. *, ** and *** denote significance at respectively the 10%, 5% and 1% level.

	CPI	**Ind. Prod**	**ISM Man.**	**ISM Non-Man.**	**Non Farm Payroll**	**Retail Sales**	**IFO (GE)**	**ZEW (GE)**
				Conditional Mean Equation				
α_0	0.0170	-0.0325	0.2375**	0.1836	0.0001	-0.0583	-0.0570	0.0875
	(0.0873)	*(0.0730)*	*(0.1135)*	*(0.1124)*	*(0.0868)*	*(0.0464)*	*(0.0634)*	*(0.0733)*
γ	-0.0092	-0.0051	0.0172	0.0247*	-0.0113	-0.0094	0.0071	-0.0216
	(0.0156)	*(0.0092)*	*(0.0134)*	*(0.0134)*	*(0.0158)*	*(0.0153)*	*(0.0107)*	*(0.0152)*
γ^{EA}	0.2963	0.0102	-0.1454	-0.1187	-0.8921***	-0.0104	-0.4900**	-0.0773
	(0.2826)	*(0.0572)*	*(0.1873)*	*(0.1006)*	*(0.2883)*	*(0.2152)*	*(0.2127)*	*(0.1000)*
α^{MA}	-1203.3502	-718.6012***	-2.8371***	-1.1484***	-0.2709***	-921.9227***	-5.8502***	-0.6106***
	(915.1262)	*(210.4553)*	*(0.4360)*	*(0.1826)*	*(0.0261)*	*(165.2997)*	*(0.8732)*	*(0.0723)*
				Conditional Volatility Equation				
β_0	4.8235***	3.4244	10.1843***	4.8292**	4.8282***	7.8179***	4.5898***	6.0343***
	(0.3998)	*(2.0813)*	*(1.3554)*	*(2.0588)*	*(0.3819)*	*(0.2277)*	*(0.3470)*	*(2.2842)*
β_1	-0.0066	-0.0108	-0.0174**	0.0366	0.0015	-0.0258	0.0124	0.0112
	(0.0041)	*(0.0084)*	*(0.0073)*	*(0.0330)*	*(0.0034)*	*(0.0338)*	*(0.0140)*	*(0.0197)*
β_2	-0.0068	0.4465	-0.0459	0.4482**	-0.0086**	0.5275***	-0.0116	-0.0591
	(0.0134)	*(0.3322)*	*(0.1017)*	*(0.2023)*	*(0.0042)*	*(0.0171)*	*(0.0236)*	*(0.2802)*
β_3	83.1122***	10.3158***	24.7031***	3.4658	224.7196***	1.3283	41.4355***	6.8850**
	(13.7385)	*(3.0985)*	*(8.4007)*	*(2.8990)*	*(40.7916)*	*(12.3403)*	*(11.4483)*	*(2.8560)*
R^2	0.0519	0.0313	0.1610	0.1036	0.6330	0.1279	0.2404	0.1763
No. observations	642	1214	770	773	641	643	1188	1113
No. announcements	54	55	51	54	53	55	56	57

Table 2.11: Estimation results for 8 macroeconomic announcements on the German Bunds futures contract using 60-minute prior return intervals. The conditional mean is for each announcement estimated as $r_t = a_0 + \gamma_k \tilde{r}_{t-1} + \gamma_k^{EA} D_k \tilde{r}_{t-1} + \alpha_k^{MA}(\zeta_t^k - v_t^k) + u_t$, where r_t is the 5-minute return after release of the announcement, $\tilde{r}_{t-1}$ is the 60-minute return before release and $(\zeta_t^k - v_t^k)$ is the surprise of the announcement. The conditional volatility is specified as a GARCH(1,1) augmented with a dummy indicating whether the announcement was released in this period, i.e. $\sigma_t^2 = \beta_0 + \beta_1 u_{t-1}^2 + \beta_2 \sigma_{t-1}^2 + \beta_3 D_k$. The hypothesis of expectations adjustments corresponds to a significantly negative γ^{EA} parameter. Bollerslev-Wooldridge robust standard errors are reported in parentheses. *, ** and *** denote significance at respectively the 10%, 5% and 1% level.

	CPI	Ind. Prod	ISM Man.	ISM Non-Man.	Non Farm Payroll	Retail Sales	IFO (GE)	ZEW (GE)
Conditional Mean Equation								
α_0	0.0749	0.0282	0.2575	0.2049	-0.3226**	-0.3098**	0.0018	0.0531
	(0.1121)	*(0.0975)*	*(0.1461)*	*(0.1447)*	*(0.1355)*	*(0.1337)*	*(0.0462)*	*(0.0488)*
γ	0.0164	0.0052	0.0260**	0.0217	-0.0181	-0.0165	-0.0165	-0.0187
	(0.0233)	*(0.0078)*	*(0.0123)*	*(0.0124)*	*(0.0238)*	*(0.0223)*	*(0.0114)*	*(0.0172)*
γ^{EA}	0.1158	0.0431	-0.1406	-0.2136	-1.0858***	-0.4403	-0.0475	-0.0273
	(0.2070)	*(0.0490)*	*(0.1900)*	*(0.1189)*	*(0.3897)*	*(0.2952)*	*(0.0742)*	*(0.0569)*
α^{MA}	-3124.0697**	-1133.0538***	-4.8608***	-1.9536***	-0.5553***	-1854.5930***	-2.0104***	-0.1960***
	(1477.3606)	*(299.1121)*	*(0.8357)*	*(0.3213)*	*(0.0511)*	*(339.1457)*	*(0.3025)*	*(0.0353)*
Conditional Volatility Equation								
β_0	23.6530**	8.6676***	18.9217***	11.5987**	11.0437***	11.3282***	2.6221***	0.0818
	(9.6827)	*(1.4193)*	*(3.0988)*	*(5.3726)*	*(0.9693)*	*(1.0593)*	*(0.2768)*	*(0.0458)*
β_1	-0.0381***	0.0484	-0.0066**	-0.0161*	-0.0008	0.0141*	0.0672*	0.0106
	(0.0054)	*(0.0450)*	*(0.0027)*	*(0.0081)*	*(0.0009)*	*(0.0076)*	*(0.0340)*	*(0.0063)*
β_2	0.4107	0.1204	-0.0987	0.2712	-0.0025	-0.0366***	-0.0978	0.9542***
	(0.2445)	*(0.1169)*	*(0.1120)*	*(0.3085)*	*(0.0040)*	*(0.0132)*	*(0.0674)*	*(0.0148)*
β_3	55.2943	24.6217***	0.0538	11.9820	756.7569***	158.9628***	6.0422***	0.0947
	(37.9495)	*(7.5684)*	*(0.0371)*	*(6.8526)*	*(135.8532)*	*(31.6633)*	*(2.2000)*	*(0.4185)*
R^2	0.0310	0.0468	0.2451	0.1402	0.6691	0.1739	0.0830	0.0492
No. observations	614	1191	768	769	614	615	1167	1092
No. announcements	54	55	53	54	54	55	53	57

Table 2.12: Estimation results for 8 macroeconomic announcements on the US T-note futures contract using 60-minute prior return intervals. The conditional mean is for each announcement estimated as $r_t = a_0 + \gamma_k \tilde{r}_{t-1} + \gamma_k^{EA} D_k \tilde{r}_{t-1} + \alpha_k^{MA}(\zeta_t^k - v_t^k) + u_t$, where r_t is the 5-minute return after release of the announcement, $\tilde{r}_{t-1}$ is the 60-minute return before release and $(\zeta_t^k - v_t^k)$ is the surprise of the announcement. The conditional volatility is specified as a GARCH(1,1) augmented with a dummy indicating whether the announcement was released in this period, i.e. $\sigma_t^2 = \beta_0 + \beta_1 u_{t-1}^2 + \beta_2 \sigma_{t-1}^2 + \beta_3 D_k$. The hypothesis of expectations adjustments corresponds to a significantly negative γ^{EA} parameter. Bollerslev-Wooldridge robust standard errors are reported in parentheses. *, ** and *** denote significance at respectively the 10%, 5% and 1% level.

Essay 2

Asymmetric Responses in Bond Risk Premia to News

Co-authored with Jesper Pedersen, DØRS.

Abstract

The impact from macroeconomic news announcements on bond yield risk premia is analyzed using intraday data around the announcements. A new method is proposed for the identification of the fundamental part of the yield curve response using intraday risk adjusted money market futures. We are hence able to identify the behavior of both the fundamental part and the risk premia. Our results suggest that changes in risk premia react asymmetrically to good and bad news while expectations of future short rates react symmetrically.

Keywords: Bond Risk Premia, Macroeconomic News, Asymmetric Response.

JEL classification: E43, E44, G15

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3.1 Introduction

Why do bond markets react more strongly to positive macroeconomic news? Our answer is: asymmetric responses in the term premia. We find that while the *fundamental* economic component of bond yields react in a similar magnitude to positive and negative macroeconomic news announcements at longer maturities, the *term premia* response is asymmetric. Positive news lead to increases in the risk premia, whereas negative news impact the risk premium less or even leaves it unchanged. These two results taken together explain why bond yields overall react asymmetrically to positive and negative macroeconomic news as described in for instance Andersen, Bollerslev, Diebold, and Vega (2003).

We believe to be the first to address the behavior of the term premia in a high-frequency framework. To do so we propose a new theoretically motivated approach of extracting the risk premia for longer-dated bonds based on changes in the monetary policy path, which in macroeconomic theory reflects changes to economic fundamentals. This allows the identification of the intraday risk premia.

Our results depend crucially on two identifying assumptions.

1. The expectation hypothesis of the yield curve with a *time-varying risk premia*, i.e. long rates are the sum of future short rates plus separate term premia dynamics, holds.
2. All fundamental economic information impact solely through changes in the monetary policy path (approximated at a 12-month horizon).

In empirical research, the existence of a time-varying risk premia is often given the blame when explaining the overwhelming empirical evidence rejecting the expectation hypothesis. For instance Tzavalis and Wickens (1997) and Dai and Singleton (2002) - using different approaches - find support for 1), but others, such as Bekaert and Hodrick (2001) and Thornton (2006) note that such approaches require a very large variability in the term premia. Whether one can claim that the expectation hypothesis holds when accounting for a time-varying risk premia is however an open question. We rely on the theoretical evidence in favour of this, as documented later in the theoretical part of this paper. Furthermore, our identification procedure rests on the expectation hypothesis to hold in small intraday intervals of 20 minutes - to our knowledge no intraday tests of the expectations hypothesis has been considered at this interval. We consequently make use of the assumption in our identification procedure, but realize that this might be a controversial choice.

The second assumption is fairly standard in most standard macroeconomic models. For instance in DSGE models, where all available information is incorporated into the monetary policy path; the monetary path being the monetary policy interest rate set by the central bank from today and into the future. This directly implies that expected monetary policy path is an indicator for market participants' view on the economy. This is in line with for instance Kozicki and Tinsley (2001), that point out that shifting endpoints of long rates is associated with shifts in long-term policy goals, thus implying that the end-points are stable within a given monetary policy regime. Any incoming information about the economy will swiftly be incorporated into the expected monetary policy path. Therefore, changes in the monetary policy path as a result of new macroeconomic information is very likely to be a good indicator for changes to fundamental macroeconomic expectations.

We use risk-adjusted Eurodollar futures contracts to construct the market expectation of the monetary policy path at a 12-month horizon. The 20-minute changes in the 12-month rate is then used as a proxy for changes in the fundamental economic component around macroeconomic releases, such as the release of the changes in the non-farm payroll. In doing so, we make use of our identifying assumptions, as news only is allowed to impact in the short end, i.e. the monetary policy path (assumption 2) and additional response at longer maturities can then be identified as risk premia (assumption 1). This allows a simple and intuitive decomposition of the fundamental and risk components.

While previously neglected in macroeconomics, the focus has lately moved away from fundamentals and on to the risk premia, see e.g. Alvarez, Atkeson, and Kehoe (2007), Alvarez, Atkeson, and Kehoe (2008), and Cochrane (2001), motivating the analysis in this paper. The provocative view of Alvarez, Atkeson, and Kehoe (2007), as an extreme example, is that moves in response to monetary policy shocks is neither inflation nor output but risk premia. This in turn implies a new modelling strategy for monetary models, namely a more thorough examination of the model properties of risk premia, for an example of the analysis of risk premia and macroeconomics, see Rudebusch, Sack, and Swanson (2007), Rudebusch and Swanson (2007), and Pedersen (2008). It also implies a need for a deeper empirical analysis of what affect risk and address the relative importance of fundamentals and risk premia. This paper address exactly these issues using bond market data.

Our paper is similar in spirit to Beechey (2007), who decomposes the U.S. curve on daily data using an affine term structure approach with a fitted time-varying risk premia. With this approach, she finds that movements from macroeconomic announcements in the term premia, and not expected future short rates, account for most of the reaction of forward rates at long horizons. Term premia account for about 75 per cent of the reaction of nominal forward rates in the long end of the yield curve, suggesting that the fundamental part in the U.S. yield curve is reasonably well anchored. Beechey (2007) finds that weaker-than-expected inflation and real-side news are associated with lower term premia.

In this paper we extend the analysis of Beechey (2007) in two ways. Firstly, we use high-frequency data from 1999 to March 2008[1], instead of daily data, to measure the market reaction to macroeconomic announcements more precisely. The use of high-frequency data should allow for a more precise measure of the market impact from macroeconomic fundamentals, as it reduces the noisiness of the daily measure. Our findings do seem to indicate that Beechey (2007) underestimates the impact from macroeconomic fundamentals, as we find that term premia only account for around 25-40 per cent of the reaction around macroeconomic announcements. This does suggest that the use of daily measures induces some noise.

Secondly, we depart from the affine term structure approach and use a theoretical derived decomposition, that is changes in the monetary policy path as a proxy for fundamentals, as suggested by standard macro models. The affine term structure approach is difficult to implement on intraday data, at least for the entire yield curve.[2]

[1] In order to separate our analysis from the financial crisis and especially the money market turmoil, we use data until the time of the Bear Stearns collapse.

[2] We tried to estimate an affine term structure for both bond yields with short maturities and longer maturies as an alternative. However, this approach is extremely cumbersome for datasets with more than 200.000 observations. Further, the fit of our model where unsatisfactory. We have therefore stuck to the methodology as presented in the text.

Piazzesi and Swanson (2008) document relatively large excess returns on federal funds futures and thereby indicate that also money market futures contracts contain a non-negligible term premia. In order to account for the risk in money market yields, an affine term structure model with a time-varying risk premium is fitted on the money market data. This estimation provided us with a risk-adjusted rates derived from the money market curve and thereby the expected risk-free monetary policy path.

The remainder of the paper is structured as follows. Section 3.2 presents the theoretical motivation for our decomposition. Section 3.3 examines the empirical issues. Specifically, section 3.3.1 describes the data used in this study, while section 3.3.2 describes our method for extracting risk premia from the short end of the yield curve. This gives us a risk-adjusted path of monetary policy, which is a good approximation for the expectation of the fundamental economic information contained in the yield curve. In section 3.4 we decompose the market reaction at 2-, 5- and 10-year maturities from macroeconomic releases into a fundamental and a risk premia component and regress the changes in the components against the most important macroeconomic announcements. In section 3.5 we discuss the implications for macroeconomic modelling. Section 3.6 concludes.

3.2 Theory

To derive the explicit theoretical decomposition of bond yields for our empirical analysis, we start with some notation. Let P_t^n denote the price at time t of a zero coupon bond with time-to-maturity n. Its log price is denoted by p_t^n, yields are defined from prices as $y_t^n = -\frac{1}{n}p_t^n$, and we denote the short rate of interest as $i_t = -p_t^1$. We denote the expected log-holding period return from holding an n-period bond for one period in excess of the risk free rate of interest as

$$E_t\left[hpr_{t+1}^n\right] \equiv E_t\left[p_{t+1}^{n-1} - p_t^n\right] - i_t \tag{3.1}$$

All variables are nominal unless stated otherwise. We assume all variables are jointly log-normal and markets are complete such that a unique pricing kernel, M_{t+1}, prices all assets in the economy.

The short rate is set by a central bank according to an interest rule. The central bank rule aims to achieve the dual goals of keeping output, Y_t, at its natural level, Y_t^n, and inflation, π_t, at its target, $\bar{\pi}$

$$i_t = F\left(\pi_t - \bar{\pi}, Y_t - Y_t^n\right) \tag{3.2}$$

with $\partial F/\partial\left(\pi_t - \bar{\pi}\right) > 0$ and $\partial F/\partial\left(Y_t - Y_t^n\right) > 0$, see e.g., Gali (2008) or Woodford (2003). As short rates are dependent on inflation and the output gap, short rates hinge on expectations of future macroeconomic variables in this framework.

In appendix 3.7 we derive the following bond yield decomposition:

$$y_t^n = \frac{1}{n}\sum_{i=0}^{n} E_t\left[i_{t+i}\right] + \frac{1}{n}\sum_{i=1}^{n-1} E_t\left[hpr_{t+i}^{n+1-i}\right] \equiv ES_t^n + TP_t^n. \tag{3.3}$$

The first term in (3.3), ES_t^n, captures expected future short rates. We therefore interpret the ES_t^n term as *fundamentals*, $\digamma_t$, a term capturing current macroeconomic variables or expectations of future macroeconomic variables like the output gap, inflation and other considerations embodied in the current stance of monetary policy. The second term in (3.3), TP_t^n, is a sum of current and future *risk* premia denoted by hpr_{t+1}^{n+1}. Consequently, the second term captures movements in the risk premia.

The decomposition in equation (3.3) states that bond yields depend on expected future short rates. From (3.2) we know that this involves expectations of future macroeconomic variables, which in turn implies bond yields implicitly depend upon expected future macroeconomic variables and, in turn fundamentals. In addition, investors demand a time varying risk premia to compensate for the uncertainty related to the expected monetary policy path.

The decomposition in (3.3) assumes the expectations hypothesis (EH) *holds once bond yields are adjusted for risk premia*. We thus assume that the empirical failure of the EH is due solely to non constant risk premia following both theory and the empirical analysis in Dai and Singleton (2002), as stated earlier in introduction.

3.3 Empirical Analysis

We decompose bond yield spreads into fundamentals and a risk premium component in order to be able to say something about the relationships between these terms and macroeconomic announcements at the same time. The idea is to estimate the impact from a vector of *US news announcement surprises*, N_t, on y_t^n, TP, and ES. In order to detect any asymmetric effects stemming from positive and negative releases, a dummy for negative surprises, D_t, is used in the following regressions:

The overall yield impact regression**:**

$$\Delta y_t^n = \alpha + \beta N_t + \beta_{NEG} D_t N_t + \varepsilon_t, \tag{3.4}$$

the risk premia regression

$$\Delta TP_t^n = \alpha + \beta^{TP} N_t + \beta_{NEG} D_t N_t + \varepsilon_t, \tag{3.5}$$

and the fundamental regression

$$\Delta ES_t^n = \alpha + \beta^{ES} N_t + \beta_{NEG} D_t N_t + \varepsilon_t, \tag{3.6}$$

where the Δx operator denotes 20 minute changes in x.

The regression setup is similar to those used in other announcement studies. See, for instance**,** Faust, Rogers, Wang, and Wright (2007).[3] We consider the changes in yields, term premia and fundamentals around the announcement for three maturities, namely $n = 2, 5$ and 10 and for 8 of the most important US releases, CPI, Factory Orders, Industrial Production, Initial Jobless Claims, ISM Manufacturing, Non-farm Payroll, Philadelphia Fed and Retail Sales. Consequently we estimate 8 regressions for each bond maturity with differing macroeconomic announcements using US bond yields - a total of 24 regressions.

[3]Another class of macroeconomic announcement studies focus on the effects on volatility stemming from these announcements. These papers include among many others Andersen and Bollerslev (1997) and Andersen, Bollerslev, Diebold, and Vega (2003). This is not considered in this paper, however we did fit an asymmetric volatility equation. This did not change our results.

In order to estimate the three regressions above, either the term premia or the fundamentals needs to be identified. As we saw in the previous section, the fundamental part, ES_t^n, can be identified as the sum of expected future short rates. In practice this is however not easily accomplished because of two main obstacles.

Firstly, as noted earlier, Piazzesi and Swanson (2008) find that also short-term rates can contain substantial risk premia. To employ the decomposition for long rates, a decomposition for short rates is consequently needed. To adjust for the risk premia on short rates, we estimate an affine term structure model with a time-varying risk premia. The method and results from this decomposition is given in section 3.3.2.

Secondly, and probably more importantly, the fundamental part, ES_t^n, is found by accumulating all short rates. For a 10-year bond, this would consist of all short rates for a 10-year period. However, as the main impact of changes to the monetary policy path is likely to be reflected in the first part of the yield curve, we approximate the ES_t^n component with 12-month rates. This is only an approximation, albeit a plausible one, and has the consequence that all changes beyond what is induced by changes at the 12-month rate becomes term premia.[4] This is where our two assumptions of i) the expectation hypothesis and ii) that fundamental economic information only impacts through the monetary policy come into play.

It is important to note that our approach only gives the response or movements in the risk premia, but does not enable us to comment on the level of the risk premia. This is probably the largest drawback of using this method instead of the affine term structure approach.

With the data and risk-adjusted money market rates at hand, the regressions (3.4), (3.5) and (3.6) can now be implemented. The results of the regressions is reported in section 3.4.

3.3.1 Data

To obtain accurate measures of the bond market response to macroeconomic announcements the use of high-frequency data is essential. All the bond- and money

[4] Data availability restricted us from looking at longer horizons, such as a 18 month horizon.

market data used in this study are of intraday frequency. All high-frequency data, i.e. money market interest rates and bond yields[5], are based on futures contract data from TickData Inc. We use US interest rates and bond yields at 3-, 6-, 9- and 12-month, 2-, 5- and 10-year horizons and announcements for 8 selected US announcements.

The sample period covers the period from January 1999 to March 2008. The initial period is determined by limited Bloomberg survey data macroeconomic surprises prior to 1999 and the end period coincides with collapse of Bear Stearns, which was the beginning of the money market turmoil under the financial crisis. To avoid any early releases or inaccuracies in time stamps, all changes in market data around the macroeconomic releases is collected in an event window from 5 minutes before the release to 15 minutes after the release, on days with the macroeconomic release. This is similar to the procedure of Faust, Rogers, Wang, and Wright (2007).

Announcement data are collected from Bloomberg and is similar to the data used in Andersson, Overby, and Sebestyén (2009). As noted previously, a selection of the most important US macroeconomic announcements is used, which includes CPI, Factory Orders, Industrial Production, Initial Jobless Claims, ISM Manufacturing[6], Non-farm Payroll, Philadelphia Fed and Retail Sales.[7] The survey of market expectations for individual macroeconomic releases is collected continuously up to the release date among market participants by Bloomberg.

The selected indicators are those that have been proven to have the highest market impact in previous studies, as in Bartolini, Goldberg, and Sacarny (2008). They note that the non-farm payroll report and ISM manufacturing tend to have the strongest impact on US asset prices. This is also confirmed by our findings.

[5] Prices on the US 2-, 5- and 10-year government futures contracts are converted into yields. The conversion is based on the internal rate of return using an exact maturity of 2, 5 and 10 years and the coupon rate on the futures contract, typically 6%. This is contrary to the use of returns in most other papers. The use of yields has the advantage of allowing a more direct comparison across maturities, as the return impact is considerably different across maturities due to differences in duration.

[6] One observation was deleted as this was distorted by an external event, Hurricane Katrina. The markets did not react to this release due to this distortion.

[7] The GDP (Advance) release is not considered, as this is only released quarterly.

The news vector N_t consists of the standardized surprises.[8]

The 3-month Eurodollar futures contract is used to determine the expected US monetary policy path, as this contract is based on the 3-month deposit rates (LIBOR) and is an excellent approximation for the actual money market rates. From the Eurodollar futures contract, 12-month money market rates are constructed. [9]

3.3.2 Money Market Decomposition

The use of an affine term structure is relatively standard and is done among others by Rudebusch, Sack, and Swanson (2007), Kim and Wright (2005), and Cochrane and Piazzesi (2006). The identification of a fundamental component is crucial to our analysis and in order to ensure robustness, a variety of term structure models is specified. The results are independent of the specification and consequently we have adopted the simplest approach possible, which amounts to fit a one-factor affine term structure model.

We interpret short rates as expectations of fundamentals and we approximate these interest rates by the futures contract. These future contracts are a way to lock in a 3-month loan today starting in, say, 6 months. Two points are clear for these contracts. Three month interest rates are closely correlated with monetary policy rates, that is the Federal Funds Rate (FFR), making these futures contracts an instrument to identify the ES_t^n -part of (3.3). However, the money market futures contract contains a risk premium, which part reflects the uncertainty related to future monetary policy. Therefore, we need to adjust for these risk premia.

We obviously face another identification problem, as we only have futures prices to identify both the risk premia and the expectation part in the money market rate. We solve this problem by estimating an affine term structure model for a panel of the future contract consisting of the 3, 6, 9 and 12 month future. We decompose the estimated futures into an expectations part related to fundamentals, $ES_{mm,t}^n$,

[8] The standardised surprise is defined as $S = \frac{Actual-Survey}{St.dev(Actual-Survey)}$, where $Actual$ and $Survey$ is respectively the actual number released and the survey observed on Bloomberg. See Kuttner (2001) for a further description.

[9] A more thorough description of the method used for the calculation of money market yields is available upon request.

and a risk premia part reflecting risk premia in the futures contract, $TP^n_{mm,t}$, as in (3.3). We thus use $y^n_t - ES^n_t$ as *risk adjusted* futures contract which we henceforth denote *risk adjusted fundamentals.* The estimation follows Ang and Piazzesi (2003), Dai and Singleton (2002) and Duffie and Kan (1996).[10] The main results from the estimation of the affine term structure model are given below.

Estimates and results

The affine term structure model used for fitting money market rates has a relatively good fit, with quite small mean fitting errors (around 0.2 basis points), see figure 1. An extra factor did not significantly improve the fit of our model, as this factor captured over 99% of the variation. This provides evidence in favour of our one-factor model. Figure 2 shows the panel of estimated term premia, $TP^n_{mm,t}$. These are both in absolute terms and relative to the money market rates small. The average risk premia is around 15 basis points at a 12-month horizon. This corresponds very well to the 'rule of thumb' used in the Federal Reserve, see Piazzesi and Swanson (2008), which states that the average risk premia is around 1 basis point pr. month + 3 basis points $\sim$15 basis points for a 12-month horizon.

However, the time-variability is very large. Under the bursting of the dot-com bubble and the more recent sub-prime crisis, risk premia have increased considerably. Figures 3 (a) and (b) show that the term premia, $TP^n_{mm,t}$, contribute relatively little to the level of the money market rates. They are, however, non-negligible and would, if not taken into account, give biased estimates in regressions (3.4), (3.5) and (3.6).

3.4 Results

Using the risk adjusted monetary path derived in the previous section, the fundamental news reaction can now easily be derived , so that we can identify the ES^n_t term in (3.3). This allows us to estimate regressions (3.4), (3.5) and (3.6). The results of these regressions for respectively 2-, 5- and 10-year bond yields on US

[10] The technical details are available upon request.

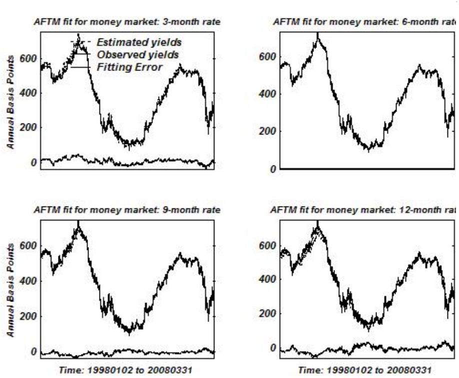


Figure 3.1: Fit of the affine term structure model for money market yields. This figure shows the fit of the 1-factor affine term structure model estimated on money market yields at the 3, 6-, 9 and the 12-month maturity together with the model implied fitting errors defined as the difference between data and estimated yields.

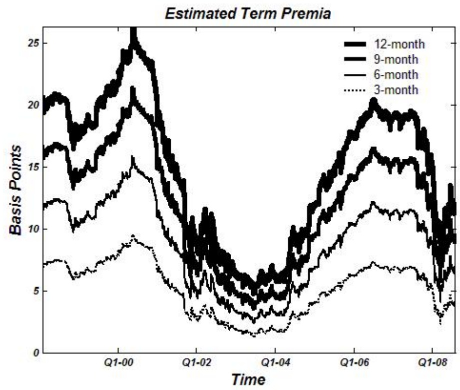


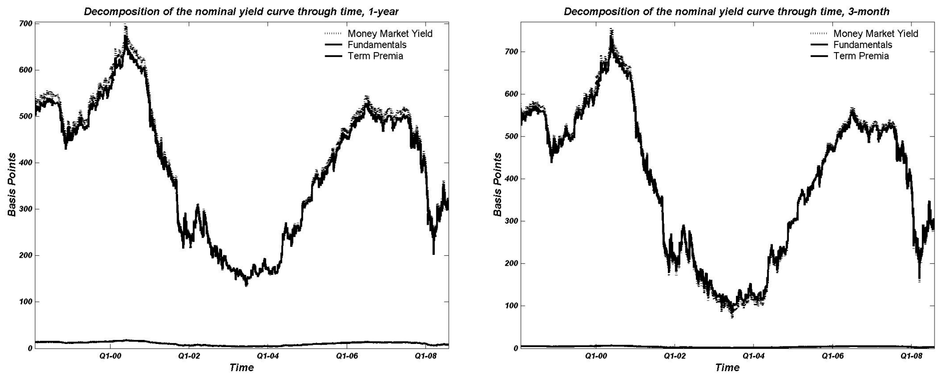
Figure 3.2: Estimated term premia for money market yields. This figure shows the estimated term premia from the affine term structure model.

data are given in the Tables 3.1 to 3.3 in the appendix.[11]

The overall picture can be summarized as follows. Firstly, the impact on the yield curve is on average greater when positive news are released than for negative news, thus causing an asymmetric response at longer maturities. Secondly, this asymmetry is explained by the term premium part of the yield curve, again mainly at longer maturities. Thirdly, the size of risk premia response from news in the yield curve is non-negligible. Finally, the risk premia appear anchored at longer maturities, causing term premia to fluctuate more at shorter maturities.

The quantitative impact from the announcements differ across maturities. Specifically, news moves the yield curve relatively more in its short end than in the long end, which again is connected to larger responses in the term premia. The

[11] In order to ensure robustness of the results, we considered a number of alternative specifications. Firstly, we considered a number of different model specifications on the extraction of money market risk premia. The overall results did not qualitatively differ with other specifications. Secondly, a volatility equation was added to the regressions, aimed at taking care of asymmetric effects in volatility. There were some signs of asymmetric volatility effects, but again it did not change our conclusions.



(a) 3-month maturity (b) 12-month maturity

Figure 3.3: Examples of the money-market decomposition. The figures show the affine term structure model implied money market decomposition for the money market yield through time.

uneven response to news suggests that term premia is more well-anchored at longer maturities.

Across the different announcements, a pattern of asymmetry does emerge. There is no statistical significant asymmetry at the 2-year maturity, but only at 5- and 10-year maturities. Retail Sales is the only release, at 5- and 10-year maturities, where there is the asymmetry is present in the overall yield response. However, for the risk component, the asymmetry effect is statistically significant at the 5-year maturity for Retail Sales and Philadelphia Fed, and at the 10-year maturity, CPI, Factory Orders, Non-Farm Payroll, Philadelphia Fed and Retails Sales is statistically significant. The fundamental component in all cases exhibit a symmetric reaction to positive and negative news.

When looking only at the signs of the coefficients, the effect becomes even more pronounced. The coefficient capturing the asymmetry is negative for all releases at 5- and 10-year maturities, except for two announcements with the overall smallest news effects, Industrial Production and Initial Jobless Claims. The pattern of asymmetry is therefore consistent, both overall, but also at the risk level.

The magnitude of the risk premia response of overall response also deserves some attention. For positive surprises, about 25% to 40% of the overall response risk premia has to be attributed to the 4 announcements with the highest overall impact (Non-farm Payroll, ISM Manufacturing, Retail Sales and Philadelphia

Fed). This is somewhat lower than the share suggested by Beechey (2007), which probably is due to her use of daily measures.

The asymmetry of the reaction is relatively large. As an example consider the impact on 10-year yields following the release of the non-farm payroll number. A one standard deviation surprise in the non-farm payroll release, i.e. about 100.000 new workers above or below the consensus, causes the yield curve to decrease around 3.1 basis points on a negative surprise and increase around 4.7 basis points on a positive surprise. The response in the money market rates, i.e. the fundamental component, is a symmetric one with a magnitude of about 3.4 basis points in the face of both negative and positive news. The asymmetry in the overall reaction comes from the risk premia. The risk premium increases by 0.2 basis point, following negative news and increases by 1.3 basis points on positive news. The risk premia consequently does not move in response to a negative surprise, but only to a positive surprise.

Our results clearly link the information content of macroeconomic variables to responses in the term premia and note that risk premia on average play a non-negligible part in the yield curve.

3.5 Implications for macroeconomic modelling

Our results suggest that up to 40% of the response in the yield curve to macroeconomic announcements is risk. Hence there is an endogenously *wedge* - in terms of a risk premia - between the bond market response predicted by macroeconomic models and the realized values. This may in part explain the so called *excess volatility puzzle*, see e.g., den Haan (1995) and Gurkaynak, Sack, and Swanson (2005); long term interest rates vary more to macroeconomic variables than what DSGE models predict for economies with quite stable inflation and small movements in output.

The excess volatility puzzle implies the models do not get the end points in the economy correct, and as expectations are everything in modern macroeconomics, this implies DSGE models do not get short-run behavior correct as indicated in the discussion in Gurkaynak, Sack, and Swanson (2005). The fundamental stance of the economy feeds back to the economy both through their direct determination of the long interest rate and its effect upon the macroeconomy, but also through the impact of future fundamentals upon expectations of future macroeconomic variables today. The excess volatility observed in the long end of the yield curve can be attributed to the term premia, which breaks both the relationships between yields and relationship between long yields, the end points of the macroeconomic variables and expectations about them today. Changes in the long end of the yield curve is simply an unreliable source of information about the stance of the economy.

The standard paradigm in macroeconomics has so far been to simply to ignore risk premia, but both theory and our results point to that this ignorance of modelling risk premia is not innocuous, as also pointed out in Alvarez, Atkeson, and Kehoe (2007). Furthermore it certainly warrants the approach to central banking advocated in Blinder (1998): *'Estimate how much you need to tighten or loosen monetary policy to "get it right". Then do less'.* Ignoring the risk premia is certainly not the way to go, the risk premia has an important role to play in future macroeconomic modelling.

Another implication of the results we have presented is that time variation in risk premia on financial assets can generate empirically plausible responses in bond yields to movements in macroeconomic variables. Furthermore, as shown in this paper, we are confident that term premia movements are significantly influenced by movements in macroeconomic variables. These insights together suggest that, firstly, risk premia should be incorporated into macroeconomic models and, secondly, risk premia derived from first principles is the road ahead as risk premia do depend on key macroeconomic variables in a meaningful way. Also it would be preferable, that preferences allow for asymmetric movements in risk premia in response to movements in macroeconomic variables. This may hopefully also help solve other puzzles than the excess volatility puzzle. We leave a deeper analysis and modelling of risk premia in macroeconomic models to future research.

3.6 Concluding Remarks

The decomposition clearly shows the asymmetry stemming from the term premia. Furthermore, the effects are particularly pronounced at longer maturities. Our decomposition method is crucial for obtaining this result. This clearly warrants some consideration, although it is remarkable that the assumptions behind the decomposition are standard in macroeconomic modelling.

Our alternative approach amounts to estimate an affine term structure model for the entire yield curve. This however also has drawbacks. Firstly the method is clearly parametric and not based on any economic intuition. Secondly, the estimation becomes very cumbersome for large data sets. Finally, and probably most importantly, there are a number of parametric choices to be made, which all can be crucial for the actual outcome of the estimation. Therefore this approach is also not perfect.

We have intentionally not touched upon the drivers behind this asymmetry, as this appears very difficult without a concrete modelling framework. A natural starting point could be loss aversion, see for instance Benartzi and Thaler (1995) and Bonomo and Garcia (1993). We however hope that our paper provides some inspiration for theoretical macro models, that may explain the asymmetric response in the bond risk premia.

3.7 Appendix: Theoretical bond yield decomposition

We start from the fundamental pricing relation for zero coupon bonds, see for instance Cambell, Lo, and MacKinlay (1997),

$$P_t^n = E_t\left[M_{t+1}P_{t+1}^{n-1}\right].$$

We then take logs of the expression, assume joint log-normality, and obtain

$$\begin{aligned} p_t^n &= E_t\left[m_{t+1}\right] + E_t\left[p_{t+1}^{n-1}\right] \\ &\quad + \frac{1}{2}V_t\left(m_{t+1}\right) + \frac{1}{2}V_t\left(p_{t+1}^{n-1}\right) + cov_t\left(m_{t+1}, p_{t+1}^{n-1}\right), \end{aligned} \tag{3.7}$$

where $m_{t+1} \equiv \log(M_{t+1})$. Note, from this expression an explicit expression for the time-varying risk premia ϕ_t^n can be obtained as $\phi_t^n \equiv \frac{1}{2}V_t\left(m_{t+1}\right) + \frac{1}{2}V_t\left(p_{t+1}^{n-1}\right) + cov_t\left(m_{t+1}, p_{t+1}^{n-1}\right)$.

By iterating (3.7) and by the use of the law of iterated expectations we get

$$p_t^n = \sum_{i=1}^{n}\left[E_t\left[m_{t+j}\right] + \frac{1}{2}V_t\left(m_{t+j}\right)\right] - \sum_{i=1}^{n-1} E_t\left[hpr_{t+j}^{n-j+1}\right].$$

The joint log-normality assumption implies that the (log) short rate of interest, i_t, can be written as:

$$i_t = -E_t\left[m_{t+1}\right] - \frac{1}{2}V_t\left(m_{t+1}\right).$$

We define risk premia as the premium part of realized excess returns; the difference between the price of an asset, p_t, and its payoff discounted with the risk free rate, or, equivalently

$$hpr_{t+1}^{n+1} = -\frac{1}{2}V_t\left(x_{t+1}\right) - cov_t\left[\beta u'\left(c_{t+1}\right), x_{t+1}\right] / u'\left(c_t\right), \tag{3.8}$$

which reduces $\phi_t^n \equiv \frac{1}{2}V_t\left(m_{t+1}\right) + \frac{1}{2}V_t\left(p_{t+1}^{n-1}\right) + cov_t\left(m_{t+1}, p_{t+1}^{n-1}\right)$ derived above if the payoff, x_{t+1}, is the future price asset price, p_{t+1}. We have further introduced a consumption based discount factor, m_{t+1}, see Cochrane (2001).

3.8 Appendix: Tables

Decomposition regressions					
	R^2	α	β	β_{NEG}	No. Obs
CPI	0.0555	-1.4185	1.9846	-2.5525	66
		(1.4582)	(2.0852)	(3.0286)	
- Fundamentals	0.0450	-0.0097	0.3319	0.1847	
		(0.6902)	(0.9272)	(1.3671)	
- Risk	0.1080	-1.4088	1.6527	-2.7373	
		(0.8467)	(1.2140)	(1.7782)	
Factory Orders	0.0454	-0.0068	0.3114	0.1242	73
		(0.3119)	(0.2566)	(0.5592)	
- Fundamentals	0.0383	0.1516	-0.0021	0.3836	
		(0.2166)	(0.1441)	(0.3491)	
- Risk	0.0452	-0.1584	0.3135**	-0.2593	
		(0.1581)	(0.1467)	(0.3015)	
Industrial Production	0.2628	-0.0659	0.9843***	-0.4016	109
		(0.2861)	(0.3304)	(0.6499)	
- Fundamentals	0.2916	-0.2270	0.9358***	-0.5907	
		(0.2330)	(0.3242)	(0.5623)	
- Risk	0.0318	0.1610	0.0484	0.1892	
		(0.1477)	(0.1801)	(0.3199)	
Initial Jobless Claims	0.1163	0.2928	-0.8131***	0.1436	
		(0.1818)	(0.2386)	(0.4447)	
- Fundamentals	0.1452	0.0323	-0.5317***	0.0318	68
		(0.1095)	(0.1494)	(0.2847)	
- Risk	0.0324	0.2606***	-0.2814**	0.1118	
		(0.1039)	(0.1304)	(0.2080)	
ISM Manufacturing	0.4403	0.5542	2.0455***	0.7943	
		(0.4645)	(0.5233)	(0.9182)	
- Fundamentals	0.4299	0.2961	1.3989**	0.6556	395
		(0.3298)	(0.5862)	(0.8550)	
- Risk	0.2022	0.2581	0.6466***	0.1387	
		(0.2284)	(0.1831)	(0.3968)	
Non-farm Payroll	0.4306	0.7163	6.0380***	-1.2732	
		(1.0283)	(2.0602)	(2.5873)	
- Fundamentals	0.4155	0.2475	3.2590***	0.1546	74
		(0.7447)	(1.1256)	(1.5484)	
- Risk	0.2722	0.4687	2.7790***	-1.4278	
		(0.4541)	(1.0454)	(1.2989)	
Philadelphia Fed	0.4407	0.4051	0.4290	1.0253	17
		(0.7054)	(0.7202)	(1.1951)	
- Fundamentals	0.4429	0.8673	-0.1485	1.4778*	
		(0.4991)	(0.4287)	(0.8022)	
- Risk	0.1428	-0.4623	0.5774	-0.4525	
		(0.4705)	(0.4287)	(0.5785)	
Retail Sales	0.2114	-0.0310	2.0453***	-1.3317	93
		(0.4903)	(0.5317)	(1.0163)	
- Fundamentals	0.2107	-0.0870	1.2171***	-0.5807	
		(0.3072)	(0.3343)	(0.6273)	
- Risk	0.1121	0.0560	0.8282***	-0.7510	
		(0.2598)	(0.3006)	(0.5038)	

Table 3.1: US yield decomposition regressions for the 2-year T-note futures contract. The table shows the estimates from the 2-year yield (denoted y_t) regression, $y_t = \alpha + \beta N_t + \beta_{NEG} D_t N_t + \epsilon_t^y$, the 2-year risk premia (denoted TP_t) regression, $TP_t = \alpha + \beta N_t + \beta_{NEG} D_t N_t + \epsilon_t^{TP}$ and the 2-year fundamental (denoted ES_t) regression, $ES_t = \alpha + \beta N_t + \beta_{NEG} D_t N_t + \epsilon_t^{ES}$, where N_t is the surprise from the relevant macroeconomic release and D_t is a dummy for negative surprises. Newey-West robust standard errors in parenthesis. ***,**, and * denotes statistical significance at the 1%, 5% and 10% level.

Decomposition regressions					
	R^2	α	β	β_{NEG}	No. Obs
CPI	0.0467	-0.6982	1.3394	-1.3908	78
		(1.1174)	(1.7397)	(2.4582)	
- Fundamentals	0.0424	0.2786	-0.0013	0.6912	
		(0.5574)	(0.7689)	(1.1123)	
- Risk	0.1029	-0.9768	1.3407	-2.0820	
		(0.6262)	(0.9967)	(1.4388)	
Factory Orders	0.0847	-0.1956	0.6096**	-0.2760	85
		(0.2386)	(0.2514)	(0.5103)	
- Fundamentals	0.0421	0.0674	0.0977	0.2380	
		(0.1775)	(0.1660)	(0.3182)	
- Risk	0.0996	-0.2630	0.5120***	-0.5140	
		(0.1518)	(0.1594)	(0.3240)	
Industrial Production	0.1576	-0.0528	0.6374*	0.0860	81
		(0.3279)	(0.3899)	(0.7733)	
- Fundamentals	0.1986	-0.2394	0.6959***	-0.3628	
		(0.2417)	(0.2744)	(0.5295)	
- Risk	0.0372	0.1865	-0.0585	0.4488	
		(0.2216)	(0.3218)	(0.5067)	
Initial Jobless Claims	0.0730	0.1247	-0.5559***	-0.0811	451
		(0.1733)	(0.1983)	(0.3732)	
- Fundamentals	0.1215	-0.0006	-0.4658***	-0.0278	
		(0.1069)	(0.1420)	(0.2728)	
- Risk	0.0078	0.1252	-0.0901	-0.0534	
		(0.1043)	(0.1128)	(0.1775)	
ISM Manufacturing	0.4826	0.3168	2.8684***	-0.4517	94
		(0.4694)	(0.3745)	(0.8045)	
- Fundamentals	0.4196	0.1477	1.6113***	0.2982	
		(0.2954)	(0.4272)	(0.7315)	
- Risk	0.2248	0.1691	1.2571***	-0.7499	
		(0.3176)	(0.4071)	(0.6606)	
Non-farm Payroll	0.3771	-0.1020	5.8721***	-1.5680	118
		(1.0326)	(1.9853)	(2.4942)	
- Fundamentals	0.3859	-0.0387	3.3264***	0.0029	
		(0.7756)	(1.1208)	(1.5890)	
- Risk	0.2073	-0.0633	2.5457***	-1.5709	
		(0.3928)	(0.9791)	(1.0880)	
Philadelphia Fed	0.2418	-0.7885*	1.8109***	-1.1712	97
		(0.4028)	(0.6231)	(0.9006)	
- Fundamentals	0.2815	-0.2038	0.8359***	0.0620	
		(0.2543)	(0.3329)	(0.5721)	
- Risk	0.1338	-0.5847***	0.9750***	-1.2332***	
		(0.2257)	(0.3585)	(0.4819)	
Retail Sales	0.1971	-0.2774	2.0421***	-1.7232**	106
		(0.3969)	(0.4543)	(0.8244)	
- Fundamentals	0.1867	-0.2035	1.2555***	-0.8915	
		(0.2768)	(0.3138)	(0.5607)	
- Risk	0.0943	-0.0739	0.7865***	-0.8316**	
		(0.2038)	(0.2716)	(0.3998)	

Table 3.2: US yield decomposition regressions for the 5-year T-note futures contract. The table shows the estimates from the 5-year yield (denoted y_t) regression, $y_t = \alpha + \beta N_t + \beta_{NEG} D_t N_t + \epsilon_t^y$, the 5-year risk premia (denoted TP_t) regression, $TP_t = \alpha + \beta N_t + \beta_{NEG} D_t N_t + \epsilon_t^{TP}$ and the 5-year fundamental (denoted ES_t) regression, $ES_t = \alpha + \beta N_t + \beta_{NEG} D_t N_t + \epsilon_t^{ES}$, where N_t is the surprise from the relevant macroeconomic release and D_t is a dummy for negative surprises. Newey-West robust standard errors in parenthesis. ***,**, and * denotes statistical significance at the 1%, 5% and 10% level.

Decomposition regressions					
	R^2	α	β	β_{NEG}	No. Obs
CPI	0.0557	-0.5386	1.0711	-1.0087	79
		(0.8485)	(1.3266)	(1.8641)	
- Fundamentals	0.0423	0.2859	-0.0075	0.7001	
		(0.5495)	(0.7619)	(1.1042)	
- Risk	0.1228	-0.8246**	1.0786*	-1.7088*	
		(0.3817)	(0.6095)	(0.8839)	
Factory Orders	0.1177	-0.2700	0.7126***	-0.4960	87
		(0.2090)	(0.2497)	(0.4704)	
- Fundamentals	0.0407	0.0194	0.1288	0.1838	
		(0.1725)	(0.1672)	(0.3207)	
- Risk	0.1405	-0.2894**	0.5838***	-0.6798**	
		(0.1394)	(0.1697)	(0.3032)	
Industrial Production	0.1768	-0.1774	0.6881**	-0.2666	82
		(0.2646)	(0.2968)	(0.5969)	
- Fundamentals	0.2238	-0.3039	0.7721***	-0.4937	
		(0.2337)	(0.2463)	(0.4911)	
- Risk	0.0071	0.1265	-0.0841	0.2271	
		(0.1689)	(0.2225)	(0.3354)	
Initial Jobless Claims	0.0672	0.1195	-0.4588***	0.0253	458
		(0.1343)	(0.1565)	(0.2966)	
- Fundamentals	0.1179	-0.0005	-0.4547***	-0.0303	
		(0.1046)	(0.1391)	(0.2660)	
- Risk	0.0009	0.1200	-0.0040	0.0555	
		(0.0739)	(0.0801)	(0.1294)	
ISM Manufacturing	0.4418	0.1263	2.3967***	-0.6644	95
		(0.3995)	(0.2935)	(0.6485)	
- Fundamentals	0.4157	0.0853	1.6537***	0.2484	
		(0.2998)	(0.4305)	(0.7300)	
- Risk	0.0606	0.0410	0.7430*	-0.9128	
		(0.2978)	(0.4434)	(0.7437)	
Non-farm Payroll	0.3692	-0.3278	4.6657***	-1.5556	118
		(0.7949)	(1.5976)	(1.9498)	
- Fundamentals	0.3859	-0.0387	3.3264***	0.0029	
		(0.7756)	(1.1208)	(1.5890)	
- Risk	0.0591	-0.2892	1.3394**	-1.5585**	
		(0.2841)	(0.6587)	(0.6829)	
Philadelphia Fed	0.2155	-0.6582*	1.4315***	-0.9933	99
		(0.3400)	(0.5197)	(0.7438)	
- Fundamentals	0.2935	-0.1992	0.8317***	0.0951	
		(0.2525)	(0.3318)	(0.5643)	
- Risk	0.1036	-0.4590**	0.5997**	-1.0884***	
		(0.1907)	(0.2757)	(0.4190)	
Retail Sales	0.2043	-0.2154	1.6357***	-1.4218**	106
		(0.2987)	(0.3556)	(0.5788)	
- Fundamentals	0.1867	-0.2035	1.2555***	-0.8915	
		(0.2768)	(0.3138)	(0.5607)	
- Risk	0.0342	-0.0118	0.3802*	-0.5303*	
		(0.1787)	(0.2248)	(0.3280)	

Table 3.3: US yield decomposition regressions for the 10-year T-note futures contract. The table shows the estimates from the 10-year yield (denoted y_t) regression, $y_t = \alpha + \beta N_t + \beta_{NEG} D_t N_t + \epsilon_t^y$, the 10-year risk premia (denoted TP_t) regression, $TP_t = \alpha + \beta N_t + \beta_{NEG} D_t N_t + \epsilon_t^{TP}$ and the 10-year fundamental (denoted ES_t) regression, $ES_t = \alpha + \beta N_t + \beta_{NEG} D_t N_t + \epsilon_t^{ES}$, where N_t is the surprise from the relevant macroeconomic release and D_t is a dummy for negative surprises. Newey-West robust standard errors in parenthesis. ***,**, and * denotes statistical significance at the 1%, 5% and 10% level.

Appendix to Essay 2

Appendix to "Asymmetric Reponses in Bond Risk Premia to News"

4.1 Data description

The futures contract contain a number of underlying futures contract with differing expiry and settlement dates. The first contract is called the front futures contract and is the contract closest to expiry. The subsequent 3 futures contracts, called the 1^{st}, 2^{nd} and 3^{rd} back contracts are the contracts respectively with the second shortest expiry, third shortest expiry and 4th shortest expiry.

The price of the Eurodollar futures contract is determined as $P_t = 100 - R_t^{i,i+3}$, where $R_t^{i,i+3}$ is the expected 3-month rate interest rate at expiry in i months. In our case, we use $i = 0, 3, 6, 9$, that is in respectively 3, 6, 9 and 12 months from today. From the price the monetary policy path at delivery dates for the futures contract is easily calculated. Specifically, the monetary policy path at the 12-month horizon is given by[1]

$$r_t^{12M} = \sum_{i=0,3,6,9} \log(1 + \frac{R_t^{i,i+3}}{100})$$

The use of interest rate futures contract data is however problematic in one minor sense. The interest rates considered, are 3-month forward rates with fixed delivery dates. Firstly, this implies that the actual levels become distorted by the

[1] In principle, a longer monetary policy path length may be chosen, such as an 18-month horizon. Data availability prevented us from using a longer period.

cost-of-carry on these futures contracts. Secondly, the 12-month rates are also forward 12-month dates, but with differing days to forward start. The procedure used in this paper is similar to that used in Faust, Rogers, Wang, and Wright (2007)[2]. They, like us, look only at intraday changes, rather than levels. The cost-of-carry argument will consequently not be a problem, as cost-of-carry changes only at a day-to-day level and similarly the small differences in differing forward start days only gives very small measurement errors (second order effects) compared to using actual 3-month rates. The gains of having access to liquid intraday developments however by far exceed the very minor inaccuracies of using futures data instead of actual money market rates.

[2]The working paper version of their paper has an elaborate description of the data, which is similar to our data.

4.2 A model for decomposing money market rates

We start by defining our affine term structure model (AFTM), see also Ang and Piazzesi (2003), Duffie and Kan (1996), Dai and Singleton (2002) and Cambell, Lo, and MacKinlay (1997). The price of a zero coupon bond at time t with time-to-maturity n in an AFTM is given by:

$$P_t^n = \exp\left[A_n + \mathbf{B}_n' \mathbf{X}_t\right] \tag{4.1}$$

$\mathbf{X}_t$ denotes a vector of state variables in the economy

$$\mathbf{X}_{t+1} = \boldsymbol{\mu} + \boldsymbol{\rho}\mathbf{X}_t + \boldsymbol{\Sigma}\boldsymbol{\varepsilon}_{t+1}$$

in which $\boldsymbol{\rho}$ is the autoregressive parameter matrix, $\boldsymbol{\mu}$ is its vector of constants, and $\boldsymbol{\Sigma}$ denotes the covariance matrix for the underlying shocks in the economy, $\boldsymbol{\varepsilon}_{t+1}$, specified to be homoscedastic. The coefficient A_n and the matrix $\mathbf{B}_n$ only depends upon the *maturity* of the bond, and respect the following recursions visualizing the no-arbitrage restrictions imposed upon the financial markets by the AFTM:

$$\begin{aligned} A_{n+1} &= A_n + \mathbf{B}_n' \left(\boldsymbol{\mu} - \boldsymbol{\Sigma}\boldsymbol{\lambda}_0\right) + \frac{1}{2}\mathbf{B}_n' \boldsymbol{\Sigma}\boldsymbol{\Sigma}' \mathbf{B}_n - \delta_0 \\ \mathbf{B}_{n+1}' &= \mathbf{B}_n' \left(\boldsymbol{\rho} - \boldsymbol{\Sigma}\boldsymbol{\lambda}_1\right) - \boldsymbol{\delta}_1' \end{aligned} \tag{4.2}$$

The yield of a bond which matures in the next period must equal risk free rate which in the AFTM follows:

$$i_t = \delta_0 + \boldsymbol{\delta}_1' \mathbf{X}_t$$

The vector $\boldsymbol{\delta}_1'$ determines the loading of the state variables in the economy to the risk free rate of interest, while δ_0 determines the level of the risk free rate of interest in the absence of any shocks.

Our task is to decompose the futures into risk premia and expectations and the key determinants behind risk premia are the parameters $\boldsymbol{\lambda}_0$ and $\boldsymbol{\lambda}_1$. This can be seen by the model implied excess holding period return:

$$\begin{aligned} E_t\left[hpr_{t+1}^n\right] &\equiv E_t\left[p_{t+1}^{n-1}-p_t^n\right]-i_t \\ &= -\frac{1}{2}Var_t\left(hpr_{t+1}^n\right)-cov_t\left(m_{t+1},hpr_{t+1}^n\right) \qquad (4.3) \\ &= -\frac{1}{2}\mathbf{B}_{n-1}^{'}\mathbf{\Sigma}\mathbf{\Sigma}^{'}\mathbf{B}_{n-1}+\mathbf{B}_{n-1}^{'}\mathbf{\Sigma}\mathbf{\Lambda}_t \qquad (4.4) \end{aligned}$$

The first term is a Jensen inequality term while the second term is a risk premium, which arises from a non-zero covariance between the discount factor and the return on the asset. From (4.4), the functional form for the risk premia in an AFTM is given by $\mathbf{B}_{n-1}^{'}\mathbf{\Sigma}\mathbf{\Lambda}_t$: $\mathbf{\Lambda}_t \equiv \boldsymbol{\lambda}_0+\boldsymbol{\lambda}_1^{'}\mathbf{X}_t$ denotes the *market price of risk*; the Sharpe ratio that an asset must earn if it loads on a specific shock.[3] The market price of risk is also equal to the Girsanov kernel used to change probability measure, so $\mathbf{A}_n, \mathbf{B}_n$ are functions of the stochastic processes for the state variables in the economy under the equivalent martingale measure. $\mathbf{B}_{n-1}^{'}$ is the loading on bond prices of a shock to the state-variables in the economy such that $\mathbf{B}_{n-1}^{'}\mathbf{\Sigma}$ together is the quantity of risk or the expected fluctuation which investors can expect from bond prices.

4.2.1 Estimation of the affine yield curve model

We need to estimate the parameter vector, $\Theta \equiv \left(\delta_0, \boldsymbol{\delta}_1^{'}, \mathbf{\Sigma}, \boldsymbol{\mu}, \boldsymbol{\rho}, \mathbf{\Lambda}_t\right)$, for the AFTM. We follow Chen and Scott (1993) and use a one-step maximum likelihood estimation, which is both a first best econometric methodology and a feasible way to estimate the parameter vector in the model. The first task in this methodology is to determine the number of latent factors sufficient to price the money market rates. Using a standard principal component analysis, the first and second latent factor explain 0.9952 per cent of the variation in the bond yields and we consequently use only a 1-factor model.[4] Having 4 yields with different maturities

[3] The Sharpe ratio is defined as the excess return above the risk free rate divided by its standard deviation. It can be shown that the standard deviation of (4.4) in an AFTM equals $B_{n-1}^T\Sigma$. Disregarding the Jensen-term, Λ_t therefore equals the Sharp ratio.

[4] Standard in the literature is to use a 3-factor model, see Dai and Singleton (2000) and Ang and Piazzesi (2003). This paper, however, estimates money market rates for the very short end of the yield curve only. Further, the second, third, and forth principal component only explain

we assume the 6-month and 12-month money market rates are measured without error, while the 3-month and 9-month money market rates are assumed to be measured with error. Equation (4.1) can thus be inverted for the state-variables, $\mathbf{X}_t$, and the parameter vector, Θ, can be estimated by maximum likelihood. The details can be found in Chen and Scott (1993) or Ang and Piazzesi (2003). Table 1 gives the estimates of the model parameters.

Factor Structure	$X_{t+1} = \mu + \rho_1 X_t + \sigma\varepsilon_t$
ρ	0.9559 (0.0089)
μ	0.0019 (0.0145)
σ	0.0008 (0.0002)
Short Rate	$i_t = \delta_0 + \delta_1 X_t$
δ_0	0.0046 (0.0105)
δ_1	1 (-)
Market Prices of Risk	$\Lambda_t = \lambda_0 + \lambda_1 X_t$
λ_0	0 (-)
λ_1	-5.1950 (0.0050)

Table 4.1: Estimates for AFTM. The table reports parameter estimates and standard errors in parenthesis for a one-factor affine yield curve model.

It is however widely known that finding the maximum of the likelihood function can be tricky as the function is likely to be quite flat and/or contains local maximum. Starting values thus become very important. We search for the global maximum by random starting values on *daily* data, as even one estimation becomes extremely time consuming when using more than 200.000 observations. We take the estimates for the estimation of the daily data as starting values for the estimation of the intra-daily data.

0.0047 per cent, 0.0001 per cent, and 0 per cent respectively of the total variation in the money market rates.

Essay 3

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

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 phenomenon 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 distinguish 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 term describes the process of market makers passing around positions among each other, until a dealer is willing to put it on its own balance sheet or has an off-setting position. The phenomenon is therefore a search process of allocating positions across dealers through direct trading. Hot potato trading is common in markets with mandatory price setting, such as most market maker arrangements. The paper by Lyons (1997) was motivated by the behavior of market makers in the currency market, but such behavior is also observed in the bond market.

This paper is the first to empirically document the implications of hot-potato trading. The paper provides detailed information about hot potato trades and examines two aspects of hot potato trading in detail based on bond market data. Firstly, the drivers behind this type of trading is identified in a probit framework - the analysis, in addition to evidence provided by 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 although hot potato trading per definition is liquidity consuming, i.e. uses liquidity in the order book, trading primarily takes place 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 enhances 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 those 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.

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 the financial crisis spilled into government bond markets from credit markets, during the financial crisis and the slow 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 5.1 reviews the existing literature. In section 5.2, the data used in this study is discussed and described. Furthermore a formal empirical definition of hot potato identification and a detailed description on the extent of hot potato trading are 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 5.3, 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 5.3.1. Secondly, the price impact of normal and hot potato trades is analytically compared in a simple regression framework in 5.3.2. Section 5.4 offers some concluding remarks.

5.1 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 in order 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.

5.2 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 the occurrence of a trade, 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.

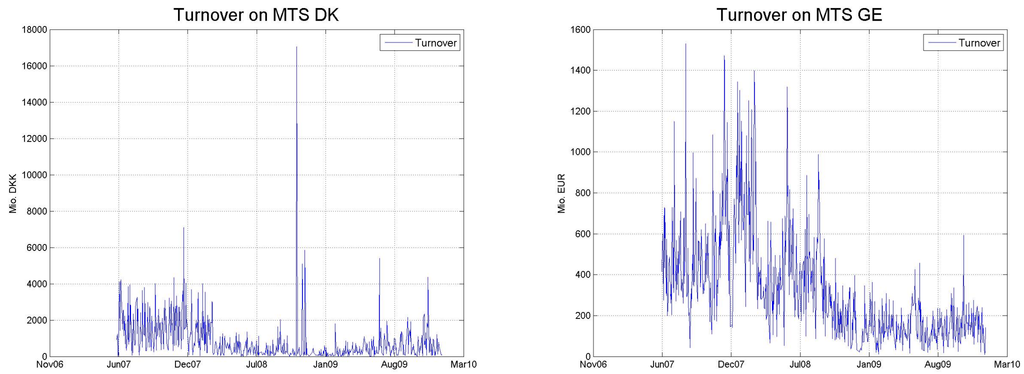


Figure 5.1: Daily turnover in MTS GE and MTS DK. June 2007 - October 2009.

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 5.1 above shows the turnover in the German market[1], where a substantial drop in turnover took place around 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.

5.2.1 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.

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

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

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.

5.2.2 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 5.2, dropped substantially on both platforms 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 5.1: 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.

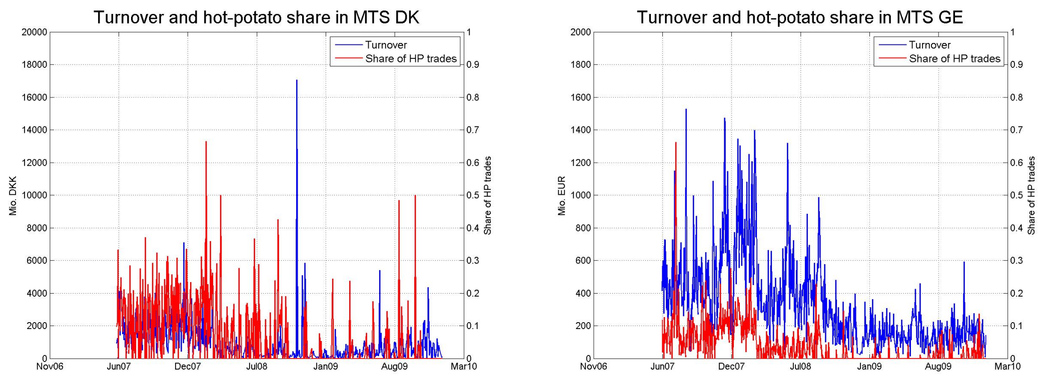


Figure 5.2: Daily turnover and hot potatoes share of daily turnover in MTS GE and MTS DK. June 2007 - December 2009.

The overall turnover and the share of hot potato trading tends to co-move, see Figure 5.3. 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.

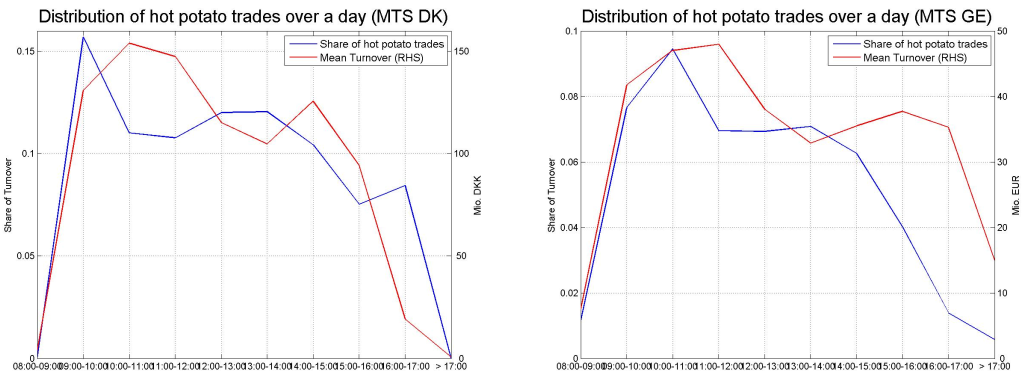


Figure 5.3: Average turnover and share of hot potato trading in hourly intervals. Averages is calculated on data from June 2007 - December 2009 for respectively the MTS GE and MTS DK trading platform.

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 5.4. 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

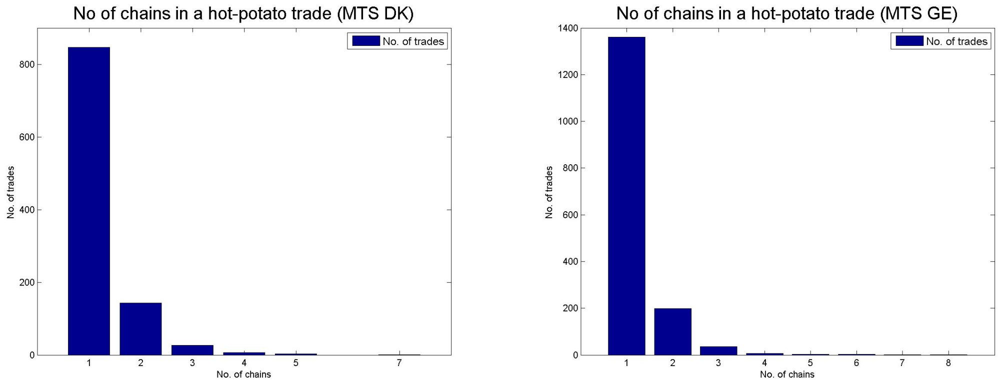


Figure 5.4: The number of hot potato trades following from an initiating trade on MTS GE and MTS DK over the period June 2007 - December 2009

this will leave some residual risk, for instance the risk stemming from changes in curvature or steepness, however this risk will be much lower than the full duration and credit risk on the principal.

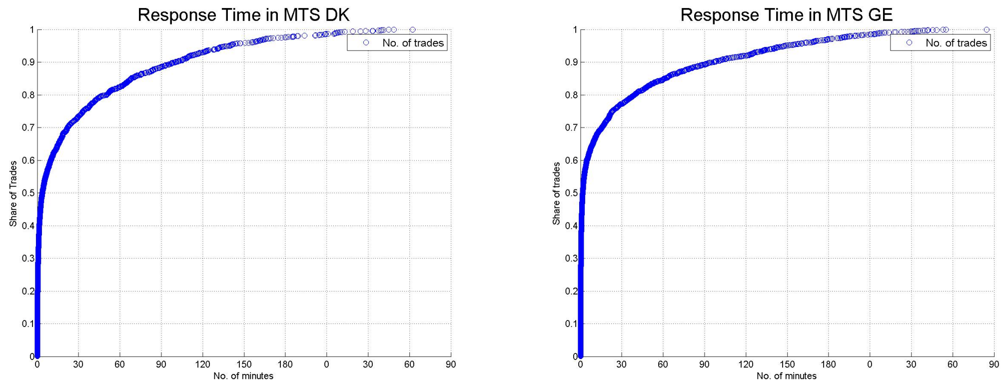


Figure 5.5: The response time from an initiating trade to the hot potato trade. The data used in this chart differs from the data used elsewhere in this paper, as the 30-minute time constraint is not used in the generation of the data for these charts. The data covers June 2007 - December 2009 on the MTS GE and MTS DK platforms

Figure 5.5, 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 5.5 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. Of all hot potato trades, around 5.5% has a lower quantity and 6.0% has a higher quantity in the Danish market, whereas the shares are10.5% and 6.0% in the German market. Therefore, the quantity matching constraint appears to be of modest importance.

5.2.3 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

[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.

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 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).

The 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 brings no new information to the market about order flows. Market participants are therefore likely to attach a lower weight on its informational value about the order flow.

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

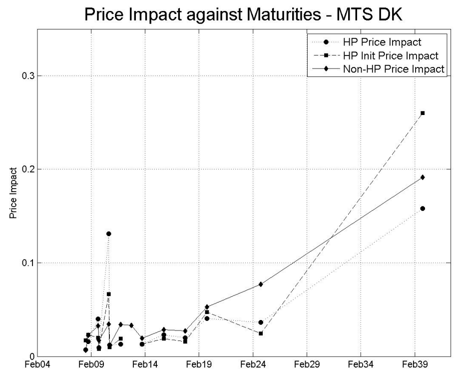
Table 5.2: Average price impact for the the period June 2007 to December 2009. Price impact is measured as the price change from the trade price to the market price 1 second after trade.

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 the trade is used. This gives a measure of whether price spirals are 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 5.3: 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.



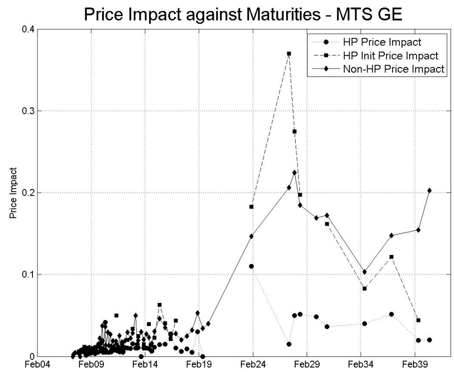


Figure 5.6: Average price impact on hot potato initiating trades, hot potato trades and other trades plotted against the maturity date on individual bonds. The data covers June 2007 - December 2009 on the MTS GE and MTS DK platforms.

As can be noted from the above Figure 5.6, 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

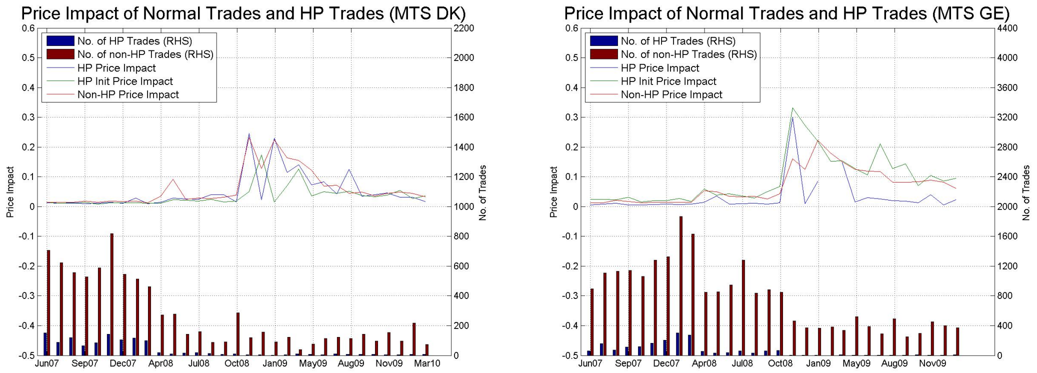


Figure 5.7: Average monthly price impact on hot potato initiating trades, hot potato trades and other trades and number of trades and hot potato trades. The data covers June 2007 - December 2009 on the MTS GE and MTS DK platforms.

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 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.

5.3 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 differs from the price impact on non-hot potato 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.

5.3.1 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 $\mathbf{X}$ 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 are 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

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

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

Table 5.4: 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, 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

[4]The Cramer (1999) only formally covers the logit model, but notes that the method also

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 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 5.5: 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.

5.3.2 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).

covers a wider range of binary choice models.

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. The hot potato trades do 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 $7\frac{1}{2}$ years to maturity becomes 0.5xBobl_return+0.5xBund_return. This gives a more correct, market-adjusted, return. As in the first measure, we look at the impact 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 5.6.

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 5.6: Price Impact

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.

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 5.7, 5.8 and 5.9. 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.

5.4 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 notes 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 do have the opportunity to distinguish and do 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.

5.5 Appendix: Tables

	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 (0.5357)	0.0015 (0.8129)	-0.0021 (-1.0285)	0.0042*** (4.0455)	0.0077*** (5.4419)	0.0153*** (9.1787)
Bid-ask spread	0.1242*** (4.5957)	0.0615** (2.3943)	0.1601*** (3.6151)	0.0037 (0.1171)	0.0738* (1.6529)	-0.0042 (-0.1180)
Kyle λ	0.6280*** (10.0624)	0.6672*** (16.5726)	0.6852*** (17.9112)	0.4632*** (6.8270)	0.3604*** (9.0343)	0.3947*** (9.9769)
Volatility	0.0606* (1.7918)	0.0159 (1.1047)	0.0140** (2.1535)	0.0285* (1.9533)	0.0056 (0.6139)	0.0040 (0.6189)
HP trade	-0.0028*** (-2.9015)	0.0003 (0.3535)	-0.0005 (-0.4338)	-0.0023*** (-3.8527)	-0.0058*** (-8.0420)	-0.0113*** (-7.2151)
HP initiating trade	-0.0010 (-1.1435)	0.0016 (0.8866)	-0.0020 (-1.5230)	0.0005 (0.3458)	-0.0007 (-0.3534)	-0.0032 (-0.7784)
Returns	0.7947*** (9.3940)	0.7080*** (11.6147)	0.7973*** (15.2331)	0.9402*** (14.4723)	0.9407*** (19.0657)	0.9037*** (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 5.7: 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 5.8: 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*** (2.4072)	0.0051*** (2.6153)	0.0008 (0.2869)	0.0068*** (6.5133)	0.0057*** (4.2579)	0.0163*** (7.9811)
Bid-ask spread	0.2308*** (3.3243)	0.0914** (2.2513)	0.2465*** (5.1508)	0.0030 (0.0591)	0.1247*** (3.1231)	-0.0056 (-0.1169)
Kyle λ	0.3438*** (4.2199)	0.5388*** (7.6371)	0.5343*** (9.2345)	0.4832*** (11.0346)	0.3037*** (5.5077)	0.3660*** (9.8642)
Volatility	0.0775 (1.2554)	0.0582** (2.3372)	0.0376*** (2.9266)	-0.0080 (-0.5959)	0.0256* (1.9001)	0.0080 (1.1705)
HP trade	-0.0042** (-2.3559)	0.0011 (0.6367)	-0.0016 (-0.9281)	-0.0026*** (-3.5369)	-0.0077*** (-5.7216)	-0.0077*** (-3.6210)
HP initiating trade	-0.0046*** (-2.5511)	0.0036 (1.4271)	-0.0028 (-1.4370)	-0.0011 (-0.6911)	-0.0014 (-0.7982)	-0.0008 (-0.2099)
Returns	0.9386*** (21.0631)	0.9534*** (34.1797)	1.0047*** (41.5563)	1.0572*** (74.3619)	1.0381*** (68.2108)	1.0804*** (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 5.9: 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 5.10: 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 5.11: 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 5.12: 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.

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Summary

Summary (english)

This thesis consists of three essays that can be read independently. All three essays employ financial high-frequency data to describe the behaviour of financial market participants. Specifically the first two essays describe the market response to macroeconomic news announcements. The third essay considers a special form of hedging behaviour, namely hot potato trading.

The first essay is about market expectations for macroeconomic news announcements. Event studies measuring the impact of macroenomic announcements rely on surveys as a measure of market expectations. However, these survey measures, such as Bloomberg or MMS surveys, are noisy indicators of actual market expectations as they are collected with a time lag and not among actual market participants. Based upon a Hellwig (1980) type market microstructure model, a market-based survey measure is proposed that takes into account orderflow/price movements prior to release in order to capture changes in market expectations. The model is tested on US and German 10-year bond futures contracts for 6 US and 2 German macroeconomic announcements and confirms the presence of expectation adjustments for the most important releases. Furthermore, the market-based survey measure captures the directionality of the surprise better than the standard Bloomberg survey measure.

The second essay also considers the impact of macroeconomic news announcements, but separate the overall effect into a bond risk premia and a fundamental component. We propose a new method for the identification of the fundamental part of the yield curve response using intraday risk adjusted money market futures. We are hence able to identify the behavior of both the fundamental part and the

risk premia. Our results suggest that changes in risk premia react asymmetrically to good and bad news while expectations of future short rates react symmetrically.

The final essay considers hot potato trading. Hot-potato trading is defined by Lyons (1997), as *"the repeated passing of inventory imbalances between dealers"*. This behaviour is predominantly found in markets with mandatory price setting, such as market maker arrangements, where market makers are obliged to quote bid and ask prices within a pre-defined bid-ask spread and for a given quantity. Upon a trade happening, the dealer has to decide how to handle the risk associated with newly obtained position. Hot potato trading is one of the hedging possibilities, where the market maker immediately decides to pass the position on to other market makers.

The essay contains 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.

Summary (dansk)

Denne afhandling består af tre essays, som kan læses uafhængigt. Alle tre essays bruger finansieller høj-frekevent dataserier til at beskrive de finansielle markedsdeltageres ageren. Specifikt beskriver de første to essays markedets reaktion til annonceringen af makroøkonomiske nyheder. The tredje essay undersøger en speciel form for afdæknings adfærd, nemlig hot potato handel.

Det første essay er om markedsforventninger til makroøkonomiske nyheder. Event studier der måler markedsreaktionen på offentliggørelsen af makroøkonomiske nyheder er baseret på rundspørger, der bruges som mål for markedets forventninger. Men, disse rundspørger, sådan som Bloomberg eller MMS surveys, er støjfyldte indikatorer for de faktisk markedsforventninger, idet de er indsamlet tidligere og ikke blandt faktiske markedsdeltagere. Ved at bruge en Hellwig (1980) type markeds microstruktur model så foreslås et markedsbaseret rundespørge mål, der tager højde for orderflow/prisbevægelser før offentliggørelsen, til at fange ændringer i markedsforventningerne. Denne model er testet på 10-årige amerikanske og tyske obligation futures kontrakter for 6 amerikanske og 2 tyske makroøkonomiske nøgletal, og denne test bekræfter tilstedeværelsen af forventningsændringer for de vigtigste nøgletal. Ydermere så fanger det markedsbaserede rundspørge mål retningen for overraskelsen bedre end det klassiske Bloomberg rundspørge mål.

Det andet essay betragter også markedsreaktionen på offentliggørelsen af makroøkonomiske nyheder, men adskiller den overordnede reaktion på en obligationsrisiko præmie og en fundamental komponent. Vi foreslår en ny metode til idenfikation af den fundamentale del af rentekurve reaktionen ved hjælp af intradag risiko-justerede pengemarked futures kontrakter. Derved er vi i stand til at identificere reaktionen af både den fundamentale og risiko præmie delen. Vores resultater antyder, at ændringer i risiko præmien reagerer asymmetrisk til gode og dårlige nyheder, men forventningen af fremtidige korte renter reagerer symmetrisk.

Det sidste essay betragter hot potato handel. Hot potato handel er defineret af Lyons (1997), som *"gentagen videregivelse af lager ubalancer mellem dealers"*. Denne opførsel findes fortrinsvis i markeder med obligatorisk prisstillelse, sådan som det observeres i market maker arrangementer, hvor market makers er forpligtet til at kvotere bud og udbuds priser indenfor et pre-defineret bud-udbudsspænd og

for en given mængde. Efter en handel, så skal dealeren beslutte hvordan risikoen på den nye position skal håndteres. Hot potato handel er en af hedging-mulighederne, hvor market maker umiddelbart beslutter sig at sælge positionen videre til andre market makers.

Essayet giver en empirisk undersøgelse af hot potato handel i det tyske og danske obligationsmarked. Der gives en detaljeret beskrivelse af fænomenet og to aspekter af hot potato handel undersøges nærmere. Den første analyse konkluderer, at hot potato handel primært finder sted under rigelige likviditets forhold og er derfor en klar indikation for et velfungerede marked, siden hot potato handel tillader risiko deling på tværs af markedsdeltagerne. For det andet, så er den estimerede pris effekt på hot potato handler lavere sammenlignet med andre handler, hvilket indikerer at market makers skelner mellem informationsindholdet i enkelte handler.