Essays on the price discovery process in bond future markets

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Abstract

The main focus of the following research is on studying the incorporation of non-public/private information in the German and US bond market. Section 1 starts with the price discovery process in the German bond future market. Section 2 tests the hypothesis of priced information risk for the German bond market and analyzes how the presence of informed traders influences the term structure of interest rates. We additionally pick up the idea that market liquidity is an important market factor and additionally consider liquidity risk in the analysis. Sections 3 and 4 analyze the finding that information and liquidity risk is priced in the term structure of interest rates.
Keywords: Bond future, order flow, bond excess returns.
Zusammenfassung

Die Forschungsarbeit befasst sich mit der Verarbeitung von nicht-öffentlichen/privaten Informationen im deutschen und US-amerikanischen Bondmarkt. Abschnitt 1 beginnt mit dem Preisfindungsprozess im deutschen Bond-Future-Markt. Abschnitt 2 testet die Hypothese ob Informationsrisiken im deutschen Bondmarkt gepreist sind und analysiert wie die Anwesenheit von informierten Händlern die Zinsstrukturkurve beeinflusst. Zudem wird die Vorstellung aufgegriffen, dass Marktliquidität eine wichtige Marktgröße ist, so dass Liquiditätsrisiko ebenfalls in der Analyse berücksichtigt wird. Abschnitte 3 und 4 analysieren wie Informations- und Liquiditätsrisiken die Zinsstrukturkurve beeinflussen.
Schlagworte: Bond Future, Order Flow, Bond-Überschussrendite.

Essays on the price discovery process in international bond markets

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Preface

The ongoing European debt crisis (2009-20??) and the decision of the European Central Bank (ECB) to consider "Outright Monetary Transactions (OMTs) in secondary markets for sovereign bonds in the euro area" (ECB, 2012a) bring back memories of the importance of "*functioning*" bond markets. The ECB's understanding of "functioning" bond markets is at least the markets' ability of ensuring the transmission of monetary policy (compare ECB, 2012b). A more general definition of "*functioning*" is given by O'Hara (2003) who sees price discovery and liquidity provision as the key functions of financial markets. An intact (bond market's) price discovery process should be able to *incorporate public information*, e.g. macroeconomic announcements, as well as *private information*, e.g. the investors' interpretation of the customer orders' pricing implications. The literature's definition of *liquidity provision* can be subsumed to be the investor's ability of buying or selling a financial contract without owning large price impacts (Hasbrouck, 2009), so that trading volume and bid-ask spreads a often considered candidates for proxying market liquidity (see Fleming, 2003).

The main focus of the following research is on studying the incorporation of non-public/private information in the German and US bond market. Private information can be understood as pricing-relevant information which are not shared by all investors. In other words, private information are owned by investors who have superior access to information and/or skills to interpret economic announcements. In order to take advantage of their information these investors are enforced to open or close positions in the market. Thus, the informed traders' behavior can be observed in trading data – namely order flow (for a theoretical foundation see for example Evans and Lyons, 2002).[1] However, as O'Hara (2003) stresses out the importance of liquidity for functioning financial

[1]Order flow (order imbalance) measures the difference between buyer- and seller-initiated trades. However, the here considered data sets do not offer the information whether a trade is buy- or sell-side initiated. The initiation side is approximated with the Lee and Ready (1991)- or the Easley et al. (2012)-algorithm. Both approaches are explained in the corresponding sections.

markets we additionally analyze the importance of liquidity (trading volume, bid-ask spreads and price impacts) for bond markets.

Section 1 starts with the price discovery process in the German bond future market. We try to answer the issue of the importance of the German bond future contracts by considering an vector error correction model (VECM) which delivers so-called *information shares*. These shares can be understood as the relative contribution of one future contract to the price process which is shared by the three considered bond contracts.

We analyze the relative importance of the most liquid European bond future contracts which are the two-, five- and ten-year German bond futures. Due to its outstanding trading volume the ten-year bond future (called Bund future) is mainly accepted as the single most important European bond contract. This benchmark status is underlined by considering the German ten-year interest rate as reference yield for computing interest rate spreads in the Euro Area. This approach assumes that the ten-year bond reflects the flow of information more precisely than any other European bond contract. However, this assumption stands in contrast to the expectation hypothesis, the theoretical workhorse of bond pricing models. This hypothesis suggests that short-term interest rate innovations role over to longer maturities which proposes that the two-year bond future contract dominates the European bond markets' price discovery process.

Our findings confirm the market view that the ten-year bond future is on average the most important future contract and leads the price discovery process. However, the two- and five-year contract contribute an economically significant amount to the shared price path whereby the former one gains substantial during days with ECB press conferences. This is an indication that the ECB mainly commands over the short end of the yield curve. The importance of the five-year contract is rooted in the average duration of bond portfolios which is roughly five years. This characteristic brings the five-year contract in a role as the major instrument for hedging bond portfolios.

For a deeper understanding of the price process we regress information shares on (i) order flow as a proxy for the price discovery process and on (ii) bid-ask spreads, trading volume and volatility as proxies for market liquidity. Information shares increase with a relative higher order flow and with a relative improvement of trading conditions which underline their importance for functioning financial markets.

Section 1 reveals that private information, proxied by order flow, is an important driver of the price discovery process in the bond market. Following the argument of Li et al. (2009), the presence of private information (order flow) in the market can be interpreted as information risk for which investors have to be compensated.

Section 2 tests this hypothesis for the German bond market and analyzes how the presence of informed traders influences the term structure of interest rates. Beside information risk, we again pick up the idea of O'Hara (2003) that market liquidity is an important market factor and additionally consider liquidity risk in the analysis.

We follow Hasbrouck (2009) and define liquidity risk as the effective cost of an order execution which is also used as a benchmark measure for liquidity (see Goyenko et al., 2009). Information risk is the possibility of a price discovery event which coincides with asymmetric information. With the presence of asymmetric information risk, investors ask for risk compensation (see O'Hara, 2003). As propagated by Easley et al. (1996) and Easley et al. (2002) we define information risk as the probability of informed trading, in short PIN, whereby PIN is defined as the number of trades from informed investors divided by total trading. In the Easley et al. (1996) model market makers learn about information events and the presence of informed traders by observing the arrival of buy and sell orders. In order to protect against potential losses to informed traders, the market maker sets prices which compensate for bearing this risk.

Regressing changes of interest rates and term structure factors on liquidity and information risk for the time period 10/2004 to 02/2009 reveals that an increase of risk results in stronger movements of Euro Area interest rates and term structure factors. Liquidity risk is priced along the whole yield curve and seems to be more important than information risk. This finding is consistent with Li et al. (2009) who document a stronger link of US Treasury bond prices to liquidity risk than to information risk. Neither controlling for trading volume, spread, order flow nor realized volatility rules out the effects of information and liquidity risks. However, information risk becomes a relevant pricing factor in the aftermath of the Lehman Brothers bankruptcy which suggests increasing risk sensitivity during the financial crisis.

Sections 3 and **4** additionally analyze the finding that information and liquidity risk is priced in the term structure of interest rates. Both sections are built on the Adrian et al. (2012) term structure model which extracts the bond market risk premium from raw interest rates.[2]

Section 3 analyzes the determinants of US realized, expected and unexpected bond excess returns on a monthly basis. Besides publicly announced information, such as consumer prices or unemployment rates, order flow (interpreted as private information) determines future bond risk premia. Additionally controlling for bond market liquidity does not change this finding. The predictability of bond excess returns stems from the strong linkage of expected excess returns to contemporaneous order flow. Changes of the macroeconomic state variables (macroeconomic factors) and order flow determine unpredictable excess returns – so-called excess return innovations.

Section 4 transfers the findings of Section 3 to a daily basis. For the US market, order flow is the main driver of innovations of the bond risk premium. Consistent with findings of Section 2, the pricing effect of liquidity risk becomes relevant in times of market stress, namely the Russian default and the LTCM crisis (1998-1999), the dot-com (2001-2002) and the subprime (2007-2009) asset price bubble. Macroeconomic information do only play a minor role.

To sum up, the bond market's price discovery process aggregates public and dispersed

[2]The risk premium is the difference between realized (observed) interest rates and model-implied risk-neutral interest rates. Risk-neutral yields are derived by setting the derived market prices of risk of the bond pricing factors to zero.

private information. As pointed out by Sections 1 and 2, liquidity provision is essential for ensuring an intact price discovery process. The economic implication of information and liquidity risk is discussed in Sections 2 to 4. Section 2 reveals that an increase of one of these risk elements leads to higher interest rate changes. The importance of market liquidity for bond pricing should be seen with recent developments in European peripheral bond markets where market liquidity dried up (ECB, 2011) and illiquidity is an important pricing factor for interest rate spreads (see De Grauwe, 2011 and Monfort and Renne, 2011).

Final remarks are offered at the end of this dissertation. This last section will discuss some policy implications of the conducted research.

1 Does the "Bund" dominate price discovery in Euro bond futures? Examining information shares*

Abstract

This paper examines the relative information shares of the Bund, i.e. the 10-year Euro bond future contract on German sovereign debt, versus two futures with shorter maturity. We find that the Bund is most important but does not dominate price discovery. The other contracts also have relevant – and at many days even higher – information shares. In examining determinants of information shares, we add order flow measures to market state variables and macroeconomic news. More order flow in a contract consistently increases this contract's information share.

1.1 Introduction

The so-called "Bund" future contract is often regarded as the single most important asset in the Euro bond markets. The Bund is a standardized contract on German sovereign bonds with ten-year maturity. Due to its benchmark status the trading of this contract is expected to reflect the flow of news into this market more accurately than other assets. According to this view, the Bund would dominate price discovery in the Euro bond markets, i.e. the formation of interest rates. However, price discovery can occur over the whole yield curve and, for example, some news may be more important at shorter interest rates than ten years. Therefore, we examine the relative weight of the Bund future in price discovery versus two other liquid Euro bond future contracts. We find that the Bund is important indeed, but that it is not dominating at all.

The Bund future derives its benchmark status for European bond markets mainly from

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three facts (see Menkveld et al., 2004). First, Germany is the largest economy in the Euro area and its federal debt has the lowest risk spread. Second, future markets seem to be often more important than spot markets in price discovery, in particular if they are more liquid as it is the case here (see Covrig et al., 2004, for equities, Mizrach and Neely, 2008, for bonds). Third, among future contracts on German sovereign debt the Bund has about twice the trading volume than contracts on shorter maturities. Overall, there are good reasons to assume a leading role for the Bund in the process of discovering the interest rate level. There is indeed empirical evidence that German debt has a dominating role in the Euro area and we know that the Bund future dominates the ten-year bond (Upper and Werner, 2007, Schlusche, 2009). However, we do not know of an empirical examination of the relative importance of the Bund in comparison to other Euro bond future contracts.

This examination has a natural motivation: we know that future contracts tend to be more important than the underlying bonds for price discovery, so, if there are several similar contracts as in our case, is any of them dominating? There is also a theoretical motivation for this research question as the expectation theory of the term structure suggests that changes in the short-term contract may roll-over to longer-term durations which Hall et al. (1992) test in a cointegration framework. Finally, Brandt and Kavajecz (2004) find a high importance of medium-term – 5 years – bonds as these best reflect average duration in bond portfolios and are thus most convenient for adjustment purposes in practice. Overall, there are good reasons to examine the Bund's dominance in price discovery.

Our research addresses exactly this issue: which contract (which market) is relatively most important in incorporating permanent price changes first, i.e. which contract is relatively most important in price discovery. We apply a standard econometric approach, i.e. the identification of "information shares". In detail, we use three related econometric techniques, i.e. information shares (Hasbrouck, 1995), modified information shares (Lien and Shrestha, 2009) and HMW-information shares (deB. Harris et al., 2002).[3] This vector error correction approach aims for identifying the relative importance of certain time series to a common development. By applying it to financial markets one can analyze, for example, the relative contribution of single stock return histories to stock market development, the relative contribution of two markets or the relative contribution of two trading instruments. In our case, we are to the best of our knowledge the first to analyze the relative contribution of three bond future con-tracts to bond price development in one market. In particular, we examine the relative information shares of the Bund in comparison to the contracts with two- and five-year maturity.

As a second contribution, we examine possible determinants of information shares in order to better understand where or when price discovery takes place. These determinants come from three directions: first, we consider market state-related variables (see Mizrach and Neely, 2008), such as trading volume, volatility and spread, second, we take up the insight that macroeconomic news influence markets which has been modeled in the literature in various ways (Fleming and Remolona, 1999, Balduzzi et al., 2001, Andersen et al., 2007). Third, and according to our knowledge new to the literature on information shares, we consider order flow which is important for incorporation of information in bond markets too (e.g. Brandt and Kavajecz, 2004, Pasquariello and Vega, 2007).

We find indeed that the Bund has the largest information share and thus seems to be most important in price discovery of the interest rate level. Interestingly, however, despite its benchmark status, the Bund does not really dominate price discovery. Instead, all three considered contracts have considerable information shares and seem thus to be relevant. We gain further insight in the special roles of the single contracts by analyzing determinants of information shares. We see that market state-related variables are im-

[3]deB. Harris et al. (2002) are the first to apply the technique of Gonzalo and Granger (1995) to financial markets. Therefore, Mizrach and Neely (2008) name this the "Harris-McInish-Wood information share"-approach, in short: HMW-approach.

portant determinants of information shares and that the effects behave quite consistently across all three future contracts. By contrast, macroeconomic news has relatively small and diverse effects. US news seem mainly to be incorporated at the Bund, i.e. at the longer end of the yield curve, whereas press conferences of the European Central Bank have effects more on the Schatz, i.e. on the shorter end of the yield curve. Finally, we confirm from our perspective that order flow is a relevant medium of information incorporation. The relative contribution of unexpected order flow is generally less important but turns significant at non-announcement days, as found by Pasquariello and Vega (2007). Medium-sized trades as an indicator about the existence of "stealth trading" are quite insignificant in our sample (Barclay and Warner, 1993, Chakravarty, 2001).

This research fits into various lines of earlier work on price discovery in bond markets and extends earlier findings, first, by focusing on the European bond futures market, and second, by including order flow as determinant of information shares. For the US market, Fleming and Remolona (1997) find the importance of news, a direction extended by Green (2004). Brandt et al. (2007) consider future markets and reveal the impact from order flow on prices. Mizrach and Neely (2008) are closest to our work as they also apply the information share-approach, although comparing for the US the information shares of spot and future markets. There is less research on European markets. Upper and Werner (2007) are relatively closest to us in this respect as they also apply the information share-approach, however, to the German ten-year maturity only and without considering any determinants. Dunne et al. (2007) question the benchmark status of German sovereign debt, although without covering the most liquid future contracts in their analysis and Andersson et al. (2009) strictly focus on volatility-effects due to macroeconomic announcements.

The paper is organized in the following steps: Section 1.2 describes the data and Section 1.3 outlines the econometric approach. Section 1.4 provides information shares and Section 1.5 examines its determinants, thus supporting an economic interpretation. Section

1.6 provides some robustness exercises and 1.7 concludes.

1.2 Data

The study is based on high frequency data of trading in the three most liquid Euro bond future contracts between 2004 and 2007. In addition, we use macroeconomic news as well as order flows for our analyses.

The data on German government bond futures' trading ranges from 01.06.2004 to 07.06.2007. The three considered contracts are – with increasing maturity – the two-year maturity "Bundesschatzanweisungen" (in short: "Schatz"), the five-year "Bundesobligationen" ("Bobl") and the ten-year "Bundesanleihen" ("Bund"). These three contracts are the most liquid futures in the Euro area and they are all AAA-rated (S&P). The underlyings are the maturity-related bonds each with a face value of 100.000 EUR and a yearly coupon payment of six per cent.

To concentrate our analyses to the most liquid contracts we make use of the "auto roll" procedure, briefly described e.g. by Andersson et al. (2009). Contracts' trading is compared on a daily basis and the one with the highest volume is included into the data set. With this in hand and combined with the findings of Brandt and Kavajecz (2004) and Pasquariello and Vega (2007) who postulate that liquidity is related to the time to maturity, we focus our attention on "on-the-run" contracts which dominate the price process (see Brandt and Kavajecz, 2004).

Our data are recorded at EUREX which is the only supplier of an electronic trading platform for fixed income futures in Germany and offers regular trading hours from 8:00 a.m. up to 6:00 p.m. till 20.11.2005 and up to 10:00 p.m. afterwards. The collected raw data provide the exact timestamp, last bid, ask and transaction price as well as its quantity. This gives us the possibility to construct trade related variables. Buy and sell identifications take place via the direct comparison of the transaction price and the

quoted bid and ask. If the trade hits or understates the bid price, the order is classified as a sell and vice versa. In order to bring this information into a final data set which gives the opportunity of a comparison at the highest possible frequency we assign each contract for each second during the trading day an average possible trading price, represented by the midquote. This virtual price is computed as the half of summing up the bid and ask price. As we cannot observe a chainsaw pattern in our time series, as reported by Brandt et al. (2007), we do not need to control or to correct for this effect. Table 1 summarizes the major characteristics of our sample. Consistent with the US Treasury market most of the trading per day is concentrated in the longer-term contract, i.e. the ten-year future (see Brandt et al., 2007). With 16,290 transactions per day on average and a total turnover of 959,056 contracts, it almost surpasses the two-year and the five-year contract by a factor of two and nurtures the view that the Bund future might be seen as the benchmark in the European bond market (Dunne et al., 2007).
Releases of macroeconomic news induce strong movements in the US bond as well as in the German Bund future market (Fleming and Remolona, 1999, Andersen et al., 2007, Andersson et al., 2009). Thus it is necessary to analyze their impact in our sample, too. We use the International Money Market Survey (MMS) and Bloomberg to collect median forecasts and realizations of the relevant macroeconomic fundamentals. In determining our data set of US, Euro Area and German specific news, our selection is strongly influenced by Fleming and Remolona (1999). We consider their five most influential US macroeconomic news (on the five-year on-the-run GovPX bond) and select their European and German equivalents, too. In detail, we take the unemployment statistics, producer and consumer price indexes, GDP and retail sales releases. We enrich the data set by adding further market-relevant announcements, i.e. the US nonfarm payroll employment (see Hautsch and Hess, 2007, or Andersen et al., 2007), the German industrial production and the German IFO industry survey of business climate (Ahn et al., 2002). Andersson et al. (2009)) report leakages regarding the official release dates of the

German unemployment rate, so that we use their correction of dates for this variable. Finally, given a high impact of the federal fund target rate (Fleming and Remolona, 1999), we include days with FOMC (Federal Open Market Committee of the US central bank) meetings or ECB (European Central Bank) press conferences. As the FOMC's policy decisions are published outside the official trading hours the corresponding dummy variable is set to one for the next trading day.

Shorter-term price discovery regarding macroeconomic data refers mainly to its surprise component and less to the announcement as such. Thus, we define the news content of announcement i, S_i, as the difference between the realization A_i and the median forecast E_i. For our purpose it does not make a difference whether the realization is larger or smaller than the median forecast. So we take the absolute difference of news as our measure (see also Chen and Gau, 2010). As the news content can differ across the announcements, we compute standardized news surprises for announcement i at day t by dividing the news content by its standard deviation σ_i,

$$S_{i,t} = \frac{|A_{i,t} - E_{i,t}|}{\sigma_i} \ . \tag{1}$$

The last kind of data which is used in the empirical work is various measures of order flow. Order flow is a measure of signed transactions and can easily be constructed from the available data on futures trading.

1.3 The econometric approach

1.3.1 Price discovery metrics

Price discovery metrics are a standardized measure of price discovery for cointegrated time series in multiple markets or assets. We apply three standard approaches, i.e. the Hasbrouck (1995), the Lien and Shrestha (2009) and the deB. Harris et al. (2002)

Table 1: Eurex future trading data: summary statistic

This table shows descriptive statistics for the underlying data set. Transactions and quotes are collected from the Eurex trading platform and cover the time range between June 01st, 2004 and June 7th, 2007. Market relevant information includes the future's specific return (multiplied with 100), the quantity and the number of buys, sells, order flow and the trading volume. The columns contain the estimated means, standard deviations, maximums, minimums and the first order autocorrelation for the two-, five- and ten-year futures. A '*', '**' or '***' shows the significance of the first-order autocorrelation at the 10%, 5% or the 1% level.

	mean	stdev.	max.	min.	$\rho(1)$	p-value
			2-year			
Daily return	-0.0035	0.0010	0.0030	-0.0040	0.0030	0.92
Number of buys per day	1931	872	7633	299	0.574	0.00***
Volume of buys per day	233,547	88,613	632,714	29,940	0.387	0.00***
Number of sells per day	-1974	920	-173	-7225	0.587	0.00***
Volume of sells per day	-235,884	91,877	-25,071	-655,901	0.393	0.00***
Binary order flow per day	-43	439	1967	-2645	0.183	0.00***
Quantitative order flow per day	-2337	31,532	138,017	-119,220	0.070	0.03**
Binary trading volume per day	3906	1738	14,558	472	0.606	0.00***
Traded contracts per day	469,432	177,745	1,288,615	55,011	0.400	0.00***
			5-year			
Daily return	-0.0100	0.0020	0.0060	-0.0100	0.0070	0.82
Number of buys per day	3617	1259	11,131	666	0.511	0.00***
Volume of buys per day	261,847	88,531	556,966	38,302	0.380	0.00***
Number of sells per day	-3636	1343	-553	-10,960	0.527	0.00***
Volume of sells per day	-262,857	90,448	-29,114	-605,430	0.375	0.00***
Binary order flow per day	-19	497	2187	-1999	0.004	0.91
Quantitative order flow per day	-1010	24,332	83,260	-85,443	0.023	0.47
Binary trading volume per day	7253	2555	22,091	1219	0.539	0.00***
Traded contracts per day	524,704	177,328	1,162,396	67,416	0.384	0.00***
			10-year			
Daily return	-0.0100	0.0030	0.0100	-0.0140	0.0120	0.70
Number of buys per day	8121	3628	25,432	1135	0.696	0.00***
Volume of buys per day	477,972	167,034	1,091,272	56,528	0.441	0.00***
Number of sells per day	-8169	3771	-1035	-24,357	0.697	0.00***
Volume of sells per day	-481,085	173,386	-42,819	-1,271,967	0.440	0.00***
Binary order flow per day	-48	770	3602	-3976	-0.059	0.06*
Quantitative order flow per day	-3113	42,736	138,790	-248,798	0.122	0.00***
Binary trading volume per day	16,290	7361	49,789	2170	0.704	0.00***
Traded contracts per day	959,056	337,787	2,295,136	101,527	0.445	0.00***

approach.

The efficient price process can be worked out by an error-correction model with the following representation (see Engle and Granger, 1987)[4]:

$$\Delta p_t = \alpha z_{t-1} + \sum_{i=1}^{s} \Gamma \Delta p_{t-i} + \varepsilon_t \ . \tag{2}$$

Δp_t defines the price changes in period t, Γ_i the corresponding coefficient matrix and α the error correction vector. z_{t-1} captures the error-correction terms between the markets:

$$z_{t-1} = \beta' p_{t-1} \tag{3}$$

with β as the cointegration vector.

Expressing the price process in a vector moving average (VMA) implies that current price changes depend on price innovations $e'_t = [e_{1,t}, e_{2,t}, e_{3,t}]$:

$$\Delta p_t = \Psi\left(L\right) e_t = e_t + \Gamma_1 e_{t-1} + \cdots + \Gamma_s e_{t-s} \tag{4}$$

where Ψ is a polynomial in the lag operator. The integrated form defines the current price as

$$p_t = \Psi\left(1\right) \sum_{i=1}^{t} e_i + \Psi^*\left(L\right) e_t \tag{5}$$

with $\Psi\left(1\right)$ as the sum of the moving average coefficients, defining the long-run impact of the disturbance terms. Johansen (1991) shows that $\Psi\left(1\right)$ depends on the orthogonal

[4]Detailed discussions about the efficient price process offer Hasbrouck (1991a) and Hasbrouck (2007).

of the error correction terms, $\alpha_{\perp}$ and $\beta_{\perp}$[5], and a scalar π,

$$\Psi(1) = \alpha_{\perp}\pi\beta_{\perp} = \pi \begin{bmatrix} \gamma_1 & \cdots & \gamma_N \\ \vdots & \ddots & \vdots \\ \gamma_1 & \cdots & \gamma_N \end{bmatrix}. \tag{6}$$

With γ as the common row vector in (6) the permanent price change due to innovations is $\gamma' e_t$. Up to this point the three measures are equal.[6]

Baillie and Booth (2002) argue that in the case of low correlation between the error terms the Hasbrouck (2002) information share might be a more sensible metric than the HMW approach. As these conditions apply to our case we prefer the Hasbrouck metric for our analysis. To be on the safe side, however, we consistently also calculate and document the modified information share approach (Lien and Shrestha, 2009) and the HMW approach (see Lehmann, 2002). They are shortly introduced in the following.

1.3.2 Information share approaches

The *Hasbrouck information share* refers to the variance contribution of an asset to the efficient price variance $var(\gamma' e_t)$. If the error terms are uncorrelated, the variancecovariance matrix of the error terms, Ω_t, is diagonal. In this case, the role of a price leader can be directly derived by weighting each variance term with its long-run impact factor. Although we follow Hasbrouck's (1995) suggestion and set the studied time interval as fine as possible,[7] we are not able to totally eliminate the covariance between the error terms.

[5] The orthogonal fulfils the following condition: $\alpha'_{\perp}\alpha = 0$, $\beta'_{\perp}\beta = 0$.

[6] Consequently, de Jong (2002) demonstrates the strong econometric relation between the Hasbrouck- and HMW-information shares. These two measures also show a high correlation in practice (see Theissen, 2002). However, Hasbrouck (2002) discusses examples in which both approaches report different results. Yan and Zivot (2010) explain these disparities by different responses to temporary price movements. Lien and Shrestha (2009) introduce the modified information share which partly outperforms the previous discussed approaches.

[7] Practical applications reveal a negative relation between error terms' correlation and a higher sampling frequency (see Hasbrouck, 1995 and Theissen, 2002).

Consequently, we conduct a Choleski decomposition of Ω to derive a lower triangular matrix M. Eq. (7) defines the information share of contract i,

$$IS_i = \frac{([\gamma M]_i)^2}{\gamma \Omega \gamma'} \tag{7}$$

with $[\gamma M]_i$ as the ith element of the row of the matrix γM. We rotate the ordering of the contracts in Ω to derive upper and lower bounds (see Hasbrouck, 1995). As the difference between both bounds is not too large, we consider the averages for our analysis (see Table 4).

The purpose of the *modified information share* is to derive a unique measure which is independent of the ordering in the variance-covariance matrix. Therefore, Lien and Shrestha (2009) suggest using a eigenvalue-eigenvector decomposition of the correlation matrix of the error terms, Φ. Define Λ as a diagonal matrix with the eigenvalues of the error terms' correlation matrix as the diagonal elements and G contains the corresponding eigenvectors in the column vectors. Let V represent a diagonal matrix with the standard deviation of the price innovations, such that $V = diag\left(\sqrt{\Omega_{11}}, \sqrt{\Omega_{22}}, \sqrt{\Omega_{33}}\right)$. Then (8) defines a unique measure:

$$MIS_i = \frac{\gamma_i^{*2}}{\gamma \Omega \gamma^T} \tag{8}$$

where $\gamma^* = \gamma[G\Lambda^{-\frac{1}{2}} G^T V^{-1}]$.

The *HMW approach* uses the permanent/transitory decomposition of Gonzalo and Granger (1995) to calculate the common component of the price innovations. In a price series framework prices split up into a permanent, f_t, and a temporary, $\tilde{p}_t$, component,

$$p_t = Af_t + \tilde{p}_t \tag{9}$$

where A is a factor loading matrix. The orthogonal of the common row vector in (6), $\gamma_{\perp}$, represents the long-run impact (Gonzalo and Granger, 1995.[8] Considering $\gamma_{\perp}$ will yield to an unbounded measure. In order to avoid interpreting negative information shares we consider the absolute magnitudes of the factor weights[9] (see Cabrera et al., 2009 and Tswei and yi Lai, 2009):

$$IS^{GG\prime} = abs\left(\gamma_{\perp}^{\prime}\right)\left(abs\left(\gamma_{\perp}^{\prime}\right)\iota\right)^{-1} \tag{10}$$

where ι is a (3x1) vector of ones.

1.4 Information shares of the future contracts

This section develops our first main result, i.e. showing that the Bund is relatively most important for price discovery although the two other future contracts also attract major information shares.

1.4.1 Preparatory analysis

As the information share-approach bases on a VECM method, the appropriateness of time series has to be tested first. The purpose of this section is thus to test for two basic requirements, i.e. non-stationarity of each contract's time-series and the cointegration of all three futures' time-series. First, analyzing the non-stationarity condition of the time series, we conduct the augmented Dickey-Fuller test on a daily basis. Here and in further analyses the applied lag length is estimated by relying on the Bayesian information criterion. Table 2 reports the results. The lag-length differs over the three

[8] Baillie and Booth (2002) demonstrate the applicability of the Gonzalo-Granger approach to financial data.

[9] The exclusion of the days with negative information shares, as suggested by Campbell and Hendry (2007), does not change our results.

contracts, ranging from 4 at the 10-year's future contract up to 7 in the 2-year's one. Over the whole sample, we cannot reject the unit root characteristic for any of the three time series.

Second, we apply the Johansen likelihood ratio (LR) test for the whole system to receive

Table 2: Augmented Dickey–Fuller test and Johansen rank test

The table reports the average results of the Augmented Dickey-Fuller-test and the Johansen rank test. The appropriate lag-length is determined by the likelihood ratio test and is in both cases on average four. The one (five / ten) percent critical value of the Augmented Dickey-Fuller-test is -3.458 (-2.871 / -2.5937). The 90% critical values of the trace and eigenvalue test of the Johansen rank test are reported in brackets.

Augmented Dickey-Fuller-Test		
	maturity	ADF t-statistic
	2-year	-1.9728
	5-year	0.4882
	10-year	0.4956
Johansen rank test		
	maturity 2-year, 5-year and 10-year	
hypothesis	trace	eigenvalue
r=0	136.18 (27.07)	108.98 (18.89)
r=1	27.20 (13.43)	25.74(12.30)
r=2	1.46 (2.71)	1.46 (2.71)
	maturity 2-year and 10-year	
hypothesis	trace	eigenvalue
r=0	51.37 (13.43)	66.54 (12.30)
r=1	2.64 (2.71)	2.52 (2.71)
	maturity 5-year and 10-year	
hypothesis	trace	eigenvalue
r=0	48.74 (13.43)	64.03 (12.30)
r=1	2.63 (2.71)	2.51 (2.71)

its rank (see Johansen, 1988). However, and consistent with Mizrach and Neely (2008), we are not able to reject the null of zero cointegration at all days. Because our intention is to receive unanimously identified information shares we drop the days where we observe no cointegration; their inclusion would produce misleading results and distort the information shares. In 405 cases we do not reject the null hypothesis of a rank of 2 (r=2). For these days the optimal lag length is on average 19. Table 2 Panel A shows the average trace- and eigenvalue test statistics which reject the null hypothesis of the existence of either none or one cointegrating vector.

For robustness and in order to expand the examination, we additionally analyze the cointegration relation of the 2- and 5-year contract, each compared to the 10-year's one.[10] Panel B reports the test statistics for the binary cases. Here we get a sample of 534 observations for the 2-year contract and 578 observations for the 5-year one on which we are able to apply the Hasbrouck information share approach.

We are aware that this procedure might possibly exclude important days at which the yield curve, especially the slope, changes. For this purpose we test whether changes of the slope, trading volume or volatility differ on days with and without cointegration (Table 3). We reject the H_0 of equal means for percentage slope changes in the case of either the 2- or the 5-year contract. Additionally, results reveal a lower trading volume in all contracts at non-cointegration days. Therefore, the significant higher volatility of the 10-year contract at days without cointegration is a result of the lower liquidity in market overall. In sum, these tests do not indicate any selection bias of our sample.

1.4.2 Information shares

This section reports information shares of the Bund, Bobl and Schatz futures. Although we find a high and dominating share of the 10-year future contract, the shorter-maturity contracts contribute in sum about 40% to price discovery.

Yearly averages of daily information shares for the 2-, 5- and 10-year contracts are reported in Table 4. Although there are some fluctuations of the estimated values, the

[10] This specification focuses on the economic most relevant relations as the Bund future might be seen as a benchmark in the price discovery process.

Table 3: Determinants of the cointegration relationship

The table provides t-statistics and p-value in brackets for testing structural differences in the mean on days with and without cointegration for the two- and five-year contract, each to the ten-year future. Slope is measured as the yield-spread between the maturities of two and ten years. Volume reflects traded contracts per day and the volatility is based on five-minute midquote changes.

	effect						
	slope		volume			volatility	
	changes	2-year	5-year	10-year	2-year	5-year	10-year
2-year							
mean							
Days with cointegration	-0.0071	497,782	536,093	1,025,654	975.0	1217.0	1130.7
Days without cointegration	-0.0099	448,351	471,074	911,851	989.1	1294.7	1193.4
t-Statistic	0.31	3.56	4.85	4.25	0.46	1.83	1.70
p-Value	(0.757)	(0.000)	(0.000)	(0.000)	(0.646)	(0.068)	(0.089)
5-year							
mean							
Days with cointegration	-0.0064	491,129	528,126	1,015,287	977.6	1223.9	1131.3
Days without cointegration	-0.0128	456,666	479,685	916,318	984.6	1291.9	1206.0
t-Statistic	0.67	2.32	3.37	3.45	0.21	1.50	1.91
p-Value	(0.501)	(0.021)	(0.001)	(0.001)	(0.833)	(0.134)	(0.057)

10-year contract is clearly the relatively most important contract for price discovery with a share of roughly 60% – i.e. there remains about 40% for the two other contracts. This 40% breaks up into 25% for the 5-year contract and 15% for the shortest maturity. The Bund's importance becomes also evident in daily data, because its information share is above 50% on more than six out of 10 days. The Bobl dominates price discovery at 10% of days and the 2-year future exceeds the 50% level only at 6% of days. In order to show permanency of the Bund's relative importance over time Figure 1 reports the daily information shares. In particular the inferior role of the 5-year Bobl may be somewhat surprising compared to related findings in the literature. Brandt and Kavajecz (2004) attribute the highest price impact to the 5-year Treasury order flow and refer to the duration of the majority of fixed income portfolios, which is close to 5 years. Considering the US spot and future market, Brandt et al. (2007) point out that the 5-year's order flow

Table 4: Yearly information shares

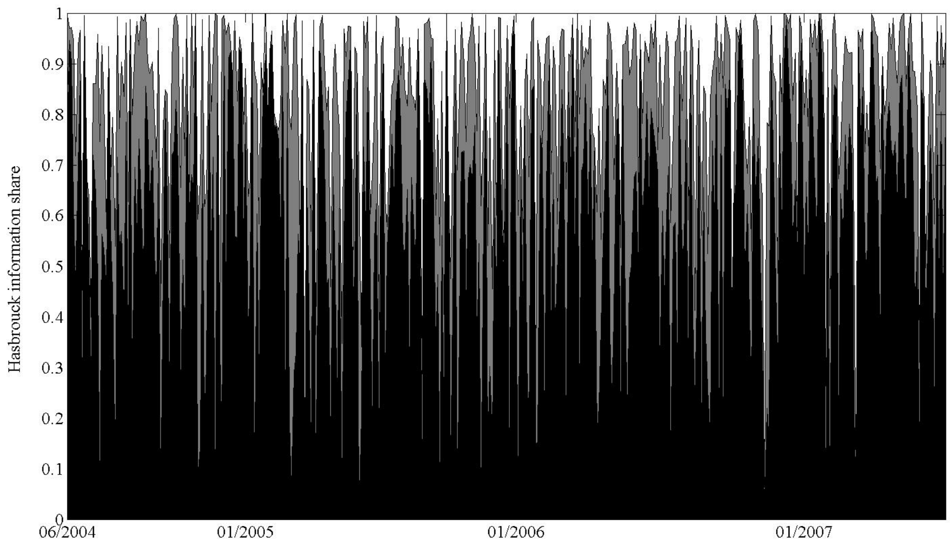
Results below are the annual averages of the daily information shares estimated by the Hasbrouck (1995) and HMW (deB. Harris et al., 2002) approaches. MIS reports the estimation of the modified information share (Lien and Shrestha, 2009). Lower and upper bounds of the Hasbrouck information shares depend on the order of the contracts in the Cholesky decomposition. The mid-point is the average of all possible orders. We report estimated and normalized HMW information shares. Days with a rank of less than two are dropped out which reduced our data set to 405 observations.

maturity	information share		year 2004	2005	2006	2007
2-Year	Hasbrouck	Lower bound	13.61%	17.39%	13.89%	13.24%
		Midpoint	15.74%	18.92%	16.10%	14.82%
		Upper bound	18.25%	20.45%	18.40%	16.66%
	MIS		15.89%	18.83%	15.87%	15.05%
	HMW		15.81%	21.16%	17.91%	19.38%
	HMW (normalized)		18.81%	23.01%	20.78%	21.60%
5-Year	Hasbrouck	Lower bound	20.45%	21.79%	21.05%	14.41%
		Midpoint	25.78%	25.56%	26.91%	20.42%
		Upper bound	29.60%	28.59%	30.98%	24.40%
	MIS		24.72%	25.00%	25.73%	19.21%
	HMW		24.12%	26.01%	25.40%	21.57%
	HMW (normalized)		24.10%	25.29%	24.45%	21.59%
10-Year	Hasbrouck	Lower bound	54.92%	52.54%	52.87%	60.85%
		Midpoint	58.48%	55.52%	56.98%	64.75%
		Upper bound	63.74%	59.41%	63.28%	71.00%
	MIS		59.39%	56.17%	58.39%	65.73%
	HMW		60.07%	52.83%	56.70%	59.05%
	HMW (normalized)		57.08%	51.70%	54.77%	56.81%
number of observations			82	124	132	67

of both markets has the most important role in pricing fixed income assets. Our result seems to be different although also in Germany the duration of bond portfolios is closest to the 5-year contract and liquidity is not particularly high in that future contract. We suggest two reasons for this. First, different from the other mentioned analyses we refer to the concept of information shares so that neither econometric approach nor the period of investigation are the same. Second, in the Euro bond future market the Bund owns the highest trading volume, whereas in the US there is also a liquid 30-year market

Figure 1: Daily information shares of the two-, five- and ten-year future

This figure shows the information shares in the two-, five and ten-year German bond future. The calculation is based on the Hasbrouck (1995) approach on a daily basis. Our data set starts at June 2004 and ends at June 2007.



segment which attracts some trading and price discovery; so, possibly the Bund has a relatively strong position in price discovery due to this institutional difference.

1.5 Determinants of information shares

This section presents the results of three groups of determinants which may help to explain information shares. Section 1.5.1 considers market state-related variables. Section 1.5.2 contains variables about macroeconomic variables and in Section 1.5.3 we introduce order flow by three new variables, i.e. (1) total order flow, (2) unexpected order flow and (3) medium-sized trades. Finally, in Section 1.5.4 the variables from the three earlier sections are considered together. Results extend our economic intuition of price discovery in the bond market.

1.5.1 Determinants of information shares: market state variables

The analysis of information shares has shown that they can vary considerably over time and that this instability may be related to variables indicating varying market states. Potentially relevant market states include spread, trading volume and volatility (see Brandt et al., 2007). The analysis of market state variables has two motivations: first, one may learn from this analysis under which market conditions information is preferably compounded into prices. Second, one may think about market state variables as exogenous control variables which help to reveal the unconditional information shares of a certain market, such as the Bund.

Our analysis in the following is inspired by Mizrach and Neely (2008) who are the first to consequently consider the three above introduced market state variables in the Hasbrouck (1995) approach. Mizrach and Neely (2008) show that spread, traded contracts and volatility are able to explain price discovery shifts between the US spot and future market. Thus, we take up these three market state variables. Moreover, in order to control for more technical (and less economical) effects of the time-to-delivery and the delivery day of future contracts and the delivery day of fixed income options, we also consider in all specifications such standard control variables.Thus we conduct the regression,

$$ln\left(IS_{i,t}/\left(1 - IS_{i,t}\right)\right) = c + b_1 TTD + b_2 DD + b_3 ODD + b_4 ln\left(Spr_{i,t}\right) + b_5 ln\left(V_{i,t}\right) + b_6 ln\left(RV_{i,t}\right) + \epsilon_{i,t} \tag{11}$$

with i representing contract's maturity and IS the maturity-specific daily information share. Spr,V and RV represent the daily shares of spread, trading volume and realized variance which are the contract specific data divided by the sum over all three future contracts. Checking for any future market specific distortions we consider the time-to-delivery (TTD) and the delivery day of futures (DD) and their corresponding options (ODD), where the latter two are dummy variables with a value of one, if a new contract or option is issued. We use a logarithmic transformation of the information shares and microstructure variables to overcome any distributional problems related to limited depend variables (see Mizrach and Neely, 2008).

The expectations on coefficient signs – according to Mizrach and Neely (2008) – are that a relative higher spread of a future contract increases the price of incorporating non-common knowledge and so hampers the tatonnement. In contrast, a higher share of trading volume indicates more information processing – or at least facilitates informed trading – and thus increases the information share. Finally, the impact from realized volatility may be ambiguous: this may be seen as an indicator of present noise traders in the market, so that more volatility decreases the information share, but it can be seen as sign of heterogeneously distribution information processing which would explain a positive sign. Although these results find confirmation for the spot-future-relation in the bond market (Mizrach and Neely, 2008), they should not be seen as stylized facts. For example, Campbell and Hendry (2007) partly report different results for the Canadian and US bond market. There, in some cases a higher share of trading volume harms the speed of price discovery. In other cases a relative increase of the spread or the volatility raises the information share. Overall, there is evidence that market state variables are important but their signs are less obvious ex ante. Our estimated coefficients – shown in Table 5 for the three econometric approaches each – confirm the observation that market state variables are able to describe fluctuations in the information shares of bond future contracts. Overall, these variables are better in explaining shifts in information shares of the Bund and the Schatz than of the Bobl.

Table 5: Responses of information shares to liquidity related variables

The table mirrors the regression results of microstructure variables on daily information shares of the two-, five- and ten-year future, which takes the following form: $ln\left(IS_{i,t}/\left(1-IS_{i,t}\right)\right) = c + b_1TTD + b_2DD + b_3ODD + b_4ln\left(Spr_{i,t}\right) + b_5ln\left(V_{i,t}\right) + b_6ln\left(RV_{i,t}\right) + \epsilon_{i,t}$, with i representing the maturities, c the intercept term, TTD the time-to-maturity, DD a dummy variable with a value of one at each delivery day and OOD a dummy variable with a values of one at each options' delivery day. Spr, Vol and RV are individual shares of the marketwide average five minute quoted spread, the number of traded futures per day and RV midquote's realized volatility for the given day. The 10% (5%, 1%) significance level is marked with a * (** / ***).

	Hasbrouck information share			modified information share			HMW information share		
	maturity			maturity			maturity		
variable	2-year	5-year	10-year	2-year	5-year	10-year	2-year	5-year	10-year
Constant	−5.1699***	5.2085**	−3.5840***	−7.1510***	5.0709**	−3.4719**	−4.1252***	1.4916	−2.9428**
TTD	0.0034***	0.0028**	−0.0027***	0.0036***	0.0039**	−0.0028***	0.0018***	0.0022***	−0.0017***
DD	−0.3512**	-0.0756	0.7325***	−0.2887*	-0.0651	0.7573***	-0.1385	-0.0801	0.3997***
Options' DD	−0.5571*	−0.9138***	0.7591**	−0.5488*	−0.9325***	0.7754**	-0.2369	−0.4587***	0.4072***
Trading related									
Spread	−4.1201***	6.2239***	−7.0834***	−5.4623***	6.2473***	−72131***	−2.2031***	3.2953***	−4.4603***
Volume	2.3578***	1.5346***	4.4477***	2.4158***	1.5212***	4.6864***	1.2065***	0.7400***	2.1019***
Volatility	0.2109	−0.9052*	−1.2163***	0.2720	-0.8497	−1.2236***	−0.2115*	−1.0301***	−1.0933***
Adjusted R^2	3.4%	1.8%	4.9%	3.5%	1.3%	4.9%	2.8%	2.5%	4.8%

A positive change of the trading volume from the 25^{th} to the 75^{th} percentile increases the information content of the 10- (5-/2-) year contract by 11.3% (3.1%, 2.7%).[11] Interestingly, increases in spreads do not indicate less information processing in general because for the 5-year contract a higher spread increases the information share; this particular role may be related to the use of the 5-year contract as a hedging instrument for traders who increase information asymmetry and thus the spread (Brandt et al., 2007). Volatility reveals the expected negative signs, where the HMW approach provides most significant relations. This may be understood in the sense of Yan and Zivot (2010) who state that the HMW approach reacts more sensible to (noise traders or) temporary price impacts.

The future market specific variables also show reasonable signs. At either futures' (DD) or options' delivery day (ODD) informed traders prefer trading the more liquid Bund future which results in a higher information share of this contract. Consequently, the time-to-delivery (TTD) variable behaves in a complementary way. The adjusted R^2s do not exceed the 5% level which is similar to the lowest value Mizrach and Neely (2008) observe in their study. This encourages us to exploit further determinants of information shares.

Overall, more favourable market states, i.e. more volume, lower spread and lower volatility, tentatively increase the information share of a certain contract. Exceptions indicate that informed traders may be willing to trade in certain instruments even under high spreads or high volatility (see Menkhoff and Schmeling, 2010).

[11] We base this calculation on the results of Table 5 and assume that the percentage spread and volatility remain at their means. The dummy variables of the delivery days of options and futures are set to zero. The time-to-maturity corresponds to its sample mean. The $25^{th}/75^{th}$ percentile of the trading volume of the 10- (5-/2-) year contract are 47.5%/52.8% (24.0%/27.3%; 22.09%/25.7%).

1.5.2 Determinants of information shares: macroeconomic news

There is no doubt that macroeconomic news is an important element of the price discovery process in bond markets and should therefore be considered in an analysis of information shares. Again, as with market state variables, this consideration may provide interesting insights by itself and may also be regarded as a consideration of necessary control variables.

Among the first in this line of research in our field are Upper and Werner (2007) who show that two markets' contributions to the common trend may depend on incoming economic news. As an example they refer to the LTCM crisis (September 24^{th}October 8^{th}, 1998) during which the importance of the German spot compared to its future market tended to be zero. Mizrach and Neely (2008) generalize this hypothesis by reporting a negative impact of macroeconomic announcements on the importance of the spot market. Andersson et al. (2009) report significant price impacts of domestic, European and US announcements for the German 10-year bond future. Furthermore, Andersen et al. (2007) detect strong but short-lived news-effects on the 5-year contract in an international context. Given these results, we regress the information shares on the absolute values of the macroeconomic news, $S_{A,t}$, and additionally control for specific effects of future contracts, i.e. their time-to-delivery and delivery day as well on their options' delivery day[12]

$$ln\left(\frac{IS_{i,t}}{1-IS_{i,t}}\right) = c + b_1 TTD + b_2 DD + b_3 ODD + b_4 S_{A,t} + \epsilon_{i,t} \ . \tag{12}$$

Table 6a confirms the importance of macroeconomic news for the relation between different maturity bonds, here estimated via the Hasbrouck approach. We discuss findings in

[12] We also control for asymmetric news responses of the information shares by considering positive and negative news separately in our regressions. This method leads to a drop of explanatory power and does not change our interpretations (results are available on request). We see this as a confirmation of the existing literature which uses either dummy variables (Mizrach and Neely, 2008) or absolute news surprises (Chen and Gau, 2010) for explaining information shares.

three steps: (1) we analyze results within countries, (2) we compare across countries and (3) we compare across econometric approaches (results of to the two other approaches are presented in separated tables).

1. Starting the within country discussion with the *US news*, their significance underlines their importance for estimating European yields (Andersen et al., 2007 and Ehrmann and Fratzscher, 2005). The importance of US news stems from the financial and economic importance of the US economy; Andersson et al. (2009) also suggest earlier US release dates as a reason. The nonfarm payroll employment has on average the highest impact on the information shares, in line with findings of Andersen et al. (2007). Whereas this information is mainly incorporated through the two shorter-term contracts, all other significant effects induce information share shifts in favour of the 10-year future. With the exception of retail sales all signs of the macroeconomic announcements are in line with the findings of Goldberg and Leonard (2003).

   Turning to the *Euro Area variables*, we observe a significant impact of all macroeconomic news in the one or other way. In contrast to the US results, coefficients' signs do not show any clear direction to one of the three contracts. The occurrence of ECB conferences heavily loads on the short end of the yield curve, indicating that the ECB mainly commands over the short-term end of the yield curve. This effect finds support by the inflation-related CPI variable. Its early release date favours the CPI as a proxy for ECB decisions. The positive impact of the GDP and CPI variable on the shorter-maturity contracts is consistent with Goldberg and Leonard (2003). Somewhat surprising is the large coefficient of GDP and retail sales on the 5-year future.

   Within the *German news* there is a pattern in that most news seem to affect the short-term contract positively but the long-term contract negatively and with the medium-term contract in between. The single most important variable is the ifo business climate which is regarded as a reliable early indicator of future growth and price pressure. The next important variable is jobless claims, which has the opposite signs to the ifo variable. The signs of the GDP and the CPI variable are consistent with Goldberg and Leonard (2003).

2. Comparing the coefficients across countries, we see that generally the size of significant US variables is larger than the sizes of Euro Area or German variables indicating the strong impact of US news on the Euro bond futures (see Ahn et al., 2002). Next, we see that the US influence is mainly channelled via the Bund whereas German news mainly affects the 2-year contract. Regarding the significance of variables across countries, three variables stand out as they are important in each country: this is, first, jobless claims and nonfarm payroll employment in the US respectively, second, consumer prices are highly significant everywhere, and, third, decision makers expectations, such as central bank meetings or important surveys in Germany, matter for price discovery. Unfortunately, the signs of variables across countries do not provide a fully consistent pattern. This indicates, as our work with various specifications demonstrates, that one should not emphasize the significance of single coefficients too much.

3. In order to compare results across the three econometric approaches, we provide the additional results in Table 6b for the modified information share-approach and in Table 6c for the HMW-approach. Taking the Hasbrouck approach as the benchmark, the modified information share-approach reproduces significant coefficients almost exactly as there is just one marginal exception (German industrial production at the 5-year contract). The HMW-approach differs a bit more from the Hasbrouck-approach and produces 12 cases (out of 60 coefficients in total) where significance is gained or lost, although there is no single case where a significant

variable would change sign. These effects might be linked to microstructure noise effects which more heavily influence the HMW-approach (see Yan and Zivot, 2010). Fortunately, these changes are almost random scattered across the table so that the above derived conclusions about pattern within and across countries still hold.

1.5.3 Determinants of information shares: order flow

This section investigates the role of order flow in shifting the share of price discovery, i.e. the information share, between the three future contracts. There are two motivations why order flow may be a relevant determinant in this analysis. First, order flow is a medium for incorporating non-common knowledge into prices (e.g. Killeen and Moore, 2006). In bonds' spot and future markets this measure plays an important role in explaining price dynamics (see Brandt and Kavajecz, 2004, Brandt et al., 2007 and Underwood, 2009). Second, Green (2004) documents the processing of news via an indirect channel, i.e. via order flow, which motivates us to distinguish between days with news and days without.

In line with earlier studies on the possible impact of order flow on prices we proceed with the analysis in three steps, from general to specific, i.e. considering (1) total order flow, (2) unexpected order flow, (3) medium-sized order flow and then including market state variables (from Section 1.5.1). We note that these time-series do not show significant correlation with each other.

Total order flow

Order flow is a measure of signed trades and thus indicates buying pressure (assuming that buys are coded positive). It is well documented that order flow is positively related to contemporaneous returns in many markets. This is often interpreted as an indication for order flow being the medium for incorporating information into prices. According to this reasoning one might expect that order flow will also impact information shares. We test this in the simplest way by regressing relative order flow, i.e. between the Bund, Bobl and the Schatz, on their information shares. In order to do so we divide the absolute value of the maturity-specific, volume-weighted order flow by the sum over all three future contracts. Moreover, in order to distinguish the net trading effect on days with and without news, we create two dummy variables, each capturing one state. These dummies are multiplied with the order flow. Table 7 Panel A shows that the 2- and 10-year contracts are indeed positive and statistically significant for days with news but also for days without news. Only the 5-year contract does not show significant coefficients which may be due to the special purpose of the 5-year contract as preferred hedging instrument. We see this preliminary result as a confirmation of the derived implications of Section 1.5.2 that the information flow takes mainly place at the short- and long end of the yield curve.

Table 6: Impact parameters on daily information shares' fluctuation

Results report regression results of trend variables, news and log-shares of microstructure variables on logarithmic transformations of the daily information shares of the two-, five- and ten-year future. Tables refer to the Hasbrouck information share, Modified information share and the HMW information share. Robust standard errors (Newey and West, 1987) are used. The intercept term, time-to-maturity and delivery days of futures and options, which are included in Panel A and B, are not reported for brevity. News variables represent the absolute values of the difference between the realized and expected value, each standardized by dividing by its standard deviation. The 10% (5%, 1%) significance level is marked with a * (** / ***).

Panel A	Hasbrouck information share					
	2-year		5-year		10-year	
variable	Panel A	Panel B	Panel A	Panel B	Panel A	Panel B
Trading-related						
Spread		-3.507***		6.203***		-6.732***
Volume		2.049***		1.759**		4.352***
Volatility		-0.362***		-0.845*		-1.251***
Macroeconomic news						
US						
Nonfarm payroll employment	0.516***	0.387***	0.533***	0.464***	-0.932***	-0.784***
Jobless claims	-0.062	-0.141	0.141*	0.067	0.008	0.115
PPI	-0.182**	-0.137	0.166	0.170*	0.043	-0.007
GDP	0.229	0.293*	0.208	0.174	-0.202	-0.345
Retail sales	-0.544***	-0.291*	-0.229*	-0.163	0.625***	0.475***
CPI	-0.508***	-0.523***	-0.023	-0.107	0.394***	0.383***
FOMC	-0.230***	-0.304***	0.046	0.037	0.474***	0.554**
Euro Area						
Jobless claims	-0.304***	-0.075	0.001	0.003	0.300***	0.171**
PPI	-0.215***	-0.264***	-0.074	-0.128	0.205**	0.175
GDP	-0.1031	-0.027	1.569***	1.827***	-0.211	-0.291
Retail sales	0.377	0.515**	0.776***	0.821***	-0.566***	-0.589***
CPI	0.411***	0.426***	0.110	0.009	-0.140	-0.063
ECB conferences	0.797***	0.706***	-0.011	-0.095	-0.302*	-0.201***
German						
Jobless claims	0.408**	0.312	0.327***	0.274***	-0.525***	-0.509***
PPI	0.075	-0.060	-0.123*	-0.131	0.1663	0.145
GDP	0.448***	0.358***	-1.227***	-1.408***	0.071	0.061
Retail sales	0.087	0.200*	-0.016	-0.128	-0.117	-0.139
CPI	0.092	0.129	0.249***	0.195***	−0.091***	-0.183***
Industrial production	0.1918	0.338**	-0.220*	-0.294**	0.214	0.129
Ifo business climate	-1.666***	-1.547***	-1.337***	-1.382***	1.637***	1.594***
informed trading related						
Order flow						
Non-announcement		-0.137		-0.034		-0.010
Announcement		0.227***		0.067***		0.248***
Unexpected order flow						
Non-announcement		-0.070		0.041		0.391**
Announcement		-0.256***		-0.169***		-0.016
Medium-size order flow						
Non-announcement		1.196		-0.600		-0.541
Announcement		1.152*		-0.523		-0.580
Adjusted R^2	0.7%	4.3%	2.1%	2.1%	3.1%	6.8%

Panel B	Modified information share					
	2-year		5-year		10-year	
variable	Panel A	Panel B	Panel A	Panel B	Panel A	Panel B
Trading-related						
Spread		-4.945***		5.625***		-6.826***
Volume		2.066***		2.140**		4.629***
Volatility		-0.356**		-0.725		-1.267***
Macroeconomic news						
US						
Nonfarm payroll employment	0.526***	0.398***	0.549***	0.477***	-0.932***	-0.773***
Jobless claims	-0.098	-0.184	0.189**	0.111	0.015	0.129
PPI	-0.459***	-0.411**	0.051	0.051	0.067	0.019
GDP	0.236	0.301*	0.190	0.153	-0.213	-0.353
Retail sales	-0.712***	-0.465**	-0.257*	-0.168	0.656***	0.507***
CPI	-0.557***	-0.569***	0.020	-0.067	0.420***	0.420***
FOMC	−0.160**	-0.251***	-0.333	-0.341	0.488***	0.574**
Euro Area						
Jobless claims	-0.253***	0.024	0.006	-0.002	0.294***	0.165*
PPI	-0.210***	-0.271***	-0.070	-0.126	0.198**	0.170
GDP	-0.287	-0.184	3.437***	3.730***	-0.140	-0.233
Retail sales	0.414	0.553**	0.904***	0.955***	-0.628***	-0.643***
CPI	0.479***	0.504***	0.144	0.042	-0.162	-0.077
ECB conferences	0.856***	0.786***	0.098	-0.008	-0.308*	-0.187***
German						
Jobless claims	0.429**	0.331	0.401***	0.345***	-0.527***	-0.504***
PPI	0.001	-0.144	-0.087	-0.093	0.159	0.146
GDP	0.583***	0.487***	-2.806***	-3.010***	0.041	0.035
Retail sales	0.0923	0.207	0.021	-0.097	-0.108	-0.125
CPI	0.121	0.155*	0.318***	0.253**	-0.088**	-0.175***
Industrial production	0.227	0.381**	-0.178	-0.259*	0.195	0.113
Ifo business climate	-2.055***	-1.956***	-1.412***	-1.460***	1.777***	1.738***
informed trading related						
Order flow						
Non-announcement		-0.124		-0.091*		-0.060
Announcement		0.199***		0.081***		0.255***
Unexpected order flow						
Non-announcement		-0.091		0.063		0.454**
Announcement		-0.268***		-0.194***		-0.018
Medium-size order flow						
Non-announcement		1.252		-1.147		-0.597
Announcement		1.236*		-1.089		-0.623
Adjusted R^2	1.4%	5.2%	4.3%	4.1%	3.1%	7.1%

Panel C	HMW information share					
	2-year		5-year		10-year	
variable	Panel A	Panel B	Panel A	Panel B	Panel A	Panel B
Trading-related						
Spread		-1.887***		3.432***		-4.078***
Volume		1.178***		0.846		2.486***
Volatility		-0.488***		-1.026**		-1.056***
Macroeconomic news						
US						
Nonfarm payroll employment	0.282**	0.258***	0.240***	0.206***	-0.465**	-0.401***
Jobless claims	0.016	-0.071	0.065	-0.002	-0.037	0.056
PPI	0.003	0.011	0.022	0.018	0.055	0.044
GDP	0.038	0.054	0.207***	0.168***	-0.098	-0.145
Retail sales	-0.306***	-0.159*	-0.110	-0.095	0.371***	0.316***
CPI	-0.278***	-0.279***	0.080**	0.016	0.215***	0.219***
FOMC	-0.073*	-0.080*	0.113	0.087	0.171	0.234**
Euro Area						
Jobless claims	-0.165***	-0.028	0.032	0.015	0.145**	0.083
PPI	-0.108***	-0.135***	-0.025	-0.079	0.104**	0.098
GDP	-0.487*	-0.596**	0.816**	0.958***	0.005	0.022
Retail sales	0.105	0.188*	0.462***	0.513***	-0.286***	-0.309***
CPI	0.305***	0.279***	0.083	-0.022	-0.176	-0.098
ECB conferences	0.272***	0.283**	0.083	0.039	-0.106	-0.055*
German						
Jobless claims	0.253***	0.193**	0.256***	0.209***	-0.340***	-0.317***
PPI	-0.003	-0.045	-0.120**	-0.135	0.12	0.119
GDP	0.517***	0.531***	-0.690***	-0.800***	-0.062	-0.096
Retail sales	0.196***	0.265***	-0.042	-0.142*	-0.149	-0.136
CPI	0.005	0.076	0.143***	0.124***	-0.019	-0.080***
Industrial production	0.160**	0.234***	-0.038	-0.119**	0.037	0.024
Ifo business climate	-0.909***	-0.806***	-0.639***	-0.697***	0.937***	0.949***
informed trading related						
Order flow						
Non-announcement		-0.103*		-0.051		-0.120
Announcement		0.191***		0.042***		0.162***
Unexpected order flow						
Non-announcement		-0.064		-0.003		0.126
Announcement		-0.137***		-0.094***		0.012
Medium-size order flow						
Non-announcement		0.585		-0.234		-0.543*
Announcement		0.472		-0.305		-0.919***
Adjusted R^2	-0.8%	3.5%	1.3%	2.9%	2.4%	6.1%

Table 7: Daily information shares' fluctuation and order flows

These table reports regression results of trend variables and step-by-step added logarithmic shares of order flows, unexpected and medium-sized order flow on the daily information shares. Tables refer to the Hasbrouck information share, Modified information share and the HMW information share. (Non-) Announcements variables are constructed by setting the variables on non-relevant days to zero. The intercept term, time-to-maturity and delivery days of futures and options, which are included in Panel A to D, are not reported for brevity. Robust standard errors (Newey and West, 1987) are used. The trend variables and the intercept term are not reported for brevity. The 10% (5%, 1%) significance level is marked with a * (** / ***).

Panel A	Hasbrouck information share											
	2-year				5-year				10-year			
variable	Panel A	Panel B	Panel C	Panel D	Panel A	Panel B	Panel C	Panel D	Panel A	Panel B	Panel C	Panel D
<u>trading-related</u>												
Spread				-3.401***				6.223***				-6.820***
Volume				2.143***				1.935***				4.597***
Volatility				-0.281**				-0.703				-1.161***
<u>order flow</u>												
non-announcement	0.107**	-0.022	-0.045	-0.114	0.024	-0.055	-0.043	-0.029	0.189*	0.033	0.023	0.006
announcement	0.186**	0.287***	0.267**	0.303***	-0.017	0.068	0.061*	0.047*	0.277***	0.379***	0.367***	0.350***
<u>unexpected order flow</u>												
non-announcement		0.009	-0.024	-0.061		0.019	0.026	0.046		0.437**	0.444**	0.403**
announcement		-0.207***	-0.240***	-0.283***		-0.153***	-0.185**	-0.161***		-0.063	-0.055	-0.048
<u>medium-sized order flow</u>												
non-announcement			1.573**	1.235			-0.165	-0.733			1.676**	-0.494
announcement			1.573***	1.153*			-0.118	-0.637			1.698	-0.559
adjusted R^2	0.5%	1.0%	2.3%	4.8%	0.9%	1.3%	0.8%	1.5%	1.7%	2.9%	3.0%	5.9%

Panel B	Modified information share											
	2-year				5-year				10-year			
variable	Panel A	Panel B	Panel C	Panel D	Panel A	Panel B	Panel C	Panel D	Panel A	Panel B	Panel C	Panel D
trading-related												
Spread				-4.677***				5.661***				-6.886***
Volume				2.136***				2.298***				4.844***
Volatility				-0.267*				-0.514				-1.175***
order flow												
non-announcement	0.095*	-0.022	-0.032	-0.100	-0.002	-0.107*	-0.107*	-0.089*	0.165	-0.014	-0.026	-0.044
announcement	0.192**	0.286***	0.259**	0.296***	-0.028	0.076	0.078*	0.066*	0.275***	0.390	0.378	0.361
unexpected order flow												
non-announcement		-0.012	-0.039	-0.080		0.048	0.043	0.067		0.506***	0.512	0.468
announcement		-0.210***	-0.251***	-0.297***		-0.172***	-0.216***	-0.175***		-0.066**	-0.057***	-0.050
medium-sized order flow												
non-announcement			1.705*	1.345			-0.319	-1.302**			1.823***	-0.502
announcement			1.738***	1.294			-0.326	-1.254**			1.836**	-0.581
adjusted R^2	0.2%	0.6%	1.9%	4.6%	0.7%	1.1%	0.7%	1.0%	1.5%	3.1%	3.3%	6.1%

Panel C	HMW information share											
	2-year				5-year				10-year			
variable	Panel A	Panel B	Panel C	Panel D	Panel A	Panel B	Panel C	Panel D	Panel A	Panel B	Panel C	Panel D
trading-related												
Spread				-1.850***				3.333***				-4.218***
Volume				1.184***				0.954*				2.580***
Volatility				-0.455***				-0.905**				-1.032***
order flow												
non-announcement	0.075**	0.000	-0.041	-0.091	0.022	-0.030	-0.048	-0.047	0.028***	-0.039	-0.100	-0.112***
announcement	0.139**	0.198***	0.204**	0.224***	-0.028	0.027	0.042***	0.028**	0.154**	0.198	0.234	0.219
unexpected order flow												
non-announcement		0.004	-0.029	-0.059		0.013	-0.010	0.000		0.187***	0.152	0.134
announcement		-0.122***	-0.120***	-0.154***		-0.099***	-0.083	-0.091***		-0.028	-0.014***	-0.007
medium-sized order flow												
non-announcement			0.527	0.641			-0.475**	-0.352			0.501***	-0.443
announcement			0.449	0.510			-0.562**	-0.413			0.146**	-0.853
adjusted R^2	0.4%	0.9%	1.0%	4.6%	0.9%	1.6%	1.6%	2.6%	1.4%	1.8%	1.6%	5.5%

Unexpected order flow

Going further, it has been argued that order flow may contain elements that are not related to information. One way to extract the truly informative part of order flow has been suggested by Pasquariello and Vega (2007). They document a linkage between unexpected order flow and information processing in the bond market which is pronounced at non-announcement days and less relevant at announcement days. To extract the pure informative part from the order flow we follow Pasquariello and Vega (2007) and run a regression of the lagged returns and order flows on the current order flow and define the residuals $\nu(OF)$ as unexpected order flow

$$OF_{i,t} = \alpha + b\,(L)\,OF_{i,t} + c\,(L)\,R_{i,t} + \nu\,(OF)_{i,t}\,,\ i = 2-, 5-, 10\ years\,. \tag{13}$$

OF and R refer to the order flow respectively return in contract i, $b(L)$ and $c(L)$ are polynomials in the lag operator. Applying the Bandi and Russell (2006) algorithm to minimize the effects of microstructure noise reveals an optimal sampling frequency of 5 min for the 2- and 5-year contract and 6 min for the 10-year's one. The Bayesian information criterion suggests using a lag length of nine for the two shorter maturity contracts and eight for the Bund future in (13). The residuals of this regression, $\nu(OF)$, reveal the amount of unexpected order flow in a trading interval and are summed up per day.[13] This gives us a measure for informed order flow, possibly nurtured by customer order flow (Menkveld et al., 2012).

In the next step we reproduce the steps as described in (1.5.3) above. The two columns in Panel B of Table 7a, Table 7b and Table 7c present the results of the following regression, whereby D^{A} (D^{NA}) stands for a dummy variable, representing announcement

[13]For robustness we apply two specifications. First, we substitute the binary measured order flow for the volume-weighted order flow. Second, we choose a sampling frequency of 30 min. The appropriate lag-lengths are chosen to eliminate the serial correlation in the trading interval and are set such that a whole trading day is covered as we can see day-to-day dependencies in the returns. Our results remain stable and underline our conclusions.

(non-announcement) days:

$$
\begin{gathered}
ln\left(\frac{IS_{i,t}}{1-IS_{i,t}}\right) = c + b_1 TTD + b_2 DD + b_3 ODD + b_4 ln\left(|OF_{i,t}|\right) D^{NA} + \\
b_5 ln\left(|OF_{i,t}|\right) D^{A} + b_6 ln\left(|UOF_{i,t}|\right) D^{NA} + b_7 ln\left(|UOF_{i,t}|\right) D^{A} + \epsilon_{i,t}
\end{gathered}
. \quad (14)
$$

Two effects are directly observable. First, while we observe a positive impact of unexpected order flow on the information share of the Bund, total order flow loses its significant impact on information shares at non-announcement days. Second, with the exception of the Bund future traders pay less attention to unexpected order flow at announcement days. In general, we are able to confirm main findings of Pasquariello and Vega (2007) that the impact of both order flow measures is state-dependent.

Medium-sized order flow

In a next step we further augment the regression by also considering medium-sized order flow. Medium-sized order flow is often found to be preferably used by informed traders according to the so-called stealth-trading hypothesis (Barclay and Warner, 1993. In order to reduce their price impact and so to lower their trading costs, informed investors split up large trades. If this applies here as well, then medium-sized trades have a larger price impact than small or large trades (evidence in Anand and Chakravarty (2007), for options, Chakravarty (2001), for equities, and in Menkhoff and Schmeling (2010); for foreign exchange).

We compute contract i's daily share of medium-sized trades, MIDi, in three steps. First, we standardize all trades of a day. Next, we define the 20% and 80% critical trade sizes of each subsample.[14] Finally, the amount of the maturity-specific trades between

[14] The choice of an upper and lower bound might change or results. Therefore, we test the robustness of our results in two ways. First, we set the thresholds to the 10% and 90% interval. Second, we adopt the methodology of Anand and Chakravarty (2007). They define trades with quantities between five and 99 contracts as medium sized trades. This corresponds to a lower (upper) bound of 2.5% (40%). However, both specifications do not change our results.

the borders is divided by the sum over the three futures. The average shares of the 2-, 5- and 10-year contract are 14.7%, 25.7% and 59.6% which nearly corresponds to the unconditional information shares.

$$ln\left(\frac{IS_{i,t}}{1-IS_{i,t}}\right) = c + b_1TTD + b_2DD + b_3ODD + b_4ln\left(|OF_{i,t}|\right)D^{NA}+$$
$$b_5ln\left(|OF_{i,t}|\right)D^{A} + b_6ln\left(|UOF_{i,t}|\right)D^{NA} + b_7ln\left(|UOF_{i,t}|\right)D^{A} + b_8ln\left(|MID_{i,t}|\right)D^{NA}+ \cdot$$
$$b_8ln\left(|MID_{i,t}|\right)D^{A} + \epsilon_{i,t} \tag{15}$$

Panel C in Table 7a, Table 7b and Table 7c reports respective results which are, however, qualitatively unchanged to the earlier reported Panels A and B.

Without going into details, we cautiously conclude that stealth-trading may be not very relevant in the bond future market; at least not as important as in other markets.

Including market states Finally, Panel D adds the market state variables to the order flow variables in joint regressions. Reassuringly, the order flow variables which were significant keep significance (and signs). At non-announcement days the previously observed positive impact of medium-sized order flow of the 2-year contract vanishes after the inclusion of spread, volume and volatility.

Comparing the results with Table 5 reveals a remarkable increase of the explanatory power. We conduct Wald Tests to evaluate the role each order flow variable plays for the information shares. Table 8 shows the results of subsequently including order flow, unexpected- and medium-sized order flow to the standard variables of Section 1.5.1. Both, the inclusion of order flow and unexpected order flow significantly improves our understanding of information shares of the shortest and longest maturity. Once again, this finding underlines the argumentation of Pasquariello and Vega (2007) that the importance of order flow depends on the existence of public signals.

Overall, we conclude that order flow is a useful determinant in explaining information shares, thus providing another form of evidence that order flow is a medium for incorporating private information.

Table 8: Test statistics for adding order flow to market-state variables

This table reports the F-statistics of different Wald-tests to test for a significant contribution of order flow variables to explain information shares. After controlling for market-state related variables, see Table 7, order flow, unexpected order flow and medium-sized order flow are successively and with rotating order added to the regression. We use a logarithmic transformation of the information shares, microstructure- and trading-related variables. The 10% (5%, 1%) significance level is marked with a * (**/ ***) and indicates whether this variable has to be considered beside market-state and the previous listed variables. Panel A shows results for the Hasbrouck approach, Panel B refers to the modified information share and Panel C to the HMW information share.

	F-statistic								
	Panel A			Panel A			Panel C		
	maturity 2-year			maturity 5-year			maturity 10-year		
Order flow	1.44	0.15	1.62	1.32	0.07	1.38	2.38*	0.45	1.38
Unexpected order flow	3.33**	1.50	2.98*	2.80*	1.51	3.73**	3.43**	1.85	1.64
Medium-sized order flow	0.36	0.36	0.80	0.28	0.70	0.84	0.46	0.33	2.52*
Unexpected order flow	1.32	1.44	2.11	1.30	1.16	2.47*	1.29	2.16	0.75
Medium-sized order flow	1.15	0.52	0.77	0.99	0.91	0.96	0.75	0.24	1.20
Order flow	2.63*	0.06	2.50*	2.09	0.22	2.52*	4.21**	0.25	3.59**
Medium-sized order flow	0.27	0.60	0.76	0.26	0.91	0.77	0.21	1.15	1.27
Order flow	2.03	0.01	2.49	1.58	0.13	2.44*	3.48**	0.20	3.68**
Unexpected order flow	2.81*	1.40	2.13	2.55*	1.24	2.72*	2.56*	1.29	0.61

1.5.4 Determinants of information shares: market state, macroeconomic news and order flow

In a final analysis, we consider all so far considered useful variables in a comprehensive approach. This provides some insight whether the variables found so far are possibly capturing common sources or whether they are orthogonal to each other. We find that only a few macroeconomic news change significance and want to remind that their overall explanatory power is very low anyway.

Formally, we test the following specification which can be seen as integrating variables from Sections 1.5.1, 1.5.2 and 1.5.3:

$$ln\left(\frac{IS_{i,t}}{1-IS_{i,t}}\right) = c + b_1TTD + b_2DD + b_3ODD + +b_4S_{A,t} + b_5ln\left(|OF_{i,t}|\right)D^{NA} +$$
$$b_6ln\left(|OF_{i,t}|\right)D^{A} + b_7ln\left(|UOF_{i,t}|\right)D^{NA} + b_8ln\left(|UOF_{i,t}|\right)D^{A} + b_9ln\left(|MID_{i,t}|\right)D^{NA} + \cdot$$
$$b_{10}ln\left(|MID_{i,t}|\right)D^{A} + \epsilon_{i,t} \tag{16}$$

Results are given in Panels B of Table 6a, Table 6b and Table 6c. Mainly, they confirm our previous results. The major deviation from the earlier presented partial regression is that there are a few changes in macroeconomic news, however, without changes that would suggest new interpretations. In particular, the order flow variables keep their significance and structure which indicates their contribution.

Overall, we do not see these minor modifications as a qualitative change in findings but rather as a confirmation of the overall message: market state variables and to a smaller extent order flow are the important determinants of information shares, whereas macroeconomic news is of less importance.

1.6 Robustness

In order to examine whether our findings are robust to modifications we aim for enlarging the number of days considered in our empirical analysis in two steps.

Table 9: Impact parameters on daily information shares' fluctuations of the 10-year future

Results report regression results of trend variables, news and log-shares of microstructure variables on logarithmic transformations of the daily information shares of the 10-year future, compared to the 2- and 5-year future. Robust standard errors (Newey and West, 1987) are used. The intercept term, time-to-maturity and delivery days of futures and options, which are included in all regressions, are not reported for brevity. News variables represent the absolute values of the difference between the realized and expected value, each standardized by dividing by its standard deviation. The 10% (5%, 1%) significance level is marked with a * (** / ***).

	10-Year to 2-Year			10-Year to 5-Year		
Variable	Hasbrouck information share	Modified information share	HMW information share	Hasbrouck information share	Modified information share	HMW information share
Trading-related						
Spread	1.120***	1.084***	1.427***	5.199**	5.168**	6.790**
Volume	3.467***	3.434***	2.887***	2.940***	2.951***	2.205***
Volatility	-1.123**	-1.041**	-4.815***	-1.221***	-1.146***	-2.146***
Macroeconomic news						
US						
Nonfarm payroll employment	-0.389***	-0.389***	-0.384***	-0.275***	-0.266***	-0.271***
Jobless claims	0.168***	0.202***	0.201***	0.021	0.035	0.089
PPI	0.018	0.021	0.017	-0.146*	-0.142*	-0.164**
GDP	-0.013	-0.018	0.015	-0.086**	-0.079*	-0.163***
Retail sales	0.326***	0.339***	0.424***	0.395***	0.382***	0.411**
CPI	0.055	0.047	0.050	0.026	0.025	-0.044
FOMC	0.139**	0.135**	0.126	-0.064	-0.074	0.020
Euro Area						
Jobless claims	-0.035	-0.041	-0.060	0.079*	0.070*	-0.015
PPI	0.116	0.112	0.065	-0.051	-0.047	-0.044
GDP	-0.864***	-0.829***	-0.657**	-0.043	-0.038	0.111
Retail sales	-0.189	-0.196	-0.171	-0.225**	-0.224**	-0.315***
CPI	-0.076	-0.075	-0.066	-0.124**	-0.124**	-0.161***
ECB conferences	-0.214**	-0.240**	-0.145	-0.037	-0.031	-0.054
German						
Jobless claims	-0.166***	-0.167***	-0.192***	-0.136***	-0.134***	-0.195***
PPI	0.071	0.064	0.085	-0.035	-0.037	-0.066

	10-Year to 2-Year			10-Year to 5-Year		
Variable	Hasbrouck information share	Modified information share	HMW information share	Hasbrouck information share	Modified information share	HMW information share
GDP	0.574***	0.551***	0.447	-0.131	-0.129	-0.230***
Retail sales	-0.084	-0.079	-0.050	0.021	0.021	0.002
CPI	-0.107***	-0.104***	-0.128**	-0.190***	-0.180***	-0.205***
Industrial production	-0.179**	-0.175**	-0.190**	-0.145*	-0.148**	-0.253***
Ifo business climate	0.354*	0.339*	0.315*	0.142	0.134	0.049
Informed trading related						
Order flow						
All days	0.171***	0.165***	0.184***	0.033	0.034	0.014
Announcement days	-0.020	-0.013	-0.035	0.180***	0.171***	0.192***
Unexpected order flow						
All days	0.064***	0.064***	0.029	0.174***	0.172***	0.155***
Announcement days	-0.113***	-0.110***	-0.078***	-0.179***	-0.179***	-0.137***
Medium-sized order flow						
All days	-1.382***	-1.275***	-0.719**	-1.196**	-1.369*	-0.305
Announcement days	1.009***	0.967***	0.636***	1.655***	1.690***	1.085***
adjusted R^2	7.2%	7.2%	6.1%	3.0%	2.7%	5.3%

1.6.1 Including further days in the analysis

We test if the above derived results are an outcome of focussing exclusively on days with a cointegration of the three future contracts. For this reason, we now estimate the information shares only for the 2- and 5-year contract, each compared to the 10-year's one. This extends the sample from 405 days to 534 days for the 2-year contract and to 578 days for the 5-year contract. For the sake of brevity Table 9 only shows the results of reproducing earlier Table 6a, Table 6b and Table 6c Panel B, which includes market states, macroeconomic news and order flow.[15] As before, market states are highly significant with the expected signs. Among news, there is hardly any change. US news show the same pattern as they mainly increase the information share of the Bund future. Especially FOMC meetings keep their strong impact. Nonfarm payroll employment, the most important macroeconomic announcement, still improves the importance of the 2- and 5-year contract. Similar findings apply to the Euro Area and German news. Finally, a higher share of order flow increases the information share of the respective future contract.

1.6.2 The joint analysis of cointegrated and non-cointegrated days

In order to consider all days in the examinations, we first analyze lead-lag-relations between the three future contracts on those days without cointegration. In a second step we bring together the results of information shares and lead-lag-relations. Overall this holistic examination supports the above gained insights.

For the lead-lag-relations we conduct a VAR-approach to yield changes. In a formal expression the model includes a constant and lagged yield changes of the three contracts

[15] Splitting the data set into two subsamples, days with either a rank of one or a rank of two, reveals no structural differences. The null hypothesis of equal coefficients in both subsamples, $H_0 : [b_{1,1} \cdots b_{1,n}] = [b_{2,1} \cdots b_{2,n}]$, is not rejected at the 10% interval.

to explain current yield changes, Δy_t,

$$\begin{bmatrix} \Delta y_{t,2-year} \\ \Delta y_{t,5-year} \\ \Delta y_{t,10-year} \end{bmatrix} = \begin{bmatrix} \alpha_1 \\ alpha_2 \\ alpha_3 \end{bmatrix} + \begin{bmatrix} \beta_{1,1} & \beta_{1,2} & \beta_{1,3} \\ \beta_{2,1} & \beta_{2,2} & \beta_{2,3} \\ \beta_{3,1} & \beta_{3,2} & \beta_{3,3} \end{bmatrix} \times \sum_{n=1}^{N} \begin{bmatrix} \Delta y_{t-n,2-year} \\ \Delta y_{t-n,5-year} \\ \Delta y_{t-n,10-year} \end{bmatrix} + \begin{bmatrix} \epsilon_{t,2-year} \\ \epsilon_{t,5-year} \\ \epsilon_{t,10-year} \end{bmatrix}. \tag{17}$$

We test the contribution power of contract j to price discovery in contract i $(i \neq j)$ with a Wald Test which compares an unrestricted (17) with a restricted model. In the restricted model the off-diagonal coefficient $_{i,j}$ is set to zero. A rejection of the null hypothesis of no contribution of contract j means, that this contract at least partly leads the price discovery process (Forte and Peña, 2009).

A further step combines the results of information shares and lead-lag-relations. The methodology is based on Forte and Peña (2009) and compares each possible pair of contracts. The leadership dummy variable of contract i compared to contract j, $D(i,j)$ takes a value of 1 if contract i has either (1) a higher information share or has (2) a price impact on future yield changes of contract j, but not vice versa.

Table 10 presents the sum and the averages of the dummy variables. Again, we see the same dominance structure as before. The Bund future is on average the major contributor to yield innovations. On more than 60% of the days the 10-year contract leads the price discovery process compared to both, the 2- and 5-year contract. We reject the null hypothesis of a mean below 50% in both cases.

However, in nearly 30% of the cases the shorter maturity contracts are the main information processors. These days might be affected by a general weakness of the 10-year contract. We exclusively test for these days for equal means of the dummy variables of the 2-year and 5-year future, each compared to the 10-year's one. Under the null hypothesis we expect that the leadership of the 2-year contract goes along with a

Table 10: Impact parameters on daily information shares' fluctuations of the 10-year future

This table summarizes the results of testing whether one contract is the main contributor in the price discovery process compared to another contract. The corresponding dummy variables take value 1 if either a higher information share or a leading role, derived from lead-lag-regressions, is observable. The total numbers of dominant days and the corresponding means are reported. Additionally, the Z-statistics and p-value are reported, testing the null hypothesis of a mean larger than 0.5.

	2-Year versus 5-year		2-Year versus 10-year		5-Year versus 10-year	
	D(2-year,5-year)	D(5-year,2-year)	D(2-year,10-year)	D(10-year,5-year)	D(5-year,10-year)	D(5-year,10-year)
Total	232	437	233	511	227	477
Mean	0.300	0.565	0.301	0.661	0.294	0.617
Z-stat	-12.117	3.662	-12.024	9.454	-12.588	6.692
(p-Value)	(1.000)	(0.000)	(1.000)	(0.000)	(1.000)	(0.000)

leadership of the 5-year contract, and vice versa. Although both subsamples reveal a strong relation of the leading roles of the shorter maturities we reject the null hypothesis of equal means at the 1% level.[16]

Our results are in line with implications derived from the information share approach and support the view that not only the strength or weakness of the Bund future matters for the price discovery process. Rather, the 2- and 5-year futures are on their own able to attract information which brings them into an outstanding role.

1.7 Conclusions

Our study analyzes price discovery in the Euro bond future market by applying the information share approach. We contribute to the literature in two ways: first, we extend the price discovery analysis in the European market to several future contracts. Second, we extend the so far considered determinants of information shares by also making use of order flow data. Both contributions reveal interesting insights.

In covering the European bond market, we calculate information shares for the Bund, i.e. the 10-year German bond future, versus two other – so far neglected – future contracts, i.e. the 2-year Schatz and the 5-year Bobl. We find that the Bund is indeed the single most important contract for price discovery but that it does not dominate to an extent that the two other contracts would become unimportant. By contrast, there are many days, where the Bund is less important than another future contract.

In extending the determinants of information shares we complement market state and macroeconomic news variables by so far neglected order flow variables. Order flow has often been found to be a relevant measure in analyzing information flows in financial markets, so that it seems a natural extension to consider it as determinant of information shares too. Indeed, it proves to be an important determinant beyond the earlier

[16]The t-statistic of equal means in the case of a leadership role of the 2-year future is 7.96 and for the 5-year future 7.37.

variables. In particular, order flow is rather more important than macroeconomic news in understanding shifts in information shares between the Bund and the other future contracts.

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2 The effects of information and liquidity risks on the Euro Area term structure – Evidence from the PIN-AACD model**

Abstract

We analyze the implications of information risk and liquidity risk on the Euro Area term structure of interest rates. The effect of information risk is more evident for shorter maturity bonds and for term structure factors which load on bond excess returns. Liquidity risk affects all interest rates and term structure factors. The importance of both information risk and liquidity risk increased after the collapse of Lehman Brothers and underlines the change of investors' risk sensitivity. Neither the inclusion of macroeconomic announcements nor market microstructure variables rules out the pricing implication of information risk and liquidity risk in the Euro Area bond market.

2.1 Introduction

Liquidity provision and price discovery are main functions of financial markets (see O'Hara, 2003). However, the ongoing financial crisis reveals the markets' vulnerability. Several Euro Area bond markets are marked by a dramatic drop of trading volume (see ECB, 2011, p. 69) and De Grauwe (2011) discusses the European debt crisis in the context of a liquidity crisis. Note that worse liquidity conditions hamper the information incorporation process (Mizrach and Neely, 2008) which might lead to mispricing of government debt in some Euro Area bond markets (De Grauwe and Ji, 2012).

This paper discusses the pricing effects of the implicit risk related to market liquidity and price discovery for the Euro Area benchmark bond market - namely the German

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bond future market. Even in the most liquid European bond contracts the importance of liquidity and information incorporation risk increased in the aftermath of the Lehman Brothers collapse. This finding suggests a higher risk sensitivity of market participants. Due to its benchmark status, the derived asset pricing effects will have pricing implications for other Euro Area bond markets.

We follow Hasbrouck (2009) and define liquidity risk as the effective cost of an order execution which is also used as a benchmark measure for liquidity (see Goyenko et al., 2009). Information risk is the possibility of a price discovery event which coincides with asymmetric information. With the presence of asymmetric information risk, investors ask for risk compensation (see O'Hara, 2003). As propagated by Easley et al. (1996) and Easley et al. (2002) we define information risk as the probability of informed trading, in short PIN, whereby PIN is defined as the number of trades from informed investors divided by total trading. In the Easley et al. (1996) model market makers learn about information events and the presence of informed traders by observing the arrival of buy and sell orders. In order to protect against potential losses to informed traders, the market maker sets prices which compensate for bearing this risk.

Regressing changes of interest rates and term structure factors on liquidity and information risk for the time period 10/2004 to 02/2009 reveals that an increase of risk results in stronger movements of Euro Area interest rates and term structure factors. Liquidity risk is priced along the whole yield curve and seems to be more important than information risk. This finding is consistent with Li et al. (2009) who document a stronger link of US Treasury bond prices to liquidity risk than to information risk. Neither controlling for trading volume, spread, order flow nor realized volatility rules out the effects of information and liquidity risks. However, information risk becomes a relevant pricing factor in the aftermath of the Lehman Brothers bankruptcy which suggests increasing risk sensitivity during the financial crisis.

Asymmetric (or private) information events should be scarce in sovereign bond markets.

The high quality of this kind of information should rule out the possibility of heterogeneous informed investors and macroeconomic announcements should be the main drivers of bond markets (Balduzzi et al., 2001 and Andersson et al., 2009). However, the interpretation of announcements or the use of bond pricing models might differ between investors and lead to asymmetric information sets. Order flow, the difference between buyer- and seller-initiated trading, is interpreted as the medium how asymmetric information is incorporated into asset prices (see Evans and Lyons, 2002). Beside economic releases, the heterogeneous access to customer order flow is an additional source of private information (Menkveld et al., 2012). The empirical link between order flow and bond prices is documented by Brandt and Kavajecz (2004) and Green (2004) and is even stronger during times of price uncertainty (see Pasquariello and Vega, 2007).

This study applies the "probability of informed trading" (PIN) model to order flow data of the most liquid bond future contracts in the Euro Area. We overcome possible downward biased PINs (see Ke and Lin, 2011) by computing information risk by an asymmetric autoregressive conditional duration model (short: AACD model) and define PIN-AACD as information risk (Tay et al., 2009).

For the US bond market, Akay et al. (2012) discuss a close relation of PIN and existing trade clusters. For stocks, Duarte and Young (2009) point out a relation of information risk to liquidity risk in small caps. We address these concerns by estimating the PIN-AACDs for each ten-minute time period and aggregate them on a daily basis. Daily information risks reveal high correlations which suggest a relation of all bond contracts in a market (e.g. Fricke and Menkhoff, 2011).

The remainder of this paper is organized as follows. Section 2.2 presents the data set and discusses the role of the German bond future market for the European bond market. Section 2.3 introduces the PIN-AACD model, its estimation and relates information risk (PIN-AACD) to macroeconomic announcements. Section 2.4 analyzes the pricing implications of liquidity and information risk for interest rates and term structure factors.

Section 2.5 discusses the robustness of the results with respect to additional microstructure variables such as trading volume, spread, order flow and realized variance and to the financial crisis. Section 2.6 concludes.

2.2 Data

The study is based on high frequency transaction data of the three most liquid Euro Area bond future contracts between 2004 and 2009. In addition, we use macroeconomic announcements to analyze the pattern of information based trading around announcement events.

Transaction data: We use the transaction record between October 2004 and February 2009 of German bond futures which are traded at Eurex. Within the future market the ten-year future contract owns a superior role as its trading volume surpasses the two-year and the five-year contract by a factor of two. In 2005 the German ten-year bond future revealed a higher trading volume than the CBOT T-bond futures (see Hautsch et al., 2011). Thus, the ten-year future contract might be seen as the benchmark in the Euro Area bond market.[17]

The data set is concentrated on the most liquid contracts by applying an "auto roll" procedure.[18] This approach ensures a focus on "on-the-run" contracts which dominate the price process (see Brandt and Kavajecz, 2004).

Eurex provides trade prices, actual bid and ask prices as well as the transaction volume and the exact time stamps. We use this information to calculate bid-ask spreads, midquote returns and order flows and apply the Lee and Ready (1991)-algorithm to identify trade directions. The duration of each trade is the time distance in seconds between two trades.

[17]For example, European yield differentials of sovereign bonds are computed relative to Germany (Favero et al., 2010).

[18]A brief description of the "auto-roll" procedure is provided by Andersson et al. (2009).

Macroeconomic announcements: Releases of US, Euro Area and German macroeconomic news induce strong movements in the German future market (Fleming and Remolona, 1999, Andersen et al., 2007, Andersson et al., 2009 and Fricke and Menkhoff, 2011). We study the effect of macroeconomic announcements by applying an event study approach and define dummy variables for each economic variable. The dummy variable owns a value of one if the official release date lies in the relevant time interval. Table 11 lists the 28 considered macroeconomic announcements and their standard release time.[19]

Table 11: Considered macroeconomic announcements

This table shows the considered macroeconomic announcements for the construction of dummy variables. Announcement time reports the standard Frankfurt (Germany) release time.

name	**announce-ment time**	**obser-vation**	**name**	**announce-ment time**	**obser-vation**
US			**Euro Area**		
GDP advanced	14:30	16	GDP preliminary	11:00	16
GDP preliminary	14:30	14	GDP final	11:00	16
GDP final	14:30	13	CPI	11:00	36
nonfarm payroll	14:30	44	Retail sales	11:00	41
Retail sales	14:30	44	unemployment	11:00	43
industrial production	15:15	30	PPI	11:00	41
personal income	14:30	40	**Germany**		
home sales	16:00	38	GDP preliminary	08:00	13
construction spendings	16:00	44	GDP final	08:00	8
factory orders	16:00	41	CPI preliminary	08:00	21
business inventories	14:30	45	CPI final	08:00	29
PPI	14:30	42	PPI	08:00	39
CPI	14:30	44	Retail sales	08:00	36
housing starts	14:30	44	unemployment	08:00	41
			ZEW	11:00	40

Lucca and Moench (2011) document a Pre-FOMC effect which accounts for more than 80% of the equity premium. As the FED policy statement lies outside the Eurex trading hours, we control for a FOMC effect by splitting the FOMC dummy into a pre-FOMC and a post-FOMC dummy variable. The former one takes a value of one for days before

[19]The release times are corrected for any differences in the daylight saving time between the US and Germany

the FED policy statement and vice versa.

2.3 The econometric approach

We review the PIN-AACD model and the underlying estimation procedure at section 2.3.1 and section 2.3.2 discusses the pattern of the PIN-AACDs.

2.3.1 PIN-AACD model

The PIN-AACD-model presents an asymmetric autoregressive conditional duration model (Bauwens and Giot, 2003) which is implemented into the traditional PIN model (Tay et al., 2009). Market markers observe trade durations instead of arrivals of buys and sells and the probability of informed trading depends on the conditional expected duration of a buyer or seller initiated trade. Further, the expected duration, $\psi^s_{j,i}$, is determined by the available information set in time $t-1$, Φ_{i-1}, which is given by the trade direction y, the trading volume ν, the duration x and the previously expected duration $\psi^s_{j,i-1}$.[20] We define the basis function of expected durations of the state s and the trade direction j $[j = -1(sell), 1(buy)]$ at time i, $f^s_{j,i}$, as follows:

$$f^s_{j,i} = \nu_{j,-1} D_{-1}\left(y_{i-1}\right) + \nu_{j,1} D_1\left(y_{i-1}\right) + \alpha_j log\left(\psi^s_{j,i-1}\right) + \beta_j log\left(x_{i-1}\right) + \zeta y_{i-1} log\left(\nu_{i-1}\right) \quad (18)$$

whereby $D_{-1}(y_{i-1})$ equals one if the previous trade was a sell, y_{i-1}, and zero otherwise. Moreover, the conditional expected duration depends on the existence of news $s \,\epsilon\, S\{G, B, N\}$. Given a good (bad) information event, informed trading arises and leads to shorter trade durations for buys (sells).[21]

[20] We follow Tay et al. (2009) and adjust for the existing intraday pattern of trade durations by a cubic smoothing spline.

[21] We allow the impact of informed traders on durations to differ for buys and sells.

For a bad news period, the expected sell duration decreases by μ^S

$$log\left(\psi^B_{-1,i}\right) = f^B_{j,i} - \mu^s \ . \tag{19}$$

Let the probability of no news at time interval D, $\pi_{N,D}$, be defined as

$$\pi_{N,D} = 1 - \Theta_E = \frac{1}{1 + exp\left(\delta_1 + \delta_2[log\left(V^B_D + V^S_D\right) - log\left(\tilde{V}^B + \tilde{V}^S\right)]\right)} \ . \tag{20}$$

$\tilde{V}^B$ ($\tilde{V}^S$) represents the sample average of trading volume which is due to buy (sell) orders and V^B_D (V^S_D) denotes trading volume at time interval D. A higher than the average trading volume at interval D is related to the existence of an information event which automatically reduces the probability of no news. Given a news event, the probability of being in a good state is

$$\Theta_{G,D} = \frac{1}{1 + exp\left(\delta_3\left(log\left(V^S\right) + log\left(\tilde{V}^S\right)\right) - \delta_4\left(log\left(V^B\right) - log\left(\tilde{V}^B\right)\right)\right)} \ . \tag{21}$$

Conditional on information set Φ_{i-1}, the joint density of a buy (sell) trade duration at time i, is defined as

$$p_i\left(x_i, k|\Phi_i\right) \quad k = -1, 1 \ . \tag{22}$$

Given an exponential distribution to model the stochastic point processes of the arrival of buys and sells. $\lambda_{j,i} = \frac{1}{\psi_{j,i}}$ defines the intensity of this process, whereby $\psi_{j,i}$ corresponds to the conditional expected duration at time i. The joint distribution in (22) can then be rewritten to

$$ps_i\left(x_i, k|\Phi_i\right) = \prod_{j=-1,1}\left(\frac{1}{\psi^s_{j,i}}\right)^{D_k(j)} exp\left(-\frac{x_i}{\psi^s_{j,i}}\right), \quad k = -1, 1; \ s \ \epsilon \ S \tag{23}$$

and the probability of informed trading in the AACD-model is defined as follows:

$$PIN - AACD = \frac{\sum_{i=1}^{N} \left(\pi_G \lambda_{1,i}^G + \pi_B \lambda_{-1,i}^B\right) x_i}{\sum_{i=1}^{N} \left(\lambda_{-1,i}^N + \lambda_{1,i}^N + \pi_G \lambda_{1,i}^G + \pi_B \lambda_{-1,i}^B\right) x_i} . \tag{24}$$

We consider 20 different sets of initial starting parameters for identifying the global maximum of the likelihood function (see Duarte and Young, 2009 and Akay et al., 2012). Table 12 reports the estimated parameters which are discussed below.

First, for all contracts we observe that $\nu_{-1,1} < \nu_{-1,-1}$ and $\nu_{1,-1} < \nu_{1,1}$ which might document a bid-ask bounce (Glosten and Harris, 1988, McInish and Wood, 1992). Second, shorter trade durations are serially correlated what underlines the existence of trade clustering (see Akay et al., 2012). The signs of the news event parameters δ_1, δ_2 and δ_3 are positive and in line with Tay et al. (2009). The average probabilities of informed trading and the existence of news are nearly identical which suggests that these probabilities are related.

2.3.2 The intraday behavior of informed trading

We discuss the PIN-AACD patterns by (i) calculating its sample averages for each ten-minute interval, (ii) identifying the maturity-specific intraday pattern of each future contract and (iii) relating the patterns to macroeconomic announcements.

Figure 2 shows the average intraday probabilities of informed trading for each bond future contract. In contrast to volatility, the PIN-AACDs do not reveal a three-pike pattern.[22] However, three points are consistent with stylized facts of financial markets. *First*, the probability of informed trading increases around the release of German (at 10:00 CET), Euro Area (11:00) and US (14:30 and 16:00) macroeconomic announce-

[22] Andersen and Bollerslev (1998) document a u-shape pattern of the intraday volatility process which is related to the market opening and closing, overlapping trading hours of different markets and to macroeconomic announcements. This leads in the German bond market to three pike pattern of the volatility pattern which are linked to the opening of the market (08:00) and at 14:30 and 16:00 when US macroeconomic announcements are released (Ahn et al., 2002).

Table 12: Parameters of the PIN-AACD model

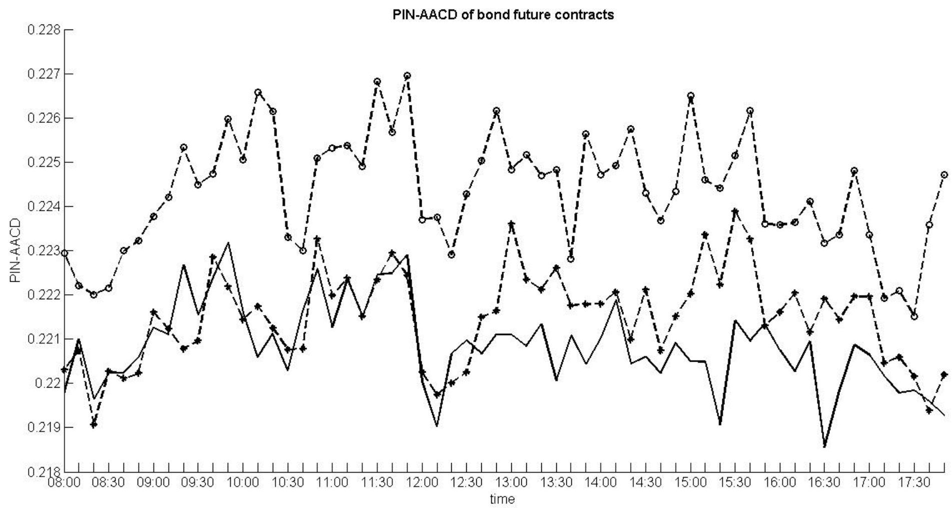
This table shows the estimated parameters of the PIN-AACD model by applying the MLE method. The distributional properties of the probabilities of informed trading of the German bond futures are reported. Estimated parameters are multiplied with 10,000.

			maturity	
Trade variables	Parameter	2-year	5-year	10-year
Sale after sale	$\nu_{-1,-1}$	141.0554	99.6402	66.7773
Sale after buy	$\nu_{-1,1}$	133.3757	84.4413	44.5477
Buy after sale	$\nu_{1,-1}$	139.2387	98.8147	66.9962
Buy after buy	$\nu_{1,1}$	133.6283	85.4971	45.4021
Conditional duration for sales	α_{-1}	11.8664	9.6894	10.9236
Lagged duration for sales	β_{-1}	13.9595	10.7942	8.9201
Conditional duration for buys	α_1	11.8976	9.7447	10.8742
Lagged duration for buys	$\beta 1$	13.9074	10.5847	8.7564
Adjustment for negative information	μ_{-1}	21.5242	24.7185	25.0768
Adjustment for positive information	μ_1	21.5249	24.7235	25.0827
Volume-direction for sales	ζ_{-1}	21.5822	24.7314	25.1006
Volume-direction for buys	ζ_1	21.5881	24.7271	24.9759
Prob. Equation, Coefficient 1	δ_1	140.7483	163.9669	174.8817
Prob. Equation, Coefficient 2	δ_2	140.7479	163.9571	174.865
Prob. Equation, Coefficient 3	δ_3	79.1989	92.2121	101.1598
Prob. Equation, Coefficient 4	δ_4	79.1978	92.2124	101.1531
Probability of good news				
Minimum		0.0000	0.0000	0.0366
Maximum		0.6950	0.9097	0.9702
Mean		0.2850	0.2849	0.2858
Std Dev		0.0672	0.0485	0.0419
Probability of no news				
Minimum		0.0203	0.0032	0.0004
Maximum		0.9782	0.9792	0.7778
Mean		0.4321	0.4313	0.4292
Std Dev		0.0818	0.0663	0.0646
Probability of bad news				
Minimum		0.0000	0.0000	0.0000
Maximum		0.7110	0.7397	0.9317
Mean		0.2829	0.2838	0.2850
10-min PIN-AACD				
Minimum		0.0108	0.0105	0.0103
Maximum		0.5339	0.8675	0.8988
Mean		0.2208	0.2215	0.2245
Std Dev		0.0276	0.0244	0.0369

ments. *Second*, the intensity of informed trading drops between 12:00 and 13:00 which is known as lunch effect (see Andersen and Bollerslev, 1998). *Third*, in the late after-

Figure 2: Intraday pattern of PIN-AACDs of bond future contracts in the whole sample

This figure shows the intraday pattern of the estimated PIN-AACDs between 2004 and 2009. The black line represents the pattern of the two-year contract, whereas the stars mark the pattern of the five-year contract and the ten-year contract is marked by circles. The time interval of the PIN-AACD estimations is ten minutes.



noon the PIN-AACDs decrease which corresponds to the documented volatility pattern of the German bond future market (Ahn et al., 2002). However, especially the ten-year bond's PIN-AACD picks up at the end of the trading day. This effect might be due to the outstanding liquidity of the ten-year future which enables traders to process orders more easily before the market shuts down.[23]

Unreported results reveal that the effect of macroeconomic announcements on PIN-AACDs is more pronounced for shorter contracts. The two-year PIN-AACD reveals a consistent relation to inflation and real output variables and the five-year contract reacts to all considered producer price variables which underline the importance of inflation

[23]We also compare PIN-AACDs across maturities. Results show that the measure is related to information incorporation. Consistent with Li et al. (2009) Wilcoxon rank-sum tests reveal higher PINs for shorter maturity bonds (here the two-year bond) and for bonds with higher trading volume (ten-year bond). At announcement days the two- and the ten-year contract's PIN-AACD do not significantly differ what underlines the importance of these contracts for the price discovery process at announcement days (see Fricke and Menkhoff, 2011).

variables for the bond market. Beside inflation the US industrial production significantly loads on the five- and ten-year bond future which underlines the importance of the US economy for global growth (see Andersson et al., 2009).

The tick size reduction led to an increase of informed trading which coincides with findings of Chen and Gau (2009). The financial crisis coincides with a decrease of informed trading which suggest that the German bond future market was exposed to a "flight to liquidity" phenomenon during the financial crisis (see Beber et al., 2009).

As macroeconomic announcements and time effects turn out to determine PIN-AACDs, we consider them as additional control variables in the following.

2.4 Pricing information and liquidity risks into the term structure of interest rates

We aggregate information and liquidity risk on a daily basis and analyze their pricing implications (i) for interest rates and (ii) for the first five term structure factors. Higher absolute changes of interest rates and of the term structure factors accompany with an increase of the risk measures. Including macroeconomic announcements does not rule out that information and liquidity risk are priced in German interest rates.

2.4.1 Estimation of daily PIN-AACDs and liquidity risk

We start with an aggregation of ten-minute PIN-AACDs on a daily basis (see Tay et al., 2009). Correlations of the state probabilities and of the PIN-AACDS are present (63% to 85%) and in line with comovements in the bond future market (e.g. Fricke and Menkhoff, 2011).

To analyze the effect of the market-wide intensity of informed trading, we apply a principal component analysis and extract the underlying factors out of daily PIN-AACDs.

The Bai and Ng (2002) information criterion suggests using two principal components whereby the first component explains 83% of the time series variation and the second one 13%. We regress each contract's PIN-AACD separately on the principal components to receive a clear interpretation. The first component loads on all bond futures' PIN-AACDs (two-year maturity: R^2 of 80%, five-year 95% and ten-year 75%) and can be interpreted as the market-wide probability of informed trading. The second principal component solely loads on the two-year (R^2 of 15%) and on the ten-year future contract (R^2 of 23%). This structure suggests the existence of an information incorporation process which exclusively affects the short-term and long-term bond future. This finding is in line with Fricke and Menkhoff (2011) who document a comparable pattern for information shares at announcement days.

The role of *liquidity risk* for bond pricing is stressed out by Li et al. (2009). Therefore, we control the effect of informed trading on the term structure for the impact of illiquidity. Liquidity risk is defined as the slope coefficient λ of the following regression (e.g. Goyenko et al., 2009):

$$r_{D,n,i} = \lambda S_{n,i} + u_{D,n,i} \tag{25}$$

with $r_{D,n,i}$ as the return of the bond future i at the n^{th} ten-minute time interval at day D. $S_{n,i}$ is the signed square-root trading volume of the future contract at the trading interval and $u_{D,n,i}$ represents an error term. The slope parameter λ is estimated for each day. The choice of using ten-minute time intervals stems from the estimation frequency of the PIN-AACDs.[24] The slope coefficients of the ten-year bond future are in all cases significant and in roughly 98% of the cases of the two- and five-year future contracts. R^2s lie between 33% (two-year future) and 46% (ten-year). Liquidity risk's principal components mirror the correlation structure of the slope coefficients as the first component loads completely on the two shorter maturity bonds and the second factor

[24]Goyenko et al. (2009) point out that the slope coefficient is robust to modifications of the time interval.

on the ten-year contract.[25] The correlation of information risk to liquidity risk does not exceed 20% and suggests that the PIN-AACDs do not proxy illiquidity (see Duarte and Young, 2009).

2.4.2 Information and liquidity effects on interest rates and the term structure

To which extent do information risk and liquidity risk affect yields and the term structure of interest rates, e.g. level, slope and curvature? We address these issues by regressing absolute changes of either interest rates or term structure factors on the principal components of information risk and liquidity risk, announcements and time dummy variables.

Interest rates: Investors facing higher risk ask for compensation, in this case higher absolute interest rate changes. We test this hypothesis by regressing absolute values of first differences of one-, two-, five- and ten-year German interest rates (i) solely on the risk measures and (ii) on all above described control variables. Interest rate changes offer the benefit to interpret them as unexpected yield changes and to overcome any problems associated with persistent interest rates. Applying an ADF-test for each time series rejects the non-stationarity property at the 1% level.

Table 13 Panel A reports an evidential effect of information and liquidity risk. A change of the market-wide *information risk*, the first factor, induces higher absolute yield changes than the information risk which is associated with the two- and ten-year future contract (factor two). Both effects are stronger for short-term yields and the impact of PIN-AACD's second principal component turns insignificant for the German ten-year interest rate. *Liquidity risk* which is associated with the most liquid bond future, the ten-year bond future, reveals the highest impact on interest rates changes. Its effect dominates both information risk measures at least by a factor of three and

[25]The correlation between the two- and five-year contract is 97.9% and correlations to the ten-year bond future are not larger than ten percent.

underlines its higher importance for bond markets (see Li et al., 2009). Nevertheless, liquidity risk of the shorter maturity bonds also leads to higher interest rate changes but the coefficients are much smaller. In sum, the effects suggest that liquidity risk is priced in the yield curve.

Panel B shows regression results for the inclusion of further control variables, such as announcement and time effects. With the exception of the five-year maturity the effects of information risk stay nearly constant and significant. In contrast, the effect of the second liquidity risk factor decreases but remains significant.

Time dummies own reasonable coefficients for the one- and two-year bond. The beginning of the financial crisis and the collapse of Lehman Brothers come along with higher yield changes, indicating more volatile financial markets. The introduction of the FED's LSAP calmed the German bond market. As significances are restricted to shorter maturity interest rates, our finding might indicate a higher uncertainty about the future path of short term interest rates and the potential introduction of additional monetary policy instruments, e.g. quantitative easing.

Interest rates do only react to a small number of macroeconomic announcements, namely the US final GDP, nonfarm payrolls and European producer prices. The effect of the nonfarm payroll employment confirms the view that this news is the king of economic announcements (see Andersen et al., 2007) and might stem from its availability to forecast European bond excess returns (see Ielpo, 2011). Longer maturity bond yields reveal lower changes at trading days before FOMC meetings.

Table 13: The effect of information risk and liquidity risk on daily interest rate changes

Panel A shows regression results of daily absolute interest rate changes on the first two principal components of the daily probability of informed trading and of liquidity risk. At Panel B macroeconomic announcement dummies are also included which own a one if the corresponding information is released. The 10% (5%, 1%) significance level is marked with a * (** / ***).

	maturity							
	1-year		2-year		5-year		10-year	
risk related variables	Panel A	Panel B	Panel A	Panel B	Panel A	Panel B	Panel A	Panel B
$PIN-AACD^{PCA1}$	0.103***	0.101***	0.128***	0.112***	0.093***	0.086***	0.079***	0.088***
$PIN-AACD^{PCA2}$	0.082***	0.067**	0.119***	0.078***	0.083***	0.046	0.007	0.003
$liquidityrisk^{PCA1}$	0.060**	0.052**	0.063**	0.053*	0.067***	0.057***	0.059***	0.050***
$liquidityrisk^{PCA2}$	0.314***	0.238***	0.307***	0.208***	0.286***	0.190***	0.239***	0.153***
US								
GDP advanced		-0.311		-0.247		-0.217		-0.118
GDP preliminary		-0.046		-0.149		0.120		-0.079
GDP final		-0.204		-0.107		-0.367**		-0.308*
nonfarm payroll		0.586**		0.565**		0.467**		0.195
retail sales		0.111		0.073		-0.290		-0.185
industrial production		0.010		-0.201		-0.305		-0.222
personal income		-0.237		-0.147		-0.181		-0.166
home sales		-0.064		-0.054		-0.080		0.000
construction spendings		-0.077		-0.185		-0.162		-0.024
factory orders		-0.104		-0.122		-0.019		-0.041
business inventories		0.062		0.073		0.384		0.391
PPI		-0.026		-0.134		0.050		0.285
CPI		0.052		-0.037		-0.142		-0.216*
housing starts		-0.217**		-0.093		0.025		0.239
Euro Area								
GDP preliminary		-0.317		-0.399		-0.632*		-0.212
GDP final		0.252		0.044		-0.193		-0.033
CPI		0.075		0.222		0.161		0.096
retail sales		0.061		-0.103		-0.140		-0.070
unemployment		-0.108		-0.038		0.029		-0.175
PPI		0.013		-0.328**		-0.314**		-0.235

	maturity							
	1-year		2-year		5-year		10-year	
risk related variables	Panel A	Panel B	Panel A	Panel B	Panel A	Panel B	Panel A	Panel B
Germany								
GDP preliminary		0.034		0.178		0.364		-0.138
GDP final		0.050		0.052		-0.219		-0.495**
CPI preliminary		-0.085		-0.185		-0.199		-0.223
CPI final		0.039		-0.156		-0.124		0.074
PPI		0.038		-0.002		-0.010		0.034
retail sales		0.283		0.175		0.050		-0.081
unemployment		0.007		-0.095		-0.176		-0.010
ZEW		-0.023		0.071		0.015		-0.258
dummy variables								
FOMC pre		-0.091		-0.202		-0.265**		-0.314***
FOMC post		0.227		0.006		-0.074		0.160
dummy Financial crisis		0.386***		0.387***		0.152		-0.101
dummy Lehman Brothers		0.898***		0.602**		0.206		0.520*
dummy LSAP		-0.973***		-0.937***		-0.150		-0.077
dummy tick size reduction		-0.381***		-0.136		0.118		0.136
adjusted R^2	13.3%	16.8%	15.1%	18.1%	11.5%	12.9%	6.0%	7.2%

The significance of the European price index underlines its importance for targeting inflation rates by the ECB. An additional reason might be the relation of producer- to consumer prices which are related to credit cycles (Ielpo, 2011). In contrast to Brière and Ielpo (2007) and Andersson et al. (2009) we do neither find an impact of the ZEW indicator nor German unemployment figures. We see this finding in line with the limited amount of significant macroeconomic announcements which suggests that information and liquidity risk partly subsume effects which are related to economic information.

Term structure: We extract the main term structure factors out of the German interest rates with a maturity of one to 120 months. Classical term structure models use three factors as they nearly completely span the whole yield curve. Guégan et al. (2009) discuss a four factor term structure model and Cochrane and Piazzesi (2005) show that the fourth and the fifth factor strongly load on bond excess returns which motivate us to include them too. In the following, we analyze unexpected changes of the term structure factors. As the first term structure factor is highly persistent, we define its unexpected changes as the first difference. For the remaining four factors an unexpected change is defined as the residual of an AR(1)-process.[26] Equations (26)-(29) show regression results whereby $TSF_{i,t}$ represents the i^{th} term structure factor and $\varepsilon_{TSF_{i,t}}$ is the regression's residual. All slope coefficients are significant at the one percent level.

$$TSF_{2,t} = 0.9507\ TSF_{2,t-1} + \varepsilon_{TSF_{2,t}}\ ; R^2 = 0.9507 \tag{26}$$

$$TSF_{3,t} = 0.8688\ TSF_{3,t-1} + \varepsilon_{TSF_{3,t}}\ ; R^2 = 0.7545 \tag{27}$$

$$TSF_{4,t} = 0.5355\ TSF_{4,t-1} + \varepsilon_{TSF_{4,t}}\ ; R^2 = 0.2866 \tag{28}$$

[26]Results are robust for defining first differences of the term structure factors as unexpected changes.

$$TSF_{5,t} = 0.8719\ TSF_{5,t-1} + \varepsilon_{TSF_{5,t}}\ ; R^2 = 0.7567 \tag{29}$$

Table 14 Panel A reports results of regressing unexpected term structure changes on risk variables. A higher market-wide information risk leads to stronger movements of all factors and is not restricted to the classical factors level, slope and curvature. The same is true for liquidity risk. Results for controlling for announcement and time effects (Panel B) are consistent with findings for interest rates. The coefficients of market-wide information risk remain significant and nearly unaffected by the inclusion of further control variables. The second information risk factor loses its impact on the level and slope of the yield curve. This effect is not surprising as the second information risk factor seems to be related to the incorporation of macroeconomic announcements (see Section 2.4.1). Therefore, we see information risk and announcement effects directly related. Both liquidity risk measures reveal significant effects on the whole term structure whereby the impact of the second liquidity factor drops by a half. This pattern is well known from the upper study of yield changes.

To sum up, this section reveals that information risk and liquidity risk are relevant drivers for yield changes as well as for term structure changes. The effects are likewise significant for classical term structure variables as well as for the fourth and fifth factor which mainly affect bond excess returns. Thus, our results suggest that information risk and liquidity risk are priced in the term structure.

Table 14: The effect of information risk and liquidity risk on term structure factors

Panel A shows regression results of daily absolute, unexpected changes and of the first five term structure factors on the first two principal components of the daily probability of informed trading and of liquidity risk. At Panel B macroeconomic announcement dummies are also included which own a one if the corresponding information is released. The 10% (5%, 1%) significance level is marked with a * (** / ***).

	term structure factor									
	first		second		third		fourth		fifth	
risk related variables	Panel A	Panel B	Panel A	Panel B	Panel A	Panel B	Panel A	Panel B	Panel A	Panel B
PIN^{PCA1}	0.084***	0.087***	0.064***	0.095***	0.100***	0.092***	0.074***	0.053**	0.055***	0.068***
PIN^{PCA2}	0.065**	0.046	-0.060**	-0.043	0.064***	0.049***	0.090***	0.066***	0.027	0.025
$liquidityrisk^{PCA1}$	0.070***	0.061***	0.045***	0.037***	0.039***	0.027***	0.032**	0.020*	0.030***	0.019***
$liquidityrisk^{PCA2}$	0.312***	0.226***	0.199***	0.136***	0.258***	0.156***	0.257***	0.145***	0.213***	0.114**
US										
GDP advanced		-0.306		0.019		0.046		0.098		0.067
GDP preliminary		0.040		-0.076		-0.085		-0.167**		-0.006
GDP final		-0.328*		-0.119		-0.114		-0.164*		-0.100
nonfarm payroll		0.378**		-0.141		-0.145		-0.203**		-0.076
Retail sales		-0.277		-0.121		0.024		-0.159**		-0.148
industrial production		-0.279		-0.121		-0.091		-0.066		-0.248**
personal income		-0.314**		-0.584**		-0.233		-0.213**		-0.365*
home sales		-0.038		0.035		-0.002		-0.099**		-0.108
construction spendings		0.209		0.790*		0.151		-0.003		0.389
factory orders		-0.040		0.188		0.173		-0.007		0.315
business inventories		0.400		0.338		0.012		0.065		0.276*
PPI		0.051		0.145		-0.081		-0.069		0.088
CPI		-0.167		-0.161		-0.167**		-0.124		-0.152
housing starts		0.060		0.177		-0.002		-0.010		-0.001
Euro Area										
GDP preliminary		-0.515*		-0.457		-0.405		-0.143		-0.523*
GDP final		-0.124		-0.135		0.028		-0.124		0.054
CPI		0.115		0.012		0.062		-0.062		0.088
Retail sales		-0.199		-0.004		-0.003		-0.169**		0.132
unemployment		-0.084		0.037		0.419		0.323		0.188
PPI		-0.246		-0.125		-0.005		-0.082		0.155

	term structure factor									
	first		second		third		fourth		fifth	
risk related variables	Panel A	Panel B	Panel A	Panel B	Panel A	Panel B	Panel A	Panel B	Panel A	Panel B
Germany										
GDP preliminary		0.255		0.004		0.188		-0.082		0.262
GDP final		-0.267		-0.299**		-0.020		-0.158***		-0.108
CPI preliminary		-0.213*		-0.018		-0.018		-0.037		-0.085
CPI final		-0.023		0.150		-0.051		0.043		-0.057
PPI		0.008		-0.048		-0.126		-0.091		-0.033
Retail sales		0.144		0.304		0.049		-0.018		0.148
unemployment		-0.205		-0.033		-0.044		0.076		0.100
ZEW		-0.039		-0.158		-0.032		-0.034		0.001
dummy variables										
FOMC pre		-0.242**		-0.241*		0.061		0.062		-0.238**
FOMC post		0.009		0.076		-0.082		-0.159*		-0.004
dummy Financial crisis		0.049		-0.090		0.241***		0.264***		0.203***
dummy Lehman Brothers		0.351		0.982**		1.479**		1.271**		1.607***
dummy LSAP		-0.121		-0.452		-1.817***		-1.764***		-1.580***
dummy tick size reduction		0.091		-0.101		-0.232***		-0.117***		-0.320***
adjusted R^2	12.3%	13.1%	3.1%	8.0%	8.8%	16.0%	9.5%	15.0%	4.9%	13.9%

2.5 Robustness tests

The robustness analysis is twofold. First, we control for additional microstructure variables such as trading volume, spread, order flow and realized variance. As these variables help to explain changes of interest rate variables, we consider them in all the following robustness tests. At the second step, we analyze the role of information and liquidity risk during the financial crisis period. In detail, we multiply the risk factors with the Lehman Brothers dummy variable and include them as further control variables.

Microstructure variables: We follow Li et al. (2009) and control the robustness of our results for several market microstructure variables which might be driving forces of yield changes and term structure factors. Admati and Pfleiderer (1988) suggest that informed traders are more active in more liquid markets which enforce us to consider the bond future markets trading volume. To be consistent with the computation of liquidity risk, we use the square-root of the trading volume. The inclusion of trading volume is also directly addressed to liquidity risk which might be inversely related to volume. We additionally control for the possibility that information and liquidity risks are proxies of the bid-ask spread which reveals positive relations to both considered risk measures (see Easley et al., 2002 for information risk and Jankowitsch et al., 2006 for liquidity). The third variable is order flow which determines term structure factors (e.g. Brandt and Kavajecz, 2004). We replace raw order flow by its absolute values as we are interested in the effect of higher order imbalances – negative or positive. These imbalances might either be nurtured by information incorporation or market's illiquidity and thus directly control for information risk and liquidity risk. Daily realized volatility is the sum of squared returns (see Andersen et al., 2003).

We include the commonality of future market's trading volume, spread, absolute order flow and realized volatility which is in each case the first principal component (see Hasbrouck and Seppi, 2001 and Dunne et al., 2011). We control for the possibility of multicollinearity by calculating the Variance Inflation Factor (VIF) which does not exceed the rule of thumb value of ten in all cases.

We start with the discussion of the effects for yield changes (Table 15). With the exception of order flow all trading-related variables reveal significant impacts on interest rate changes. An increase of either trading volume, spread or volatility coincides with higher yield changes. The positive sign of trading volume suggests that it more likely mirror information incorporation into prices instead of illiquidity. The signs of spread and volatility do not bear a clear interpretation as their increase can be related to information and illiquidity. However, turning the focus to the risk factors reveals that the inclusion of trading variables mainly absorbs information risk effects. Now, significant effects of the probability of informed trading only remain at the short end of the yield curve. The impact of liquidity risk also decreases with the inclusion of the trading-related variables but stays significant for nearly all yields. The importance of economic announcements is more pronounced for the five-year interest rate. This finding underlines the hump-shaped effect of economic announcements as it is pointed out by Fleming and Remolona (1999), Brière and Ielpo (2007) and Guégan et al. (2009).

Next, we discuss the effects on the term structure. After the inclusion of further microstructure variables the effect of market-wide information risk still loads on the second, third and fifth term structure factor. An increase of the second information risk factor mainly coincides with higher changes of the slope. This effect is not surprising as this exogenous variable subsumes information risk which is related to the short and long end of the yield curve. An increase of liquidity risk corresponds with higher changes of all term structure factors.

Table 15: Robustness test: The joint consideration of risk and trading related variables

This table reports results for regressing absolute changes of interest rates and of term structure factors on information and liquidity risks, macroeconomic announcement dummy variables, dummy variables to account for special effects of the analyzed time period and trading related varia-bles. Macroeconomic announcement dummies own a value of one if the corresponding information is released. Trading-related variables each are the first principal component of trading volume, spread, order flow and realized volatility. The 10% (5%, 1%) significance level is marked with a * (** / ***).

	maturity				term structure factors				
risk related variables	1-year	2-year	5-year	10-year	first	second	third	fourth	fifth
PIN^{PCA1}	0.041*	0.053**	0.035	0.035	0.040	0.051*	0.064**	0.029	0.052*
PIN^{PCA2}	-0.010	-0.024	0.000	0.037	-0.013	0.067**	-0.025	-0.036*	-0.004
$liquidityrisk^{PCA1}$	0.024***	0.011	0.034***	0.041***	0.040***	0.050***	0.039***	0.012	0.026***
$liquidityrisk^{PCA2}$	0.192***	0.167***	0.162***	0.144***	0.231***	0.158***	0.151***	0.125***	0.109*
US									
GDP advanced	-0.354*	-0.292*	-0.260	-0.174	-0.350*	-0.042	0.023	0.090	0.063
GDP preliminary	0.015	-0.096	0.146	-0.088	0.035	-0.115	-0.061	-0.122	0.013
GDP final	-0.211	-0.117	-0.376**	-0.344**	-0.379**	-0.160	-0.123	-0.160	-0.095
nonfarm payroll	0.545**	0.521**	0.429**	0.140	0.335**	-0.199	-0.161	−0.204**	-0.070
retail sales	0.149	0.123	-0.236	-0.175	-0.257	-0.114	0.045	-0.151**	-0.133
industrial production	0.002	-0.210	-0.315*	-0.246	-0.306*	-0.160	-0.104	-0.067	-0.253**
personal income	-0.141	-0.066	-0.142	-0.150	-0.211	-0.563**	-0.219	−0.185**	-0.343*
home sales	-0.066	-0.057	-0.084	-0.025	-0.077	-0.008	0.011	-0.074*	-0.097
construction spendings	-0.042	-0.148	-0.144	-0.023	0.074	0.753*	0.140	0.005	0.372
factory orders	-0.125	-0.145	-0.044	-0.085	-0.091	0.143	0.147	-0.025	0.301
business inventories	-0.004	-0.007	0.308	0.349	0.335	0.285	-0.024	0.057	0.260*
PPI	-0.069	-0.176	0.010	0.244	0.020	0.112	-0.096	-0.085	0.075
CPI	0.043	-0.046	-0.148	−0.233*	-0.189*	-0.190	-0.172**	-0.121	-0.149
housing starts	-0.275**	-0.150	-0.028	0.180	-0.002	0.117	-0.038	-0.034	-0.024
Euro Area									
GDP preliminary	-0.146	-0.265	-0.487*	-0.060	-0.306	-0.359	-0.369	-0.147	-0.427
GDP final	0.214	0.007	-0.225	-0.073	-0.165	-0.175	0.012	-0.132	0.049
CPI	0.015	0.163	0.111	0.044	0.065	-0.040	0.036	-0.077	0.075
retail sales	0.119	-0.045	-0.089	-0.029	-0.163	0.010	0.022	-0.135*	0.152
unemployment	-0.142	-0.077	-0.009	-0.222	-0.070	0.015	0.404	0.310	0.186
PPI	0.052	-0.287**	-0.275*	-0.201	-0.228	-0.117	0.021	-0.048	0.175

	maturity				term structure factors				
risk related variables	1-year	2-year	5-year	10-year	first	second	third	fourth	fifth
Germany									
GDP preliminary	-0.093	0.144	0.308	-0.332	0.078	-0.117	0.215	-0.024	0.178
GDP final	0.284	0.304	0.168	-0.157	0.011	-0.097	-0.039	-0.096	0.092
CPI preliminary	-0.049	-0.147	-0.158	-0.201	-0.213*	-0.030	0.002	-0.001	-0.059
CPI final	0.062	-0.138	-0.112	0.073	-0.041	0.113	-0.051	0.065	-0.047
PPI	0.081	0.040	0.024	0.043	0.006	-0.073	-0.116	-0.062	-0.020
retail sales	0.193	0.105	0.066	-0.084	-0.030	0.295	0.088	0.003	0.189
unemployment	0.012	-0.085	-0.173	-0.011	-0.202	-0.081	-0.066	0.070	0.076
ZEW	-0.039	0.061	0.024	-0.277*	-0.040	-0.174	-0.022	-0.029	0.026
dummy variables									
FOMC pre	-0.026	-0.137	-0.206	-0.257**	-0.191*	-0.211*	0.094	0.100	-0.215**
FOMC post	0.151	-0.073	-0.146	0.094	-0.045	0.013	-0.131*	-0.200**	-0.033
dummy Financial crisis	0.372***	0.373***	0.127	-0.108	0.052	-0.073	0.215***	0.225***	0.166**
dummy Lehman Brothers	0.735**	0.437	0.053	0.438	0.307	1.012**	1.388**	1.124**	1.506***
dummy LSAP	-2.057***	-1.989***	-0.994***	-0.602	-0.424	-0.457	-2.089***	-2.234***	-1.788***
dummy tick size reduction	-0.308***	-0.066	0.181*	0.191	0.146	-0.068	-0.192***	-0.073**	−0.287***
trading related variables									
trading volume	0.154***	0.154***	0.138***	0.165***	0.158***	0.173***	0.084*	0.052	0.043*
spread	0.025***	0.045***	0.022***	0.005	0.023***	-0.020***	-0.019**	0.005	-0.013*
order flow	-0.051	-0.052	-0.024	-0.015	-0.001	0.006	0.031	0.032	0.050
realized volatility	0.384***	0.374***	0.303***	0.203**	0.125	0.030	0.107	0.168**	0.077
adjusted R^2	21.3%	22.6%	16.0%	9.9%	15.2%	10.1%	16.8%	15.8%	14.3%

In sum, the inclusion of market microstructure variables enhances our understanding of changes of interest rates and term structure factors. Although the majority of the additionally included control variables are seen as alternative liquidity measures, their inclusion does not affect the impact of liquidity risks. However, in some cases information risk factors turn to be insignificant which partially puts the questions if information risk is priced in the term structure. To answer this question we analyze the role of information and liquidity risks during the financial crisis in the following.

Financial crisis: This subsection analyzes the role of the risk factors during the financial crisis period.[27] Therefore, we define further control variables by multiplying information risk and liquidity risk with the Lehman Brothers collapse dummy variable. Table 16 presents results for interest rates and term structure factors.

The pricing effect of market-wide information risk, PIN^{PCA1}, emerges in the aftermath of the collapse of Lehman Brothers.[28] We interpret this finding as a higher sensibility of market participants to asymmetric information in the aftermath of the Lehman Brothers default. This higher sensibility might stem from new sources of asymmetric information such as the consideration of counterparty risks or the possible implementation of new monetary policy instruments like quantitative easing. The increasing sensibility of term structure factors to liquidity risk is in line with Aragon and Strahan (2012) who report illiquidity effects due to the Lehman Brothers bankruptcy.

Overall, the inclusion of further control variables does not rule out the effect of risk variables on interest rates and the term structure. These effects are even stronger during financial stress, which is in our case modeled by the Lehman Brothers collapse. This finding underlines the increased risk sensitivity of investors during the financial crisis.

[27] Further robustness checks address issues which are related to the financial crisis. In short, splitting the sample into a pre-Lehman Brothers and post Lehman Brothers collapse period or using the financial crisis period and running regressions in the same form as at Table 16 confirm our findings.

[28] Alternatively, we analyze other possible effects which are related to the financial crisis. We multiply risk variables with the financial crisis dummy and the LSAP dummy variable. Both approaches reveal insignificant regression coefficients which underline the outstanding effect of the Lehman Brothers collapse.

Table 16: Robustness test: Information and liquidity risks in the aftermath of the Lehman Brothers' collapse

This table reports results for regressing absolute changes of interest rates and of term structure factors on information and liquidity risks, macroeconomic announcement dummy variables, dummy variables to account for special effects of the analyzed time period and trading related variables. Both, information and liquidity risk are multiplied with the Lehman Brothers dummy variable to analyze the influence of the risk variables after the collapse of Lehman Brothers. The 10% (5%, 1%) significance level is marked with a * (** / ***).

	maturity				term structure factors				
risk related variables	1-year	2-year	5-year	10-year	first	second	third	fourth	fifth
PIN^{PCA1}	0.019	0.029	0.018	0.021	0.007	0.033	0.017	-0.009	0.028
PIN^{PCA2}	-0.008	-0.021	0.005	0.042	-0.012	0.053*	-0.026	-0.038**	-0.005
PIN^{PCA1} x dummy Lehman Brothers	0.491*	0.590***	0.477**	0.380	0.733***	0.644*	1.329**	1.062**	0.817**
PIN^{PCA2} x dummy Lehman Brothers	-0.372	-0.322	-0.266	-0.488	0.083	0.139	-0.241	-0.314	-0.107
$liquidityrisk^{PCA1}$	0.039***	0.043*	0.051***	0.046***	0.046***	0.038***	0.022***	0.013*	0.020**
$liquidityrisk^{PCA2}$	0.154**	0.153**	0.166***	0.157***	0.159***	0.208***	0.170***	0.128***	0.163**
$liquidityrisk^{PCA1}$ x dummy Lehman Brothers	0.025	0.437	-0.409	0.228	3.366	2.761	5.442**	6.003**	3.684**
$liquidityrisk^{PCA2}$ x dummy Lehman Brothers	0.154	-0.037	-0.024	-0.068	-0.174	-0.417	-0.702**	-0.653**	-0.657**
US									
GDP advanced	-0.349*	-0.294*	-0.266	-0.196	-0.318	-0.023	0.038	0.102	0.061
GDP preliminary	0.006	-0.101	0.142	-0.113	0.061	-0.100	-0.046	-0.128	0.027
GDP final	-0.241*	-0.151	-0.399**	-0.384**	-0.389**	-0.225	-0.211**	-0.241**	-0.157
nonfarm payroll	0.536**	0.506**	0.411**	0.141	0.309*	-0.192	-0.168	-0.189**	-0.074
retail sales	0.157	0.134	-0.230	-0.184	-0.222	-0.134	0.060	-0.142**	-0.143
industrial production	0.014	-0.204	-0.312*	-0.239	-0.278	-0.138	-0.065	-0.026**	-0.229*
personal income	-0.144	-0.061	-0.144	-0.159	-0.200	-0.572**	-0.245	−0.235**	-0.357**
home sales	-0.057	-0.044	-0.077	-0.022	-0.065	-0.007	0.026	-0.080	-0.084
construction spendings	-0.088	-0.196	-0.169	-0.079	0.048	0.674*	0.024	-0.112	0.301
factory orders	-0.133	-0.167	-0.059	-0.106	-0.116	0.105	0.074	-0.089	0.243
business inventories	-0.013	-0.016	0.306	0.350	0.311	0.292	-0.040	0.041	0.262*
PPI	-0.054	-0.169	0.013	0.259	-0.020	0.080	-0.127	-0.104	0.035
CPI	0.042	-0.043	-0.149	-0.250	-0.185	-0.199*	-0.180**	-0.132	-0.168*
housing starts	-0.257**	-0.130	-0.012	0.198	0.037	0.144	0.029	0.027 0.021	
Euro Area									
GDP preliminary	-0.117	-0.255	-0.501*	-0.058	-0.299	-0.434	-0.408**	-0.147	-0.499*
GDP final	0.198	-0.011	-0.240	-0.084	-0.189	-0.186	-0.010	-0.146	0.030
CPI	0.011	0.187	0.125	0.034	0.054	-0.097	0.012	-0.111	0.036
retail sales	0.091	-0.056	-0.089	-0.048	-0.157	0.005	0.019	-0.154	0.168

	maturity				term structure factors				
risk related variables	1-year	2-year	5-year	10-year	first	second	third	fourth	fifth
unemployment	-0.174	-0.109	-0.036	-0.231	-0.132	0.002	0.336	0.262	0.153
PPI	0.040	-0.285**	-0.267*	-0.216	-0.194	-0.113	0.045	-0.042	0.200
Germany									
GDP preliminary	-0.064	0.167	0.323	-0.316	0.107	-0.074	0.277	0.035	0.204
GDP final	0.320	0.350	0.208	-0.158	0.132	-0.040	0.084	-0.003	0.160
CPI preliminary	0.097	-0.006	0.022	-0.068	-0.044	0.059	0.188*	0.244	0.006
CPI final	0.057	-0.076	0.002	0.121	0.025	0.144	0.003	0.012	0.135
PPI	0.060	0.014	0.007	0.016	0.007	-0.120	-0.177*	-0.118	-0.059
retail sales	0.177	0.104	0.069	-0.088	-0.009	0.288	0.102	0.014	0.208
unemployment	0.031	-0.050	-0.139	0.034	-0.195	-0.027	0.024	0.150	0.152
ZEW	-0.066	0.036	0.001	-0.306	-0.022	-0.163	-0.018	-0.022	0.031
dummy variables									
FOMC pre	-0.054	-0.152	-0.217	-0.280**	-0.180	-0.237**	0.071	0.067	-0.218**
FOMC post	0.138	-0.077	-0.143	0.092	-0.045	0.007	-0.134*	-0.211**	-0.024
dummy Financial crisis	0.375***	0.371***	0.122	-0.111	0.072	-0.097	0.205***	0.214***	0.153**
dummy Lehman Brothers	0.077	0.183	0.004	0.011	0.224	1.536*	1.640*	0.973	2.100**
dummy LSAP	-1.583***	-1.367***	-0.505	-0.169	0.489	0.142	-0.556	-0.960*	-0.801*
dummy tick size reduction	-0.285***	-0.072	0.163	0.216*	0.052	-0.009	-0.218***	-0.062	-0.320***
trading related variables									
trading volume	0.150***	0.159***	0.144***	0.165***	0.167***	0.174***	0.096**	0.055	0.057**
spread	0.004	-0.026	-0.032	0.023	-0.140*	0.071	-0.051	-0.012	-0.035
order flow	-0.026	-0.027	-0.008	0.005	0.029	0.036	0.089**	0.087*	0.081*
realized volatility	0.372***	0.317***	0.247**	0.179*	-0.007	-0.025	-0.084	0.033	-0.072
adjusted R^2	22.4%	23.7%	16.6%	10.4%	17.7%	11.7%	24.0%	21.3%	17.0%

2.6 Conclusion

This paper discusses the role of information risk and liquidity risk for the Euro Area term structure. Information risk is proxied by the probability of informed trading in the German bond future market. We apply the PIN-AACD framework to the most liquid European bond future market. Liquidity risk is measured as the slope coefficient of a regression of bond future returns on order flow.

Our results confirm findings for the US Treasury market that both information and liquidity risk are priced in the bond market. Both, informed trading and liquidity affect interest rates and the underlying term structure. Increases of these risk factors result in higher absolute changes of German interest rates and unexpected term structure factors. These effects are even more pronounced in the aftermath of the Lehman Brothers collapse which underlines the increased risk sensitivity of investors during the financial crisis. Due to the benchmark status of the here analyzed German bond market, the here derived asset pricing effects might have pricing implications for other European bond markets.

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3 Expected and unexpected bond excess returns: Macroeconomic and market microstructure effects***

Abstract

This paper shows that order flow predicts bond excess returns. This effect cannot be captured by macroeconomic or forward rate information. To understand how these variables influence bond excess returns, we decompose excess returns into expected and unexpected excess returns. Expected returns crucially depend on the available information set which is spanned by order flow, forward rates and macroeconomic variables. Thus, the predictability of bond excess returns stems from the strong linkage of expected excess returns to economic state variables and order flow. The analysis of unexpected excess returns reveals contemporaneous order flow and changes of the economic environment as main drivers.

3.1 Introduction

Buying a long-term bond and selling it after a one-month holding period yields on average a positive excess return. As shown empirically macroeconomic variables and forward rates are known drivers of bond market excess returns (see Ludvigson and Ng, 2009 and Cochrane and Piazzesi, 2005). As these information are public available, they should fully represent the information set of bond investors. However, for bond markets Menkveld et al. (2012) stress out the importance of non-public (dispersed) economic information which are incorporated through the trading of bond contracts.

This paper picks up the idea of dispersed information in bond markets and widens the

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spectrum of bond excess return determinants by introducing order flow which reflects the incorporation of non-public economic information through trading (Brandt and Kavajecz, 2004; Green, 2004 and Pasquariello and Vega, 2007).[29] A theoretical motivation for considering order flow in the context of bond excess returns is given by Evans and Lyons (2002) who directly relate order flow to risk premia and thus to excess returns:

> ". . . *(order flows) include ... speculative demands from varying risk tolerance*"
>
> Evans and Lyons (2002), p.173.

We test the holding of the Evans and Lyons (2002) statement by regressing US one-month bond excess returns on the "on-the-run" ten-year Treasury bond future contract's order flow for the period 01/1999 – 10/2011.[30] Given the importance of the FED's "Permanent Market Operations" in the US bond market (see Pasquariello et al., 2012) we decompose order flow into OF_t^{QE}, which is order flow at days when the FED conducts "Permanent Market Operations", and OF_t, which is order flow at days without central bank interventions:[31]

$$rx_t = 0.0449 OF_t^{QE} + 0.3571^{***} OF_t + \epsilon_t; R^2 = 0.1447 \tag{30}$$

[29] Order flow is a measure of signed trades and indicates buying pressure in financial markets (assuming that buys are coded positive).

[30] Data are taken from the Gurkaynak et al. (2007) data set to construct the US zero coupon yield curve for 01/1999–10/2011. Bond excess return is the difference between the return of holding a long-run bond for one month and selling it and the one-month yield. Order flows are monthly aggregates and are derived from the "on-the-run" ten-year Treasury bond future contract. The 5% (1%) significance level is marked with a ** (***).

[31] Permanent open market operations (POMOs) are conducted on the behalf of the Federal Reserve System to achieve the FOMC's Fed Funds target rate. Pasquariello et al. (2012) reveal liquidity improvements in the US bond markets at these intervention days.

What is the economic significance of this regression? The finding that order flow influences contemporaneous excess returns suggests order flow as a potential bond pricing factor. Causality should run from order flow to bond excess returns as order flow mirrors information incorporation through trading (Brandt and Kavajecz, 2004, Green, 2004, Pasquariello and Vega, 2007, Fricke and Menkhoff, 2011, and Menkveld et al., 2012). We bring the idea of order flow as bond pricing factor a step further and regress one-month ahead bond excess returns on order flow:

$$rx_{t+1} = -0.1142 OF_t^{QE} + 0.00019^{**} OF_t + \epsilon_t; R^2 = 0.0410 \tag{31}$$

The significant order flow coefficient shows that order flow seems to have forecasting power what might mean that order flow proxies information which are relevant for backing out expectations about future bond excess returns.

These two characteristics of order flow, the forecasting power and the contemporaneous effect on bond excess returns, are the points where this paper steps in. For a deeper understanding of bond excess return predictability, we decompose excess returns into expected and unexpected excess returns by adopting the Adrian et al. (2012) term structure model. In the core of the paper, we regress raw bond excess returns and both expected and unexpected excess returns on economic variables. Besides well established variables like macroeconomic factors (Ludvigson and Ng, 2009) and forward rates (Cochrane and Piazzesi, 2005), we follow the market microstructure literature and consider bond market order flow as a proxy for dispersed (private) economic information. Neither the use of forward rates nor macroeconomic variables can capture all information which order flow offers. Thus, order flow seems to incorporate a risk factor which cannot be captured by publicly available variables.

Expected excess returns crucially depend on the available information set which is spanned by order flow, forward rates and macroeconomic variables. These variables explain between 50% and 70% of expected excess returns. Thus, the predictability of bond excess returns stems from the strong linkage of expected excess returns to contemporaneous economic state variables and order flow. The analysis of excess return innovations reveals contemporaneous order flow and macroeconomic shocks as main drivers.

Analyzing expected and unexpected excess returns offers two implications. First, bond excess returns reveal a close relation to public information – macro variables and forward rates – which underlines the need of macro-finance term structure models (see Wu, 2006 and Rudebusch and Wu, 2008). However, order flow seems to incorporate a *non-public* risk factor which cannot be fully captured by other (public) variables. This finding suggests a deeper discussion of the role of order flow (private information) in the term structure model literature.

Second, the high explainable power of expected excess returns rules out irrational expectations which is assumed to be a reason for the failure of the pure expectation hypothesis (Campbell and Shiller, 1991). The importance of macroeconomic state variables suggests a business-cycle dependent risk premium as the source of the empirical rejection of the pure expectation hypothesis (Fama and Bliss, 1987, Campbell and Shiller, 1991, Bekaert and Hodrick, 2001, Ludvigson and Ng, 2009 or Cooper and Priestley, 2009).

In sum, the contribution of the paper is as follows. We establish bond market order flow as an additional determinant of future bond market excess returns. Beside order flow, the empirical part of the paper is built on forwards rates and macroeconomic variables. Especially the latter ones reveal an impact on bond excess returns and underline a business cycle pattern of the bond risk premium (Ludvigson and Ng, 2009).

This paper is organized in the following steps: Section 3.2 reviews the existing literature. Section 3.3 outlines the econometric approach, Section 3.4 describes the data and section 3.5 provides and interprets the main results. Robustness tests in Section 3.6 confirm the main findings and Section 3.7 concludes.

3.2 Literature Overview

This section starts with a discussion of the relation between bond excess returns to (i) yields and forward rates and (ii) to macroeconomic information. Hereafter, we discuss the role of order flow for pricing bonds and motivate for considering order flow for explaining bond excess returns.

Fama and Bliss (1987) are the first who document the predictability of bond excess returns with the difference between forward rates and the one-year yield. In an extension of this research Cochrane and Piazzesi (2005) demonstrate that that a linear combination of forward rates, called CP-factor, explains one third of one-year ahead excess returns. The economic importance of the CP-factor for international bond markets is stressed out by Kessler and Scherer (2009) and Sekkel (2011).

Duffee (2011) shows that excess returns covary with expectations about the future path of the short-term yield which reveal a close relation to changes of the whole yield curve - the "*level*". This finding is consistent with Cochrane and Piazzesi (2008) who show that the risk premium is a compensation for shifts of the yield curve's level.[32]

Beside interest rates, bond excess returns reveal a close relation to the business cycle. For example, Joslin et al. (2011) show that the market prices of risk of the term structure's level, slope and curvature are affected by macroeconomic variables, real output and inflation. This mechanism explains the counter-cyclical pattern of bond excess returns and the predictive power of industrial production and the output gap for excess returns (Cooper and Priestley, 2009 and Duffee, 2011). Ludvigson and Ng (2009) apply a factor analysis approach to a broad set of economic variables and document a close relation of the real economy, inflation and financial variables to one-year ahead bond excess returns.

Our consideration of order flow for the analysis of bond risk premia is inspired by differ-

[32] The first three principal components of the term structure are labeled as level, slope and curvature.

ent strands of the literature. A theoretical motivation directly relates order flow to risk premia as it coincides with "*speculative demands from varying risk tolerance*" (Evans and Lyons, 2002, p.173). Additional, Harvey (1989) shows that investors who expect an economic downturn rebalance their portfolio by demanding long-term bonds. These portfolio shifts will induce positive order flow. Empirical applications suggest the existence of an indirect effect as order flow owns a *level effect* on the term structure (see Brandt and Kavajecz, 2004).

Following the argumentation of Joslin et al. (2010), level effects might stem from an economic-driven change of the market prices of risk. Order flow can be understood as a source of economic information (Green, 2004, Pasquariello and Vega, 2007, and Menkveld et al., 2012) and is related to the price of risk (Evans and Lyons, 2002). Underwood (2009) and Brandt et al. (2007) show that order flow determines contemporaneous spot- and future market returns. For the bond future market, Fricke and Menkhoff (2011) reveal that contracts with a higher market share of order flow stronger influence other bond future contracts. Moreover, order flow forecasts future economic variables (Evans and Lyons, 2009, and Rime et al., 2010).

Further motivation for the consideration of order flow in the context of bond excess returns stems from two market microstructure effects on excess returns. First, Li et al. (2009) show that the probability of informed trading (PIN) is a determinant of bond excess returns whereby the computation of the PIN-measure bases on the idea that order flow is a medium how information is incorporated into prices. Second, Wright and Zhou (2009) and Duyvesteyn et al. (2011) point out that the intensity of jumps (strong price shifts) predicts future excess returns, even after the inclusion of the CP-factor. As suggested by Duyvesteyn et al. (2011) and Lahaye et al. (2011), the jump intensity is a proxy of the market's interpretation of macroeconomic news. As discussed above, order flow might be a more appropriate candidate for modeling the flow of new information.

Further motivation to consider order flow is given by Lahaye et al. (2011) who show that announcement releases and liquidity shocks are the key drivers of jumps. Liquidity shocks are caused by abnormal trading activities into or out of the market. The market microstructure literature suggests the use of order flow to model liquidity shocks. Thus, order flow is related to jumps too. To disentangle the effects of order flow, information incorporation or market's illiquidity, we explicitly control for illiquidity by including the Amihud (2002) liquidity measure.

The novel aspect of this paper is the joint consideration of established determinants of bond excess returns, forward rates and macroeconomic factors, and order flow. The former ones are heavily discussed in the term structure literature as economic variables and forward rates are public available and therefore seen as candidates which totally span the information set of bond investors. The importance of order flow is discussed in a separate strand of the literature which reveals that order flow is medium through which non-public information are incorporated into bond markets. Therefore, it seems as a natural starting point to discuss the role of forward rates, macroeconomic factors *and* private information (order flow) for determining bond excess returns.

3.3 Term structure modeling and estimation

This section introduces the Adrian et al. (2012) term structure model (AMTSM) and the results for the US zero-coupon yield curve between 01/1999 and 10/2011.[33] We derive market prices of risk from a three-step OLS–estimator and decompose excess returns into an expectation and an innovation-term.[34] For the term structure analysis we use the following notations and definitions. p_t^n defines the log price of a zero-coupon bond with maturity n at time t and $y_t^{(n)}$ the implied yield of a bond which matures in n month. The log forward rate at time t for payments between period $t+n-1$ and $t+n$

[33]We use the Gurkaynak et al. (2007) data set to construct the US zero coupon yield curve.

[34]Beside Adrian et al. (2012), Joslin et al. (2010) consider ordinary least squares estimations in a Gaussian dynamic term structure model (GDTSM).

is expressed as

$$f^{(n-1\to n)} = p_t^{(n-1)} - p_t^{(n)} \tag{32}$$

and the log one-period return for holding an n-period bond is

$$r_{t+1}^{(n)} = p_{t+1}^{(n-1)} - p_t^{(n)} \,. \tag{33}$$

The difference of the holding period return in (33) and the return of a one-period bond, the yield $y_t^{(1)}$, defines the log excess return rx:

$$rx_{t+1}^{(n)} = p_{t+1}^{(n-1)} - p_t^{(n)} - y_t^{(1)} \tag{34}$$

and $\bar{rx}_t^{(N)}$ the average excess return for bonds with a maturity up to N months at time t:

$$\bar{rx}_t^{(N)} = \frac{1}{N}\sum_{n=1}^{N} rx_t^{(n)} \,. \tag{35}$$

3.3.1 Term structure modeling

This section presents the theoretical background of the AMTSM with *spanned* and *unspanned* factors, both together denoted as X_t. In detail, spanned pricing factors depend on the first K^s principal components of the yield curve and their innovations. The core elements of the model are affine structures of log bond prices to market prices of risk and of market prices of risk to the yield curve.

At the first step we model the dynamics of the first K^s principal components of interest rates with a maturity of n={3,4,...,120} months, state vector X_{t+1}^s, as a VAR(1)–process with the innovation term ν_{t+1} which has, conditional on X_t^s, a mean of zero and variance Σ:

$$X_{t+1}^s = \mu + \Phi X_t^s + \nu_{t+1} \,. \tag{36}$$

Note, that we use demeaned yields for the estimation of principal components which sets the vector μ in equation (36) to zero.

The second step relates log one-month excess returns, rx_{t+1}, to the state variables X_t and the innovation term ν_{t+1}. Bond market investors know the vector X_t at time t to form expectations about the future excess return of maturity $(n-1)$, $rx_{t+1}^{(n-1)}$. Therefore, we formulate the expected future excess return as a term which depends on a constant and the available information set at time t which is represented by X_t. The vector ν_{t+1} reflects unexpected term structure innovations of the first K^s factors and has also pricing implications for excess returns.

Without *unspanned* factors, we rewrite the log excess holding period return as a function of an expected return, a convexity adjustment term, return innovations which are related to ν_{t+1} and a priced error term, e_{t+1}, with variance σ^2:

$$rx_{t+1}^{(n-1)} = \underbrace{\beta^{(n-1)\prime}(\lambda_0 + \lambda_1 X_t^s)}_{\text{Expected return}} - \underbrace{\frac{1}{2}(\beta^{(n-1)\prime}\Sigma\beta^{(n-1)} + \sigma^2)}_{\text{Convexity adjustment}} + \underbrace{\beta^{(n-1)\prime}\nu_{t+1}}_{\substack{\text{priced return}\\ \text{innovation}}} + \underbrace{e_{t+1}^{(n-1)}}_{\substack{\text{Return pricing}\\ \text{error}}} . \tag{37}$$

To compute parameters we transform equation (37) to

$$rx_{t+1}^{(n-1)} = \alpha^{(n-1)} + \beta^{(n-1)\prime}\nu_{t+1} + c^{(n-1)\prime}X_t^s + e_{t+1}^{(n-1)} . \tag{38}$$

Duffee (2011) discusses the presence of *unspanned* factors which are not captured (unspanned) by term structure factors as they reveal no relation to the contemporaneous short rate. However, these unspanned factors predict future short term rates and bond excess returns and should be considered in term structure models. *Unspanned* factors enrich the state vector to $X_{t+1} = [X_{t+1}^s, X_{t+1}^u]'$ where X_{t+1}^u represents unspanned factors. More specific, we subdivide the regression coefficient $\beta^{(n)}$ of equation (38) into spanned and unspanned related components, $\beta^{(n)} = [\beta_s^{(n)} \beta_u^{(n)}]'$. The characteristic of no relation between unspanned factors to the short term rate restricts $\beta_u^{(n)}$ to be set to zero. Thus, the pricing equation of excess returns, equation (37), transforms to

$$rx_{t+1}^{(n-1)} = \beta_s^{(n-1)\prime}(\lambda_s^0 + \lambda_s^1 X_t) - \frac{1}{2}(\beta_s^{(n-1)\prime}\Sigma_{ss}\beta_s^{(n-1)} + \frac{1}{2}\sigma^2) + \beta_s^{(n-1)\prime}\nu_{t+1}^s \tag{39}$$

where Σ_{ss} denotes the upper K_sxK_s coefficients of Σ. λ_s^0 and λ_s^1 are the first K_s upper rows of λ^0 and λ^1. We derive coefficients by estimating (38) with spanned and unspanned factors and define $\widehat{\alpha} = (\widehat{\alpha}^{(1)}, \ldots, \widehat{\alpha}^{(N)})$, $\widehat{\beta} = (\widehat{\beta}^{(1)\prime}, \ldots, \widehat{\beta}^{(N)\prime})$ and $\widehat{c} = (\widehat{c}^{(1)\prime}, \ldots, \widehat{c}^{(N)\prime})$. Finally, we derive the quasi prices of risk of spanned factors, λ_0 and λ_1, from the following conditions:

$$\widehat{\lambda}_s^0 = (\widehat{\beta}_s'\widehat{\beta}_s)^{-1}\widehat{\beta}_s'(\widehat{\alpha} + \frac{1}{2}(\widehat{B}^{s*}vec(\widehat{\Sigma}_{ss}) + \widehat{d}_e)) \tag{40}$$

$$\widehat{\lambda}_s^1 = (\widehat{\beta}_s'\widehat{\beta}_s)^{-1}\widehat{\beta}_s'\widehat{c}_s \tag{41}$$

with $B^* = [vec(\beta^{(1)}\beta^{(1)\prime}), \ldots, vec(\beta^{(N)}\beta^{(N)\prime})]$ and $\widehat{d}_e = \widehat{\sigma}^2 i_N$. i_N is a Nx1 vector of ones. Beside affine excess returns, log bond prices also follow affine processes which depend on the state vector X_t and an error term u_t:

$$\ln P_{t+1}^n = A_n + B_n' X_{t+1} + u_{t+1}\,. \tag{42}$$

A reformulation of (42) leads to the following restrictions for bond pricing which can be solved recursive (see Adrian et al., 2012):

$$A_n = A_{n-1} + B_{n-1}'(\mu - \lambda_0) + \frac{1}{2}(B^{(n-1)\prime}\Sigma B^{(n-1)} + \sigma^2) - \delta_0 \tag{43}$$

$$B'_n = B'_{n-1}(\Phi - \lambda_1) - \delta_1 \tag{44}$$

$$A_0 = 0; B'_0 = 0 \tag{45}$$

$$\beta'_n = B'_n \,. \tag{46}$$

The starting parameters are defined as $A_1 = -\delta_0$ and $B_1 = -\delta_1$. We derive the parameters δ_0 and δ_1 from a linear projection of the log one-month interest rate, $y_t^{(1)}$, on a constant and X_t. δ_0 is the intercept coefficient and δ_1 the coefficient vector of X_t. If (46) holds, the estimation of the model is exact. The estimation process is discussed in the following.

3.3.2 Term structure estimation

This section discusses the estimation properties of the AMTSM with *spanned* and *unspanned* factors. Beside pricing factors which are extracted from interest rates (spanned factors), recent literature suggests the existence of *unspanned* factors (see Duffee, 2011, Joslin et al., 2010 and Wright, 2011). These *unspanned* factors forecast future interest rates but perform poor for explaining current yields. Previously considered unspanned factors are industrial production (Duffee, 2011 and Joslin et al., 2010), consumer prices (Duffee, 2011, Joslin et al., 2011 and Wright, 2011) and GDP growth (Wright, 2011). To ensure comparison to the closest related paper, we follow Adrian et al. (2012) and define unspanned information as the first two principal components of monthly core CPI, monthly core personal consumption expenditures (PCE) price index and the Federal Reserve Bank of Chicago real activity index.

According to Adrian et al. (2012), we prefer a model specification with five *spanned* term structure factors. Model selection bases on three objective measures which all underline a better performance of the five factor model compared to a three or four factor model specification. Briefly, we discuss the five factor case for pricing excess returns with a maturity of n={6,18,24,...,60,84,120} months.[35]

First, we use equation (46) and compare model implied (equation (44)) and regression based betas (equation (38)) at Figure 3. The estimated betas show only small deviations from their implied values which suggests a good fit of the term structure model. Second, we follow Almeida et al. (2011) and estimate a modified R^2 statistic for expected excess returns:

$$R_n^2 = 1 - \frac{mean[(rx_{t+1}^{(n)} - \mathbb{E}_t[rx_{t+1}^{(n)}])^2]}{var[rx_{t+1}^{(n)}]} \,. \tag{47}$$

The R^2s decrease from 20% at the maturity of six months to 15% for ten-year bonds but are always higher than for the three factor case.

Third, we analyze the model fit by comparing model-implied and observed interest rates. The five factor model reveals smaller deviations for one-, two-, five- and ten-year bonds which underline the good fit of the model.

Duffee (2011) and Joslin et al. (2011) point out that the consideration of five spanned and some unspanned factors might cause over-fitting which results in miscalibrated yields outside the considered maturities. We address this issue by computing absolute deviations of observed and model-implied interest rates for maturities of 180, 240, 300 and 360 month of the three and five factor model. For all maturities the five factor specification reveals lower deviations and the Wilcoxon rank sum test rejects the null hypothesis of equal medians at the one percent level. Thus, we find a clear preference for a term structure model with five spanned factors.

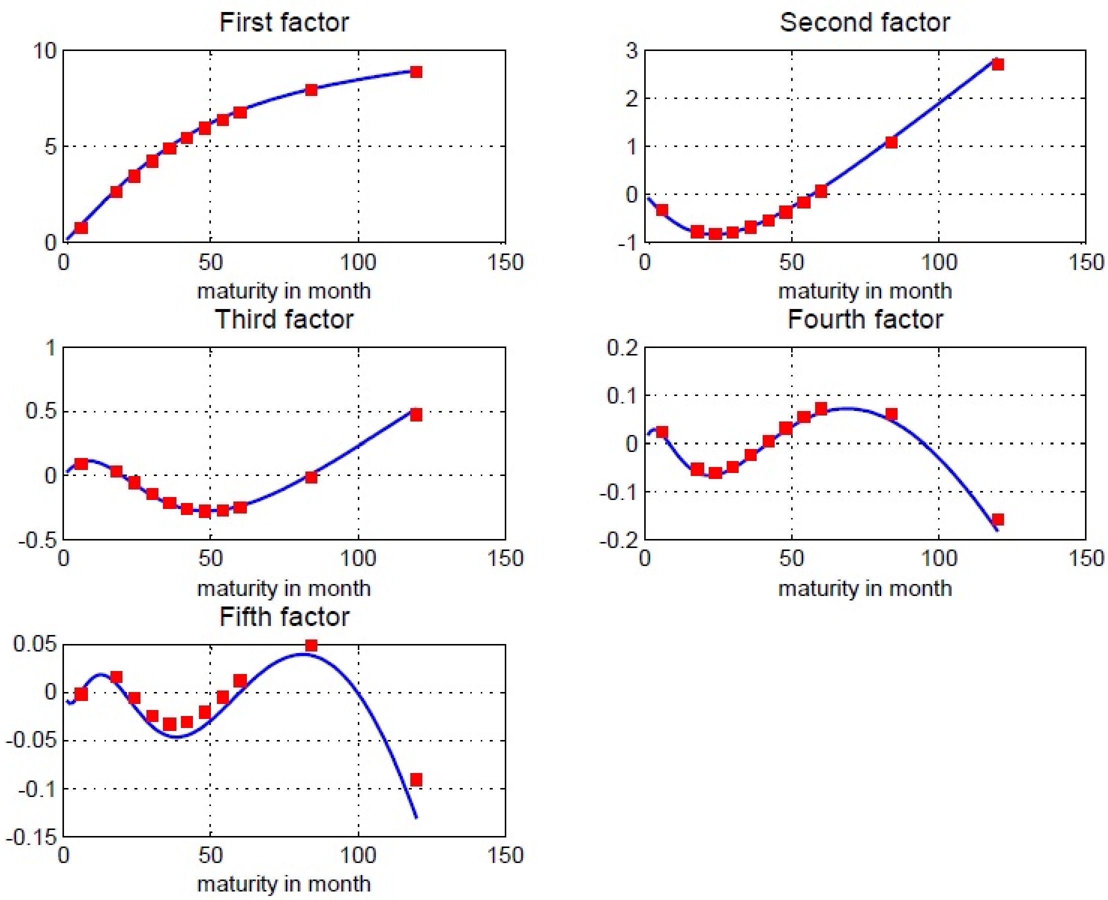
The first three term structure factors load in a well known pattern on the yield curve.[36]

[35] As Adrian et al. (2012), we also compare the observed and model-implied first and second moment of interest rates. For the sake of brevity we do not discuss them as both moments are perfectly described by the five factor model.

[36] We follow Adrian et al. (2012) and define yield loadings as $-\frac{1}{n}B_n$.

Figure 3: Regression coefficients and model-implied parameters

These figures compare the regression coefficients $\beta^{(n)}$ from equation (38) with the model implied coefficients B_n from equation (44). The blue line represents the regression coefficients for all considered maturities n=$\{1, \ldots, 120\}$. The red data points show the recursive estimated B_n coefficients.



The first factor can be labeled as the "*level effect*" of the yield curve as it smoothly increases with longer maturities. The second factor steepens the yield curve which characterizes the "*slope effect*". A "*curvature effect*" is revealed by the third factor. Additional, the fourth and the fifth factor negligibly influence the yield curve which is consistent with findings of Adrian et al. (2012), Cochrane and Piazzesi (2005) and Duffee (2011). In sum, the five factor model will be a more appropriate model than the three factor specification. Table 17 reports the estimated market prices of risk, λ_0 and λ_1.

Table 17: Market prices of risk

This table reports the model implied market prices of risk of spanned pricing factors of equation (40) and (41) of the five-factor term structure model. The prices are used for calculations of expected excess returns in equation (37).

	maturity					
pricing factor	λ_0	$\lambda^s_{1,1}$	$\lambda^s_{1,2}$	$\lambda^s_{1,3}$	$\lambda^s_{1,4}$	$\lambda^s_{1,5}$
X_1	0.0261	0.0067	-0.0616	-0.0309	-0.0252	-0.0453
X_2	0.0316	0.0536	-0.1098	-0.0617	0.0135	-0.0745
X_3	-0.0328	-0.0022	0.0133	-0.2173	0.1808	0.0485
X_4	-0.0256	0.0296	0.1149	-0.0081	-0.1476	-0.1650
X_5	0.0848	0.0575	-0.0766	0.0369	-0.1866	-0.2138

3.4 Data

This section discusses the underlying data sets for the estimation of bond pricing factors which are based on US forward rates (CP-factor) and US macroeconomic time series (macro factors). Additional, we extract order flow from trading data of the ten-year US treasury bond future between 01/1999 and 10/2011. The estimation period of the CP-factor and the macro factors correspond to the available trading data. The data sample covers two US recessions (03-11/2001 and 12/2007-06/2009), two asset price bubbles (dot-com and sub-prime), the European debt crisis (2009-2011) as well as some relatively calm periods (1999-2000 and 2002-2007).

3.4.1 CP-factor

The CP-factor is a linear combination of the one-year yield and forward rates. Cochrane and Piazzesi (2005) suggest to derive the weights of the components from a regression of the average one-year excess returns of the maturities n={12,24,...,60} months, $\bar{rx}_{t+12}$, on an intercept, the one-year yield and forward rates for maturities of two to five years:

$$\bar{rx}_{t+12} = \gamma_0 + \gamma_1 y_t^{(12)} + \gamma_2 f_t^{(12\to24)} + \gamma_3 f_t^{(24\to36)} + \gamma_4 f_t^{(36\to48)} + \gamma_5 f_t^{(48\to60)} + \varepsilon_{t+1}\,. \quad (48)$$

Table 18 reports the regression results for maturities of two to five years for the time period 01/1999 to 10/2011.[37]

3.4.2 Order flow

Order flow estimation bases on the US ten-year bond future contract which owns the highest trading volume in the US bond future market. Brandt and Kavajecz (2004) suggest focusing on the more informative "on-the-run" bonds as they provide a higher liquidity than "off-the-run" bonds. We incorporate this finding and make use of a daily "auto roll" procedure which compares maturity-equivalent bond futures and include the one with the highest trading volume. We construct order flow by comparing trade prices with the available bid and ask price (Lee and Ready (1991)-algorithm) and code order flow to be buyer-initiated if the trade price is equal or above the ask price and vice versa. Order flow is aggregated on a monthly basis.

[37]Note, that the annual horizon for calculating and forecasting excess returns in equation (48) diverts from the monthly excess return in the term structure model (see equation (37)). This divergence avoids to have one-month excess returns as exogenous variable and an equivalent proxy, the CP-factor, as endogenous variable in latter regressions.

Table 18: Cochrane-Piazzesi regression coefficients

This table shows regression results of one-year excess holding bond returns with maturities of two- to five years on standardized values of the one-yield yield and on forward rates with a maturity of two- to five years. The time period reaches from 01/1999 to 10/2011.

		maturity			
Variable	**coeff.**	**2-year**	**3-year**	**4-year**	**5-year**
const.	γ_0	-2.79	-4.60	-5.93	-7.21
$y^(1)$	γ_1	0.84	0.77	0.14	-0.74
$y^(2)$	γ_2	1.65	5.15	9.92	14.91
$y^(3)$	γ_3	-14.79	-30.24	-45.97	-60.11
$y^(4)$	γ_4	22.50	43.67	63.33	79.67
$y^(5)$	γ_5	-9.38	-17.99	-25.65	-31.63
adj. R^2		0.26	0.23	0.23	0.24

Melvin et al. (2009) point out that central bank interventions affect the price impact of order flow. Therefore, we allow order flow diverting effects for days when the FED announces or conducts market operations which are related to the quantitative easing program or not. OF^{QE} presents order flow at days with "Permanent Open Market Operations" (POMO) and/or FOMC meetings since 2008. OF subsumes order flow at all other days.

3.4.3 Estimation and interpretation of macroeconomic factors

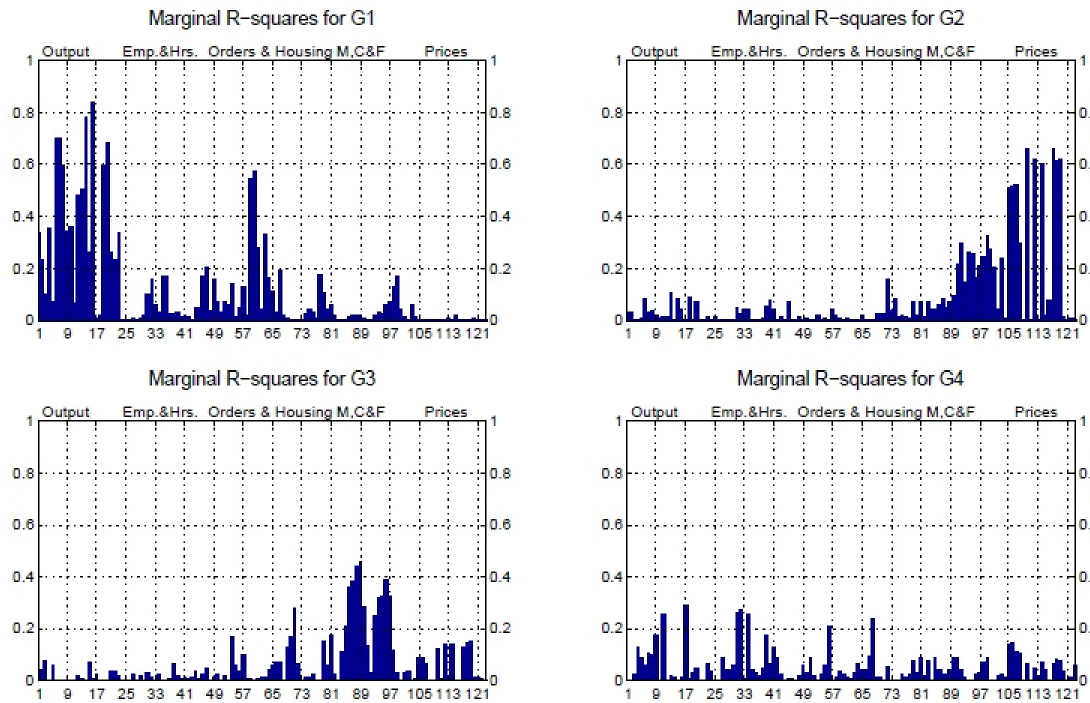
We follow Ludvigson and Ng (2009) and apply a factor analysis approach and consider the first k macroeconomic factors of the US.[38] The optimal number of factors, k, is derived from the Bai and Ng (2002) information criterion.

Estimation: We derive US macro factors (further LN-factors) from the Ludvigson and Ng (2009) data set. Variables are transformed in a way which ensures stationarity.

[38]The following shows a brief description of the principal component analysis. Define the matrix of economic observations as the $[T\text{x}N]$ matrix X. The $[T\text{x}k]$ factor matrix consists of $\sqrt{T}$ multiplied with the k largest eigenvalues of the matrix $[XX]'$. For a detailed discussion see Stock and Watson (2002).

Figure 4: Marginal R-squares of the US macro factors

This figure plots the marginal R-squares which are derived from regressing all Ludvigson and Ng (2009) macro time series on the corresponding US macro factor. The time period is 01/1999–10/2011.



Outliers in the transformed time series are handled as missing values and any detected seasonality is corrected by an X11-ARIMA process (see Marcellino, 2003).

The Bai and Ng (2002) information criterium suggests considering the the first four macroeconomic factors . The factors describe more than 30% of the variation in the macroeconomic variables whereby the first factor explains 12%. The inclusion of the second and third factor more than doubles the explainable variance to 27% and the last factor adds five percent. Consistent with Ludvigson and Ng (2009), the factors' persistence reveal strong heterogeneity. The first factor reveals the highest first order autocorrelation with 0.56 and the fourth factor owns a lag-dependence of -0.31.

Interpretation: To derive an economic intuition of the macro factors, we regress each time series on the underlying four macro factors and plot the marginal R^2s at Figure 4. The interpretation of the macro factors corresponds to Ludvigson and Ng (2009). The first factor, LN_1, reveals a close relation to several industrial production- and employment components. Thus, we see LN_1 being related to the *real economy*. LN_2 positively loads on several inflation and interest rate measures what propose that this factor is an *inflation factor*. The third macro factor mainly represents increasing interest rates and interest rate spreads. We name LN_4 *unemployment* factor as it loads on *real activity* variables, mainly unemployment and industrial production.[39]

3.5 Determinants of excess returns

This section identifies the pricing implications of the CP-factor, economic variables and order flow for (1) excess returns, (2) expected returns and (3) return innovations. We analyze bonds with a maturity of two-, five- and ten years and additional mean returns of two- to ten-year bonds. For the sake of brevity we do not report results for the CP-factor as single regressor. However, in order to compare these outcomes with the following results, the last row of each table presents changes of the adjusted R^2s.
Section 3.5.1 considers the CP-factor, macroeconomic variables and order flow to forecast excess returns. Section 3.5.2 discusses the relation of these variables to expected excess returns. Section 3.5.3 relates return innovations to order flow and economic innovations. All coefficients and standard errors of the following regressions are block bootstrapped (see Politis and Romano, 1994, and Politis and White, 2004).

[39] As unemployment rates and industrial production are inversely related, we construct the factor such that its increase can be interpreted as an increase of unemployment rates and a drop of industrial production.

3.5.1 Forecasting excess returns

At the first step, we discuss the forecasting properties of the CP-factor and macroeconomic variables for excess returns. This methodology is comparable to Ludvigson and Ng (2009) and can be understood as benchmark.[40] At the second step, we discuss order flow's ability to forecast future excess returns. Table 19 reports regression results for subsequently including lagged variables of the CP-factor, macro factors and order flow. The CP-factor forecasts excess returns at all maturities whereby the R^2s lie in a narrow range between seven and nine percent for all maturities. Panel A reports results of regressing excess returns on the CP-factor and US macro factors. The effect of the economic state variables is more pronounced for longer maturity bonds as adjusted R^2s gradually increase by 5.8% at the shortest maturity and by 9.0% at the longest. With the exception of the two-year maturity, the strongest impact stems from the *inflation* factor LN_2. However, note that LN_3 (interest rates and spreads) reveals no impact on excess returns. These results suggest that it is inflation, instead of interest rates, which drives excess returns and supports the view of the existence of an inflation risk premium (see Buraschi and Jiltsov, 2005). Besides inflation, the real economy matters for excess returns. At the shortest maturity, the first real factor owns the highest impact on future excess returns whereby the negative sign suggests that a lower economic activity coincides with a higher risk premium. For maturities beyond two years, the importance of the real economy switches from the real factor to the *unemployment* factor. Again, an economic downturn, now higher unemployment, comes along with higher excess returns. In sum, our results underline the view of a countercyclical bond risk premium (see Ludvigson and Ng, 2009, and Wright and Zhou, 2009).

Next, we explore the role of *order flow* by regressing excess returns on the CP-factor and order flow (Panel B). For all maturities the inclusion of order flow increases the

[40] The formulation of the regression is comparable to Ludvigson and Ng (2009). However, we analyze one-month excess returns instead of one-year excess returns.

Table 19: Forecasting excess returns

This table reports regression results of two-year, five-year, ten-year and average excess returns on standardized values of the CP-factor, order flow and macro factors. The last row of this table reports the change of the adjusted R^2 compared to a reduced regression which only includes a constant and the CP-factor. Regression coefficients and standard errors are block-bootstrapped with 10,000 bootstrap samples. The 10% (5%, 1%) significance level is marked with a * (** / ***).

	excess returns					
	maturity					
	2-year			**5-year**		
Variable	**Panel A**	**Panel B**	**Panel C**	**Panel A**	**Panel B**	**Panel C**
CP_{t-1}	0.2558***	0.2823***	0.2481***	0.2452***	0.2949***	0.2427***
OF^{QE}_{t-1}		-0.0522	-0.0013		-0.0617	-0.0237
OF_{t-1}		0.1889**	0.1606**		0.1831**	0.1606**
$LN_{1,t-1}$	-0.1844**		-0.1762**	-0.0846		-0.0819
$LN_{2,t-1}$	0.1590**		0.1531**	0.2238***		0.2202***
$LN_{3,t-1}$	0.1209*		0.0986	0.1027		0.0784
$LN_{4,t-1}$	0.0872		0.0975	0.1469**		0.1556**
adj. R^2	0.1397	0.1035	0.1536	0.1536	0.1085	0.1675
ΔR^2	0.0579	0.0217	0.0718	0.0658	0.0207	0.0797
	maturity					
	10-year			**mean**		
Variable	**Panel A**	**Panel B**	**Panel C**	**Panel A**	**Panel B**	**Panel C**
CP_{t-1}	0.1957***	0.2613***	0.199**	0.2544***	0.2866***	0.2375***
OF^{QE}_{t-1}		-0.0128	0.0061		-0.0476	-0.0161
OF_{t-1}		0.1144	0.0996		0.1728**	0.15**
$LN_{1,t-1}$	0.0012		-0.0018	-0.0864		-0.0798
$LN_{2,t-1}$	0.3065***		0.3067***	0.2444***		0.2376***
$LN_{3,t-1}$	0.0523		0.0404	0.0989		0.0823
$LN_{4,t-1}$	0.1526**		0.1478**	0.1425*		0.145**
adj. R^2	0.1594	0.0708	0.1587	0.1595	0.1058	0.1707
ΔR^2	0.0895	0.0009	0.0888	0.0709	0.0172	0.0821

adjusted R^2s whereby the strongest effect exists for shorter maturities and vanishes for long-term bonds. In the absence of the FED's quantitative easing operations, the order flow coefficient is positive and significant for maturities up to five years. How to interpret this effect? Following the argument of Harvey (1989), expectations about an economic downturn increase the demand for long-term bonds and lead to positive order flow. As Panel A documents countercyclical excess returns, we should expect a positive relation between order flow and excess returns.

At days when the FED conducts permanent open market operations (POMO) or announces information related to the "Large-Scale Asset Purchase" (LSAP) program, an increase of order flow coincides with lower excess returns. Although the coefficients are insignificant, they might suggest that LSAP announcements lowered the risk premium of interest rates (see Gagnon et al., 2011).

On an intraday basis, Green (2004) and Pasquariello and Vega (2007) show that order flow incorporates information related to economic announcements. On a monthly basis, one might question whether order flow and economic factors represent the same kind of information. Panel C addresses this point by including all previous considered variables in the regressions. Higher R^2s and consistent significances of the variables underline the hypothesis that order flow incorporates information which is not spanned by traditional pricing factors.

3.5.2 Forecasting expected excess returns

This section discusses if the predictive power of macroeconomic factors and order flow stems from a compensation for bearing economic risk. If so, this effect is captured by model-implied *expected returns*. The economic motivation for forecasting expected excess returns directly stems from their definition in equation (37):

$$\mathbb{E}_t[rx_{t+1}^{(n-1)}] = \beta^{(n-1)\prime}(\lambda_0 + \lambda_1 X_t)\,. \tag{49}$$

If expectations are rationally formed we will observe a strong relation between the exogenous variables at time t and the expected excess returns at t+1 which are nurtured by information at time t.

First, we analyze how the CP-factor interacts with expected returns. Although the CP-factor is constructed from yearly excess return series, it mirrors the pattern of one-month expected returns nearly perfectly and regressions report R^2s between 56% and nearly 70%.[41]

Table 20, Panel A presents results for including macro factors. Economic variables increase R^2s between 1.5% and more than 15%, whereby the strongest impact is detected at the shortest maturity. Consistent with Section 3.5.1, inflation- and real economy-related information are significant pricing factors and underline the relation of excess returns to the business cycle. Additional, interest rate spreads in form of $LN_{3,t}$ own significant coefficients for maturities up to five years. It illustrates that public available risk measures, such as yield spreads and the CP-factor, capture important information for the formation of expected bond excess returns.

Panel B reveals that the effect of order flow is more pronounced for shorter maturities. However, at the ten-year maturity order flow is significant at least at the ten percent level. The coefficients' interpretation corresponds to Section 3.5.1 where higher order flow coincides with higher excess returns. Again, order flow at days with quantitative easing operations of the FED coincides with lower excess returns.

Panel C shows that the order flow effect is robust to the inclusion of the CP-factor and economic variables. Again, order flow seems to incorporate information which can not be captured by pure economic information.

In sum, our results confirm the view that economic information matters for expected returns (Brandt and Wang, 2003). Going further, the findings explain how future excess returns depend on the economy and contain one major implication. Kim (2007) shows that the predictability of excess returns might lead to a failure of the rational expectation hypothesis. In this context, Campbell and Shiller (1991) argue that the

[41] Both, expected returns and the CP-factor are slightly downward sloping. However, we reject non-stationarity tests with and without trend.

predictability of interest rates contradicts rational expectations. However, our results reveal that available information explain the lion's share of expected returns.[42]

Table 20: Forecasting expected excess returns

This table shows regression results of two-year, five-year, ten-year and average expected excess returns on standardized values of the CP-factor, order flow and macro factors. The last row of this table reports the change of the adjusted R^2 compared to a reduced regression which only includes a constant and the CP-factor. Regression coefficients and standard errors are block-bootstrapped with 10,000 bootstrap samples. The 10% (5%, 1%) significance level is marked with a * (** / ***).

expected excess returns						
maturity						
	2-year			**5-year**		
Variable	**Panel A**	**Panel B**	**Panel C**	**Panel A**	**Panel B**	**Panel C**
CP_{t-1}	0.7508***	0.7260***	0.7289***	0.7864***	0.7827***	0.7742***
OF^{QE}_{t-1}		-0.1520**	-0.0755*		-0.1117**	-0.0683
OF_{t-1}		0.1604***	0.1205**		0.1589***	0.1369***
$LN_{1,t-1}$	-0.3585***		-0.3488***	-0.1892**		-0.1684**
$LN_{2,t-1}$	0.0924**		0.0812**	0.0983**		0.0926**
$LN_{3,t-1}$	0.1561***		0.1313***	0.1103***		0.0867**
$LN_{4,t-1}$	0.0251		0.0263	0.0381		0.0420
adj. R^2	0.7115	0.5856	0.7227	0.6776	0.6542	0.6910
ΔR^2	0.1566	0.0307	0.1678	0.0476	0.0242	0.0610
maturity						
	10-year			**mean**		
Variable	**Panel A**	**Panel B**	**Panel C**	**Panel A**	**Panel B**	**Panel C**
CP_{t-1}	0.8188***	0.8231***	0.8102***	0.8116***	0.8073***	0.8002***
OF^{QE}_{t-1}		-0.0555	-0.0379		-0.1124**	-0.0639
OF_{t-1}		0.1004*	0.0841*		0.1499***	0.1245**
$LN_{1,t-1}$	-0.0485		-0.0487	-0.1921**		-0.1841***
$LN_{2,t-1}$	0.1264***		0.1231***	0.1065***		0.1010***
$LN_{3,t-1}$	0.0577		0.0431	0.1118***		0.0909**
$LN_{4,t-1}$	0.0409		0.0456	0.0397		0.0418
adj. R^2	0.6907	0.6816	0.6936	0.7189	0.6857	0.7301
ΔR^2	0.0151	0.0060	0.0180	0.0550	0.0218	0.0662

[42]Given rationality, *return innovations* have to be unpredictable by any variables. Unreported results document nearly no forecasting power of the CP-factor, economic information and order flow for return innovations which is underlined by R^2s between zero and three percent. In sum, the formation of expected excess returns is consistent with investors' rationality.

3.5.3 Explaining excess return innovations

The view of rational expectation building of bond market excess returns is supported by the finding that expected excess returns strongly depend on the set of available macroeconomic information (see section 3.5.2). For a deeper understanding of the inability of completely forecasting excess returns it is crucial to understand the source of return innovations, so-called unexpected bond excess returns. The following exercise reveals that return innovations are an outcome of the flow of information. In detail, the flow of information is a change in the previous considered forward rate and macroeconomic information and contemporaneous order flow.

As observed above, the importance of the CP-factor increases for longer maturities. R^2s increase from nearly 0% at the two-year maturity to more than 20% at the longest considered maturity. Including macro factors further enhances our understanding of unexpected bond excess returns (Table 21, Panel A). In line with realized and expected excess returns, inflation and interest rate spreads are main drivers of returns.

At Panel B we replace macro factors by order flow to capture the flow of information through trading. Jumps of the R^2s of nearly 10% reveal that order flow is a major driver of return innovations. Including macro factors (Panel C) underline the previous finding that order flow offers information which cannot be represented by economic factors. This impression is underlined by simply summing up the changes of the R^2s at Panel A and B which correspond to the changes at Panel C.

Next, we turn the focus to realized excess returns (see Table 22). Results map the findings for excess return innovations at Table 21. To keep it short, the CP-factor is more important for longer maturities and LN_2 and LN_3 are the main economic drivers of excess returns. However, compared to order flow, the effect of macroeconomic factors is negligible for maturities up to five years.

Table 21: Explaining excess return innovations

This table shows regression results of two-year, five-year, ten-year and average one-month excess return innovations on standardized values of the change of the CP-factor, order flow and changes of the macro factors. The last row of this table reports the change of the adjusted R^2 compared to a reduced regression which only includes a constant and the change of the CP-factor. Regression coefficients and standard errors are block-bootstrapped with 10,000 bootstrap samples. The 10% (5%, 1%) significance level is marked with a * (** / ***).

	excess return innovations					
	maturity					
	2-year			**5-year**		
Variable	**Panel A**	**Panel B**	**Panel C**	**Panel A**	**Panel B**	**Panel C**
ΔCP_t	0.0302	-0.0286	0.0688	-0.2448***	-0.3007***	-0.2024**
OF_t^{QE}		0.0403	0.0540		0.0970	0.0974
OF_t		0.3137***	0.3057***		0.2723***	0.2708***
$\Delta LN_{1,t}$	0.0229		0.0275	-0.0144		-0.0082
$\Delta LN_{2,t}$	-0.1541**		-0.1551**	-0.1858**		-0.186**
$\Delta LN_{3,t}$	0.2043***		0.1893**	0.1545**		0.1458**
$\Delta LN_{4,t}$	-0.0286		-0.0479	-0.0530		-0.0619
adj. R^2	0.0441	0.0989	0.1383	0.1540	0.2019	0.2397
ΔR^2	0.0392	0.0940	0.1334	0.0364	0.0843	0.1221
	maturity					
	10-year			**mean**		
Variable	**Panel A**	**Panel B**	**Panel C**	**Panel A**	**Panel B**	**Panel C**
ΔCP_t	-0.3582***	-0.4216***	-0.3286***	-0.2422***	-0.301***	-0.1917**
OF_t^{QE}		-0.0058	-0.0140		0.0980	0.0997
OF_t		0.3368***	0.3424***		0.2785***	0.2747***
$\Delta LN_{1,t}$	-0.0405		-0.0373	-0.0177		-0.0085
$\Delta LN_{2,t}$	-0.1817**		-0.1931***	-0.2042***		-0.1986***
$\Delta LN_{3,t}$	0.1562**		0.1351**	0.1557*		0.1576**
$\Delta LN_{4,t}$	-0.0526		-0.0748	-0.0479		-0.0705
adj. R^2	0.2478	0.3126	0.3524	0.1625	0.2058	0.2521
ΔR^2	0.0384	0.1032	0.1430	0.0449	0.0882	0.1345

3.6 Robustness tests

This section discusses the robustness of the derived results in three ways. First, we extent the set of control variables by (1) controlling for the short term rate, (2) considering

Table 22: Explaining excess returns

This table shows regression results of two-year, five-year, ten-year and average one-month excess returns on standardized values of the change of the CP-factor, order flow and changes of the macro factors. The last row of this table reports the change of the adjusted R^2 compared to a reduced regression which only includes a constant and the change of the CP-factor. Regression coefficients and standard errors are block-bootstrapped with 10,000 bootstrap samples. The 10% (5%, 1%) significance level is marked with a * (** / ***).

	excess returns					
	maturity					
	2-year			**5-year**		
Variable	**Panel A**	**Panel B**	**Panel C**	**Panel A**	**Panel B**	**Panel C**
ΔCP_t	-0.1030	-0.1633**	-0.0668	-0.3666***	-0.4278***	-0.3352***
OF_t^{QE}		-0.0704	-0.0698		-0.0102	-0.0126
OF_t		0.3601***	0.3551***		0.3347***	0.3318***
$\Delta LN_{1,t}$	0.0243		0.0148	-0.0363		-0.0312
$\Delta LN_{2,t}$	-0.1461*		-0.1685**	-0.1573**		-0.1695**
$\Delta LN_{3,t}$	0.1658**		0.1367*	0.1540**		0.1306*
$\Delta LN_{4,t}$	-0.0338		-0.0556	-0.0445		-0.0684
adj. R^2	0.0617	0.1472	0.1750	0.2409	0.3119	0.3426
ΔR^2	0.0271	0.1126	0.1404	0.0296	0.1006	0.1313
	maturity					
	10-year			**mean**		
Variable	**Panel A**	**Panel B**	**Panel C**	**Panel A**	**Panel B**	**Panel C**
ΔCP_t	-0.4971***	-0.5630***	-0.4586***	-0.3582***	-0.4216***	-0.3286***
OF_t^{QE}		0.0443	0.0407		-0.0058	-0.0140
OF_t		0.2716***	0.2742***		0.3368***	0.3424***
$\Delta LN_{1,t}$	-0.0889		-0.0898	-0.0405		-0.0373
$\Delta LN_{2,t}$	-0.2083***		-0.211***	-0.1817**		-0.1931***
$\Delta LN_{3,t}$	0.1431**		0.1311**	0.1562**		0.1351**
$\Delta LN_{4,t}$	-0.0628		-0.0785	-0.0526		-0.0748
adj. R^2	0.4080	0.4286	0.4828	0.2478	0.3126	0.3524
ΔR^2	0.0532	0.0738	0.1280	0.0384	0.1032	0.1430

liquidity risk and (3) volatility innovations. Second, we conduct subsample analysis by excluding (1) the financial crisis and (2) by analyzing the effect of order flow in times of financial stress and market uncertainty. Third, we analyze the behavior of the model implied error terms e and thus control for any model misspecification.

3.6.1 Extending the set of control variables

(1) Viceira (2012) underline the importance of the short-term interest rate for bond excess returns. The short-term rate might reflect *inflation* and *real economy* uncertainty and therefore presents a natural candidate for explaining excess returns. We include first differences of the short term rate to ensure stationarity.

(2) Li et al. (2009) point out that liquidity risk appears as additional pricing factor for US bond excess returns. For each month we define *liquidity risk* as the average of the daily Amihud (2002) "price impact - volume" ratios which are defined as

$$liquidity\ risk_t = \frac{|r_t|}{volume_t} \tag{50}$$

where r_t is the daily return of the ten-year Treasury bond future and $volume_t$ is the contract's trading volume at day t.

(3) Adrian et al. (2012) discuss a positive relation between bond returns and the Merrill Lynch *Move* index which represents implied volatilities from options on Treasury future contracts. At this point, we follow the FX literature and consider volatility innovations as an excess return determinant (Menkhoff et al., 2012). Innovations are modeled as differences of the monthly *Move* index. Results also hold for volatility levels. The upper panel of Table 23 shows results for forecasting expected returns and the lower panel reports results for regressing realized returns on contemporaneous order flow and changes of all other state variables.

Expected returns do not reveal any exposure to the short rate, liquidity risk or volatility innovations. The only exception is the ten-year maturity where volatility reveals some impact on returns. Turning the focus to the order flow coefficients reveals no changes of signs or significances.

Table 23: Interest rate and volatility innovations, liquidity risk and excess returns

This table shows regression results of two-year, five-year, ten-year and average excess returns on standardized values of changes of the CP-factor, order flow, changes of the macro factors and of the one-year interest rate and liquidity risk. Liquidity risk is defined as the monthly average of liquidity risk as it is defined in equation (50). The last row of this table reports the change of the adjusted R^2 compared to corresponding R^2 of Table 19 Panel C. Regression coefficients and standard errors are block-bootstrapped with 10,000 bootstrap samples. The 10% (5%, 1%) significance level is marked with a * (** / ***).

	expected excess return			
	maturity			
Variable	**2-year**	**5-year**	**10-year**	**mean**
CP_{t-1}	0.6953***	0.7645***	0.8004***	0.7754***
OF^{QE}_{t-1}	-0.0841*	-0.0744*	-0.0399	-0.0731*
OF_{t-1}	0.0987**	0.1260**	0.0765	0.1135**
$LN_{1,t-1}$	-0.3224***	-0.1588**	-0.0392	-0.1690**
$LN_{2,t-1}$	0.0898**	0.0973**	0.1351***	0.1136***
$LN_{3,t-1}$	0.1093***	0.0765	0.0301	0.0723
$LN_{4,t-1}$	0.0287	0.0398	0.0361	0.0383
$\Delta y^{(1)}_{t-1}$	-0.0567	-0.0254	-0.0258	-0.0370
$liquidity\ risk_{t-1}$	0.0614	0.0128	-0.0173	0.0170
$\Delta\ move\ index_{t-1}$	0.0277	0.0402	0.0723**	0.0501
adj. R^2	0.7255	0.6877	0.6929	0.7285
	excess returns			
	maturity			
Variable	**2-year**	**5-year**	**10-year**	**mean**
ΔCP_t	0.0186	-0.2559***	-0.3836***	-0.2432***
OF^{QE}_{t}	0.0235	0.0530	0.0876*	0.0613
OF_t	0.1045***	0.1567***	0.1716***	0.1567***
$\Delta LN_{1,t}$	-0.0063	-0.0457	-0.0917*	-0.0531
$\Delta LN_{2,t}$	-0.0287	-0.0773	-0.1685***	-0.0963**
$\Delta LN_{3,t}$	0.0664**	0.0881*	0.1136**	0.0956**
$\Delta LN_{4,t}$	-0.0285	-0.0431	-0.0494	-0.0447
$\Delta\ y^{(1)}_{t}$	-0.8479***	-0.6015***	-0.3656***	-0.6107***
$\Delta\ liquidity\ risk_t$	0.0799**	0.0491	0.0365	0.0544
$\Delta\ move\ index_t$	-0.0816**	-0.1265***	-0.1775***	-0.1380***
adj. R^2	0.8376	0.6729	0.6131	0.6975

Excess returns reveal a strong relation to contemporaneous innovations in the short term rate which qualifies it as additional control variable (see Table 23). The negative sign confirms our expectation as the short-term rate is a cyclical indicator. A drop of the short-term rate, mirroring an (expected) economic downturn, coincides with higher excess returns (a counter-cyclical variable). The inclusion of the short-rate lifts R^2s by ten percent at the ten-year maturity and by more than 60% at the two-year maturity. Including interest rate innovations kicks out the inflation factor for two- and five-year excess returns. Both maturities reveal a strong exposure to the short-term rate which proxies economic uncertainty (see Viceira, 2012). Uncertainty about long-run inflation seems to be limited as the inflation factor remains significant at the ten-year maturity and the change of the R^2 is the lowest of all maturities.

Liquidity risk reveals a positive relation to contemporaneous excess returns of the two-year contract. The interpretation of the coefficient is straight forward. Investing under higher liquidity risk has to be compensated by higher (excess) returns.

The negative signs of volatility innovations contradict expectations which complicates the interpretation. Therefore, we conduct subsample analysis with respect to volatility innovations to access the robustness of order flow.

To sum up, the inclusion of further control variables does not rule out the linkage between order flow and excess returns and thus underlines results of Section 3.5.

3.6.2 Subsample analysis

(1) *Excluding the financial crisis*: The order flow effect might be driven by the financial crisis. Beber et al. (2009) discuss the "*flight-to-quality*"- and "*flight-to-liquidity*"-phenomenons which coincide with higher market uncertainty and portfolio rebalances toward saver and more liquid assets such as bonds. The ten-year bond future order flow might be affected by these phenomenons as the underlying contract is seen as a safe-haven investment and the future contract offers an outstanding trading liquidity. We address this problem and follow Thorton and Valente (2012) by excluding the financial

crisis period January 2007 to December 2009 from our sample and rerun regressions. We only report results for realized returns. Results also hold for expected excess returns. Table 24 shows the results for excluding the financial crisis. Results consist with previous findings and again underline the importance of order flow for excess returns.

(2) *Regime shifts*: We sort the sample with respect to (i) the FED's St. Louis Financial Stress Index (STLFSI) and (ii) volatility innovations.[43] Financial stress controls for the "flight-to-quality"-phenomenon. Given that order flow mainly mirrors a search for quality and liquidity in times of stress, the order flow coefficient should increase with financial stress. An increase of volatility should reflect higher uncertainty. Pasquariello and Vega (2007) and Menkveld et al. (2012) show that the importance of order flow increases with higher uncertainty. Adrian et al. (2012) reveal a relation between bond market volatility (*Move* index). Further, Underwood (2009) reveals that the effect of order flow depends on the level of the CBOE volatility index (VIX) which is the average model-implied volatility of S&P 100 index options. Thus, we sort for bond market volatility (*Move* index) and stock market volatility (VIX). We apply a rolling regression approach to average excess returns and set the sample length to 30. Figure 5 plots of the slope parameters of the derived order flow coefficients.

We start with financial stress. The impact is highest during calm periods and sharply decreases for medium stress. During high stress periods the order flow effect slightly increases. Especially the high slope coefficients during calm periods contradict the hypothesis that the order flow effect is solely driven by a "flight-to-quality".

[43] Note that high financial stress and volatility states are not exclusively related to the financial crisis. The sorted time series are chronological mixed.

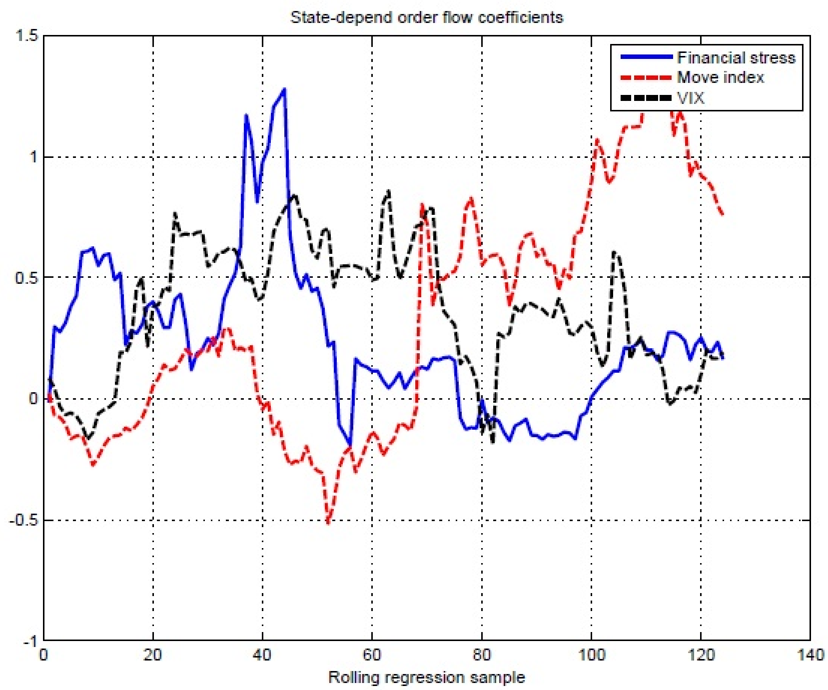
Table 24: Predicting excess returns in the absence of the financial crisis 2007–2009

This table reports regression results of two-, five-, ten-year and average bond excess returns on standardized values of the CP- and macro factors, order flow, changes of the one-year rate and liquidity risk (equation (50)). The analysis excludes the financial crisis period between January 2007 and December 2009 (see Thorton and Valente, 2012). Regression coefficients and standard errors are block-bootstrapped with 10,000 bootstrap samples. The 10% (5%, 1%) significance level is marked with a * (** / ***).

	excess return			
	maturity			
Variable	**2-year**	**5-year**	**10-year**	**mean**
CP_{t-1}	0.1974**	0.1935**	0.1486*	0.1899**
OF^{QE}_{t-1}	0.0407	0.0527	0.0649	0.0561
OF_{t-1}	0.0797***	0.0686**	0.0078	0.0571**
$LN_{1,t-1}$	-0.1338	-0.0594	-0.0236	-0.0669
$LN_{2,t-1}$	0.0735	0.1129	0.1136	0.1103
$LN_{3,t-1}$	0.1481*	0.1803**	0.1689*	0.1790**
$LN_{4,t-1}$	0.1784**	0.2206***	0.1955**	0.2140**
$\Delta y^{(1)}_{t-1}$	0.1307	0.1597	0.1472	0.1567
$liquidity\ risk_{t-1}$	0.2666***	0.2279**	0.1825**	0.2329**
$\Delta\ move\ index_{t-1}$	-0.0734	-0.1558*	-0.1258	-0.1380*
adj. R^2	0.1486	0.1307	0.0752	0.1264

Figure 5: State-dependent effect of order flow

This figure shows order flow coefficients of rolling regressions of excess returns on lagged standardized values of the CP-factor, order flow, macro factors, short rate, liquidity risk and volatility innovations. The sample is sorted with respect to financial stress, bond market volatility (Move index) and equity market volatility (VIX).



Next, we discuss the pattern for the *Move* index. Consistent with Pasquariello and Vega (2007) and Menkveld et al. (2012), we find that order flow owns a higher importance during times of market uncertainty. Sorting for equity volatility does not show the same pattern as for sorting for bond market volatility. For VIX, the estimated coefficients do not show a unique pattern. Some peaks are located at medium volatility periods whereas high and low volatility states are marked by small order flow coefficients. These results support findings of Underwood (2009) but rule out that order flow is driven by a search for liquidity or quality.

3.6.3 Explaining the error term e

A misspecification of the term structure model would bias results. Beside Section 3.5.3, where the predictability of excess return innovations is mainly denied, we again address to the concern of model misspecification. Another possibility to detect the failure of the model will be a systematic relation of the model implied error terms e of equation (37) and any exogenous variables. Therefore, we run regressions of error terms on lagged and differenced values of the CP-factor, macro factors and order flow. The model's correctness is marked by no significant relation between the error terms and the exogenous variables.

Forecasting error terms relates to the question if e_{t+1} captures any systematic component which is related to time t variables. A correct model subsumes all available information in time t in the expected excess return term. Table 25 shows the results for forecasting the error term. At no individual maturity, neither two years nor ten years, we observe any predictability which is underlined by negative R^2s. The one-year yield turns out to be significant for the error terms of five- and ten-year bonds. However, the positive signs conflict with results of Table 23 where the short rate own negative signs. Analyzing the relation between the error terms and contemporaneous changes of the economic variables deals with the question if the model correctly picks up the impact of term structure innovations ν_t. Panel B reports the results. The CP-factor and the real factor reveal some impact on error terms. However, signs switch from positive to negative and reveal no systematic pattern.

In sum, we see these results as confirmation of a correct model specification.

Table 25: The relation of pricing factors and error terms

This table shows regression results of two-year, five-year, ten-year and average error terms of equation 37 on standardized levels and changes of the CP-factor, order flow, changes of the macro factors and of the one-year interest rate and liquidity risk. Liquidity risk is defined as the monthly average of liquidity risk as it is defined in equation (50). The last row of this table reports the change of the adjusted R^2 compared to a regression with the CP-factor as only regressor. Regression coefficients and standard errors are block-bootstrapped with 10,000 bootstrap samples. The 10% (5%, 1%) significance level is marked with a * (** / ***).

	error term			
	maturity			
Variable	**2-year**	**5-year**	**10-year**	**mean**
CP_{t-1}	0.0450	0.0985	0.1210	0.1597
OF_{t-1}^{QE}	0.0517	-0.0558	-0.0419	-0.0372
OF_{t-1}	-0.0664	-0.0243	-0.0341	-0.0790
$LN_{1,t-1}$	0.0932	-0.1127	-0.1063	-0.0877
$LN_{2,t-1}$	0.0227	-0.0566	-0.0503	-0.0623
$LN_{3,t-1}$	0.1717*	-0.0221	-0.0171	0.0844
$LN_{4,t-1}$	0.0810	-0.0011	0.0095	0.0299
$\Delta y_{t-1}^{(1)}$	-0.0124	0.1839*	0.1667	0.2438**
$liquidity\ risk_{t-1}$	-0.0491	0.0437	0.0289	0.0297
$\Delta\ move\ index_{t-1}$	0.0022	-0.0039	-0.0192	0.0471
adj. R^2	-0.0063	-0.0047	-0.0084	0.0225
ΔR^2	-0.0067	-0.0120	-0.0173	0.0074
	maturity			
Variable	**2-year**	**5-year**	**10-year**	**mean**
ΔCP_t	0.1463	-0.1836**	-0.1893**	-0.0936
OF_t^{QE}	-0.0831	0.0118	0.0334	-0.0312
OF_t	-0.1673**	0.1368	0.1303	0.0626
$\Delta LN_{1,t}$	-0.1656**	0.2025**	0.1929**	0.1671**
$\Delta LN_{2,t}$	-0.1674**	0.0839	0.0933	-0.0122
$\Delta LN_{3,t}$	-0.0803	0.0011	-0.0058	-0.0418
$\Delta LN_{4,t}$	-0.0750	0.0024	-0.0075	-0.0451
$\Delta\ y_t^{(1)}$	-0.0307	0.0379	0.0277	-0.0033
$liquidity\ risk_t$	0.0298	-0.0859	-0.0758	-0.1563*
$\Delta\ move\ index_{t-1}$	0.0204	-0.0058	-0.0104	-0.0137
adj. R^2	0.0533	0.0422	0.0492	0.0095
ΔR^2	0.0332	0.0110	0.0137	-0.0030

3.7 Conclusion

This study adds bond market's order flow as an additional variable for forecasting bond excess returns. We use a large economic data set for the US and construct macro factors. Additional, we include the Cochrane and Piazzesi (2005)-factor to control for information provided by forward rates. The information of order flow is not fully captured by macroeconomic variables nor by forward rates. Thus, our analysis suggests that order flow incorporates a risk factor.

The effect of order flow is consistent with the view that order flow incorporates information (see Brandt and Kavajecz, 2004, Pasquariello and Vega, 2007, and Menkveld et al., 2012). Moreover, order flow might explain why other microstructure effects are priced in excess returns. Li et al. (2009) argue that information risk is a determinant for bond market excess returns. An additional predictor is the intensity of strong bond price movements which can be induced by information releases or liquidity reasons Wright and Zhou (2009). Both variables are by definition directly related to order flow.

To understand the pricing implication of order flow and public information we apply the Adrian et al. (2012) term structure model and decompose excess returns into expected returns and return innovations. Expected excess returns crucially depend on the available information set which is spanned by order flow, forward rates and macroeconomic variables. Return innovations are unpredictable but reveal a strong dependence on contemporaneous order flow and changes of the economic environment.

This article sheds some light on the reasons for the high rejection rate of the expectation hypothesis (Fama and Bliss, 1987, or Bekaert and Hodrick, 2001). The strong linkage between expected excess returns and (non-)public available information can rule out one argument for its failure: irrational expectations.

Evidence for a time-varying risk premium is strong. We detect a counter-cyclical pattern in both excess returns and the expectation components. This result underlines the business-cycle dependence of excess returns (Ludvigson and Ng, 2009, Cooper and Priestley, 2009, and Duffee, 2011).

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4 Daily US bond risk premium determinants[****]

Abstract

We extract the implied risk premium from US interest rates between 1995 and 2009. For this period, order flow is the main driver of the US bond risk premium innovations. The impact of macroeconomic announcements is limited. Our findings suggest the existence of an *unpublic* economic risk premium as order flow reflects the incorporation of dispersed economic information. Although illiquidity is priced in times of financial stress, the effect of order flow is not driven by the ”flight-to-liquidity” phenomenon. Our results suggest that the bond risk premium is closely related to bond market conditions.

4.1 Introduction

What determines daily innovations of the bond risk premium? Not as much as you might expect. Order flow, the aggregated flow of information through trading, is the dominant factor. The effect of macroeconomic announcements is limited and is in contrast to analysis of monthly or yearly bond risk premiums (see e.g. Ludvigson and Ng, 2009). Beside order flow, illiquidity, volatility innovations and personal income releases reveal an impact on the US bond risk premium. We find no impact from FOMC meetings nor from nonfarm payroll releases. This result is very surprising as the latter one is often seen as the ”king” of macroeconomic announcements in the US bond market (see Andersen and Bollerslev, 1998).

The link between the bond risk premium and order flow is indirect but obvious. Cochrane and Piazzesi (2008) show that yearly bond excess returns are a compensation for bearing risk which is associated with the level of interest rates. As it is earlier shown by Brandt and Kavajecz (2004) order flow owns such a level effect. A step further, Fricke (2012)

[****] Preliminary results: Please do not quote without author’s permission

link order flow to monthly expected excess returns and to return innovations.

This paper brings the analysis of the bond risk premium from a long-term perspective to a daily basis. We run a horserace of macroeconomic announcements and order flow for explaining daily risk premium innovations of the time period 01/1995 to 08/2009. The winner is order flow which explains more than ten percent of the bond risk variation at all maturities. The performance of economic announcements is limited to less then one percent.

We derive the US bond risk premium from the Adrian et al. (2012) term structure model. We control for any relation of the term structure pricing factors to order flow by considering forward rates and forward spreads as pricing factors (see Cochrane and Piazzesi, 2008). The remaining relation of order flow to the interest rate level factor is overcome by replacing it by the Nelson and Siegel (1987) level parameter (see Diebold and Li, 2006 and Balduzzi and Moneta, 2011).

For robustness, we exclude times of financial stress such as Russian default, LTCM-crisis and the dotcom- and subprime-bubble. With and without financial stress, order flow remains the driving force of the bond risk premium. However, the impact is even stronger during financial stress periods which consists with the idea of a "flight-to-liquidity" and/or "flight-to-quality" phenomenon (Beber et al., 2009). In sum, the here documented effect of order flow on the US bond risk premium does neither stem from a direct relation of order flow to the pricing factors of the term structure model nor from a "flight-to-liquidity" phenomenon.

The structure of the paper is as follows. Section 4.2 reviews the relevant literature and section 4.3 discusses the data sets. Section 4.4 discusses the theoretical and empirical aspects of the Adrian et al. (2012) term structure model and section 4.5 presents results for explaining term premium innovations. Section 4.6 discusses the robustness of the results and section 4.7 concludes.

4.2 Literature overview

Two strands of the literature try to identify the driving forces of the bond risk premium – macroeconomic and market microstructure related factors.

Macroeconomic aspects for pricing the term structure are picked up by Ang and Piazzesi (2003) who implement macroeconomic information into an affine term-structure model. Cochrane and Piazzesi (2008) show that bond excess returns covary with the interest rate level. This effect rules out monetary policy decisions as these move short- and long-term yields in opposite directions – characterizing a slope effect (see Cochrane and Piazzesi, 2008). Consequently, Lucca and Moench (2011) document no significant bond excess returns which are associated with FOMC announcements. Ludvigson and Ng (2009) estimate macroeconomic pricing factors by applying a factor analysis to a broad set of economic variables and document a countercyclical pattern of excess returns. Returns mainly covary with industrial production and the output gap (Cooper and Priestley, 2009, Cieslak and Povala, 2010, Joslin et al., 2010 and Duffee, 2011) and with inflation (Buraschi and Jiltsov, 2005, Buraschi and Jiltsov, 2010 and Joslin et al., 2010). Beside the contemporaneous state of the economy, the dispersion about the expected future path of the economy is also related to the bond risk premium (see Buraschi and Jiltsov, 2010).

Market microstructure effects are discussed in a detached way from macroeconomic aspects. Li et al. (2009) document the role of liquidity and information risk in bond markets. Both components are strongly related to bond excess returns which suggests that the pricing of the bond risk premium is not solely based on macroeconomic information. Joslin (2010) reveals that bond market volatility is an important determinant for long-term bond excess returns. Volatility might be caused by sharp price changes, so–called jumps. The intensity of jumps' occurrence owns predictive power for bond excess returns (Wright and Zhou, 2009 and Duyvesteyn et al., 2011).

However, macroeconomic and market microstructure effects are related. Lahaye et al. (2011) claim out that announcement releases are key drivers of jumps. Hence, macroeconomic announcements increase market volatility (Jones et al., 1998 and de Goeij and Marquering, 2006).

One instrument of interest of the market microstructure literature is order flow. Order flow measures the difference between buy-side and sell-side initiated trades and represents the order imbalance. Order flow's importance for asset pricing relies on the idea that the incorporation of private/dispersed information requires trading in order to be reflected in asset prices (Evans and Lyons, 2002). In analogy with Buraschi and Jiltsov (2010), order flow's pricing implications are even more pronounced when market expectations about future macroeconomic announcement is more dispersed (Pasquariello and Vega, 2007). Beside a contemporaneous relation between order flow and economic information, Evans and Lyons (2009) and Rime et al. (2010) document that order flow forecasts future economic variables. Thus, order flow can be understood as an additional source of economic information.

Yearly or monthly frequencies are classical time horizons for studying bond excess returns (for example Cochrane and Piazzesi, 2005, Cochrane and Piazzesi, 2008, Wright, 2011 and Ludvigson and Ng, 2009). However, the focus of interest switches to higher frequencies. Pozzi and Wolswijk (2008) estimate the risk premium on a weekly basis and Adrian et al. (2012) and Hellerstein (2011) analyze daily risk premium.

The closest related paper to ours is Balduzzi and Moneta (2011). Based on US bond future return data they identify a bond risk premium which is associated with macroeconomic announcements. The focus of our paper is different. We are not interested on the existence of an economic risk premium which is implied by bond future returns. Rather, we are looking on the pricing implications of macroeconomic announcements, order flow, volatility and liquidity risk for the term structure model implied term premium.

4.3 Data

This section discusses the data set for explaining term premium innovations. We discuss of the construction of order flow, volatility and liquidity and describe the considered macroeconomic announcements.

4.3.1 Order flow

Order flow data consist on the "*on-the-run*" US bond future contracts with a maturity of two-, five-, ten- and thirty years for the period 01/1995–08/2009. Due to their outstanding trading volume, on-the-run bonds offer a higher liquidity than "off-the-run" bonds and dominate the price discovery process in the US Treasury market (Brandt and Kavajecz, 2004). We incorporate this finding and make use of a daily "auto roll" procedure which compares maturity-equivalent bond futures and include the one with the highest trading volume.

The data set is "Time and Sales" which only reports trade prices. The absence of quote data hamper computing order flow by comparing trade prices with available quotes (Lee and Ready, 1991). Therefore, we apply the Easley et al. (2012)-algorithm to compute order flow which defines for each five minute time interval the probability that trading is buy- or sell-side initiated. Buy-side initiated order flow, V_τ^B, is defined as

$$V_\tau^B = V_\tau \cdot Z(\frac{P_t - P_{t-1}}{\sigma_{\Delta p}}) \tag{51}$$

where V_τ is the amount of trades in time period τ and Z is the cumulative distribution function of the normal distribution. $P_t - P_{t-1}$ is the price change between two time periods and $\sigma_{\Delta p}$ the standard deviation of price changes within the period. Sell-side order flow is defined as $V_\tau^S = V - V_\tau^B$.

We follow Hasbrouck and Seppi (2001) and estimate the commonality of order flow by applying a factor analysis. Due to the significant increase of trading volume and structural changes (e.g. algorithm trading) we standardize each month of order flow data by subtracting the mean and setting the standard deviation to one. Thereafter, we extract the first principal component out of the order flow series. At Table 26 we regress order flows on the common factor and receive a clear interpretation. The first factor affects all maturities and explains more than 50% of the variance of the shortest maturity and up to 70% at the five- and ten-year maturity. The pattern looks familiar to a "level" effect. Regressing term structure factors on the commonality of order flow confirms this finding (see Table 27) and is in line with Brandt and Kavajecz (2004).

Table 26: Commonality of order flows

This table reports adjusted R^2s which are derived from regressing each order flow series on the first common factor, OF_t^{PC1}.

variable	**adj.** R^2 **of** OF_t^{PC1}
OF^{2-year}	0.5136
OF^{5-year}	0.6994
$OF^{10-year}$	0.7139
$OF^{30-year}$	0.6182

4.3.2 Macroeconomic announcements

Ludvigson and Ng (2009) and Duffee (2011) outline a countercyclical risk premium as it covaries with real activity and inflation variables. The estimation of a daily risk premium enables us to apply an event study approach. We create dummy variables for 14 US macroeconomic announcements which are associated with productivity or inflation. In detail, we consider releases of the advanced, preliminary and final GDP, nonfarm payroll employments, retail sales, industrial production and capacity utilization, personal income, home sales, construction spending, factory orders, business inventories, home sales, producer prices and consumer prices. Additional, we control for any monetary effects by considering FOMC meetings too.

4.3.3 Further microstructure variables

Volatility

Adrian et al. (2012) reveal a high correlation between bond market volatility, the *Move* index, and the term premium. In our sample we find an impressive correlation of 75%. However, as we are interested in term premium innovations, partly due to non-stationary term premiums, we compute percentage changes of the *Move* index and still find correlations close to ten percent.

Liquidity

We follow Li et al. (2009) and discuss the role of liquidity for bond excess returns by calculating the Amihud (2002) illiquidity measure

$$liquidity\ risk_t = \frac{|r_t|}{volume_t}\ . \tag{52}$$

r_t is the daily return of the ten-year Treasury bond future and $volume_t$ is the contract's trading volume at day t.

4.4 Term structure modeling and estimation

This section discusses the Adrian et al. (2012) term structure model and its application to daily data. The term structure of interest rates is backed out from the Gurkaynak et al. (2007) zero coupon data set. Pricing factors differ from the "classical" *level*, *slope* and *curvature* as these factors reveal a strong relation to order flow (see Section 4.3.1).

To estimate a clear and isolated effect of order flow on the risk premium, pricing factors are defined in the Cochrane and Piazzesi (2008) style. *Level*, *slope* and *curvature* are derived from forward rates and forward spreads which reveal only marginal correlations to order flow. However, order flow remains correlated with the Cochrane and Piazzesi (2008) level factor. Therefore, we follow Balduzzi and Moneta (2011) and consider the parameter $b_{0,t}$ of the Gurkaynak et al. (2007) US zero coupon yield curve as level factor.[44] We use the following notations and definitions. $p_t^{(n)}$ defines the log price of a zero-coupon bond with maturity n at time t and $y_t^{(n)}$ the implied yield of a bond which matures in n month. The log forward rate at time t for payments between period $t+n-1$ and $t+n$ is expressed as

$$f_t^{(n-1\to n)} = p_t^{(n-1)} - p_t^{(n)} \tag{53}$$

and the log excess return rx_t as

$$rx_{t+1}^{(n)} = p_{t+1}^{(n-1)} - p_t^{(n)} - y_t^{(1)} \ . \tag{54}$$

4.4.1 The Cochrane and Piazzesi (2008) return-forecasting factor x

We account for the fact that the Adrian et al. (2012) term structure model considers one-month excess returns and modify x_t such that it is the one-month excess return-forecasting factor. Cochrane and Piazzesi (2008) propose forward spreads as a more appropriate candidate for forecasting excess returns. We denote the forward spread as

$$\tilde{f}_t^{(n)} = f_t^{(n)} - y_t^{(1)} \tag{55}$$

[44] The Gurkaynak et al. (2007) US zero coupon yield curve is extracted from the US bond yield universe by fitting a six parameter model to the interest rates. In this model the parameter $b_{0,t}$ is often regarded as the interest rate level.

and define $\tilde{f}_t = [f_t^{(6)}, f_t^{(18)}, f_t^{(24)}, \ldots, f_t^{(60)}, f_t^{(84)}, f_t^{(120)}]$.

Forward spreads reveal correlations above 99% which enforces us to apply a factor analysis to $\tilde{f}$. The first factor explains 99.9% of the forward rate variance. However, to be consistent with Cochrane and Piazzesi (2008) we consider four spreads - in our case the first four factors.

To extract expected returns we regress excess returns on forward spreads in the following fashion

$$rx_{t+1} = \alpha + \beta \tilde{f}_t + \varepsilon_{t+1} \tag{56}$$

where rx_{t+1} is the one-month ahead excess return. Let $\mathbb{E}_t[rx_{t+1}] = \beta \tilde{f}_t$ be the expected return. We derive a factor structure of expected returns by a factor analysis. Consistent with Cochrane and Piazzesi (2008) and results above, we find a one-factor specification as sufficient. This factor picks up 99.99% of expected returns' variance and can easily be labeled as "level" factor. The factor loadings are gradually higher for larger maturities. We follow Cochrane and Piazzesi (2008) and drop all other factors as they seem to be driven by measurement- or iid pricing errors.

Define x_t as the weighted function of expected returns by the factor loadings of the first principal component

$$x_t = q_r' \mathbb{E}(rx_{t+1}) = q_r'(\alpha + \beta \tilde{f}_t) = q_r'\alpha + \gamma' \tilde{f}_t \tag{57}$$

where q_r' defines the factor loadings and $\gamma' = q_r'\beta$. As β from equation (56) owns a tent-shape pattern and q_r' is in all cases positive, we derive the well known ten-shaped function of γ' (see Cochrane and Piazzesi, 2005, 2008).

4.4.2 Term structure factors

We follow Cochrane and Piazzesi (2008) and extent the set of pricing factors by constructing *level*, *slope* and *curvature* to be not spanned by the return-forecasting factor. To loosen x_t from the term structure, we regress forward rates $f_t^{(n)}$ on x_t and set $n = [6, 18, 24, \ldots, 60, 84, 120]$

$$f_t^{(n)} = c + dx_t + e_t \; . \tag{58}$$

We apply a factor analysis to the residuals e_t and define the first three factors as

$$level_t = Q(:,1)'(c + e_t) \tag{59}$$

$$slope_t = Q(:,2)'(c + e_t) \tag{60}$$

$$curvature_t = Q(:,3)'(c + e_t) \; . \tag{61}$$

$Q(:,i)$ is the loading of the corresponding factor.

We follow Balduzzi and Moneta (2011) and replace the Cochrane and Piazzesi (2008) level factor by $beta_{0,t}$ of the Gurkaynak et al. (2007) term structure parameters. We additional use information from equation (59) and regress $level_t$ on $beta_{0,t}$ and consider the residual, $level_t^{resid}$, as additional pricing factor:[45]

$$level_t = -0.000097^{***} - 0.000007^{***} \cdot beta_{0,t} + level_t^{resid} \; . \tag{62}$$

[45] Note, that Hellerstein (2011) also uses residuals of level, slope and curvature as pricing factors. A '****' marks significances at the 1% level.

The derived variables span our state variables for the term structure model, X_t:

$$X_t = [x_t \; beta_{0,t} \; slope_t \; curvature_t \; level_t^{resid}] \; . \tag{63}$$

We test the relation of order flow to pricing factors by running regressions of X_t on order flow (Table 27) and find R^2s below 7%.

Table 27: Order Flow and pricing factors of the term structure

This table reports regression results of state variables which are possible pricing factors of the term structure model. Panel A shows results for factors derived from interest rates and Panel B reports results for pricing factors which are derived from forward rates and -spreads (see Cochrane and Piazzesi, 2008). The 5% (1%) significance level is marked with a ** (***). Robust standard errors (Newey and West, 1987) are used.

		pricing factor			
variable	OF_t^{PC1}	**adj.** R^2	**variable**	OF_t^{PC1}	**adj.** R^2
$level_t^{TSF}$	0.6411***	0.4111	x_t	-0.0183	0.0003
$slope_t^{TSF}$	0.5398***	0.2914	$beta_{0,t}$	0.2311***	0.0534
$curvature_t^{TSF}$	-0.1885***	0.0356	$slope_t$	0.0391**	0.0015
$fourth\ factor_t^{TSF}$	0.0887***	0.0079	$curvature_t$	-0.2530***	0.0640
$fifth\ factor_t^{TSF}$	-0.0131	0.0002	$level_t^{resid}$	0.0081	0.0001

4.4.3 Adrian et al. (2012) term structure model

This section discusses the estimation strategy of the Adrian et al. (2012) term structure model with pricing factors X_t. The core elements of the model are affine structures of log bond prices to market prices of risk and of market prices of risk to the yield curve. We follow Adrian et al. (2012) and Hellerstein (2011) and estimate parameters on a monthly basis and apply parameters to the daily data.

The general set up

We start with modeling the dynamics of the pricing factors X_t which follow a VAR(1)–

process with the innovation term ν_{t+1} which has, conditional on X_t, a mean of zero and variance Σ:

$$X_{t+1} = \mu + \Phi X_t + \nu_{t+1}\,. \tag{64}$$

We demean the pricing factors and therefore set μ to zero. Next, we relate log one-month excess returns, rx_{t+1}, to the state variables X_t and the innovation term ν_{t+1}. Expected future excess returns depend on a constant and the available information set at time t which is represented by X_t. The vector ν_{t+1} reflects unexpected term structure innovations of the pricing factors and represents excess return innovations.

Thus, the log excess holding period return is a function of an expected return, a convexity adjustment term, return innovations which are related to ν_{t+1} and a priced error term, e_{t+1}, with variance $\widehat{\sigma}^2$:

$$rx_{t+1}^{(n-1)} = \underbrace{\beta^{(n-1)\prime}(\lambda_0 + \lambda_1 X_t^s)}_{\text{Expected return}} - \underbrace{\frac{1}{2}(\beta^{(n-1)\prime}\Sigma\beta^{(n-1)} + \sigma^2)}_{\text{Convexity adjustment}} + \underbrace{\beta^{(n-1)\prime}\nu_{t+1}}_{\substack{\text{priced return}\\ \text{innovation}}} + \underbrace{e_{t+1}^{(n-1)}}_{\substack{\text{Return pricing}\\ \text{error}}}\,. \tag{65}$$

To compute parameters, equation (65) is transformed to

$$rx_{t+1}^{(n-1)} = \alpha^{(n-1)} + \beta^{(n-1)\prime}\nu_{t+1} + c^{(n-1)\prime}X_t^s + e_{t+1}^{(n-1)}\,. \tag{66}$$

Market prices of risk are derived from a three step regression approach which is described in the following. *First*, we derive the parameters from equation (64) and compute the variance-covariance matrix Σ. *Second*, we stack the vectors into equation (66) and save the estimated parameters and *third* derive market prices of risk, λ_0 and λ_1. Risk vectors are defined by the model as:

$$\widehat{\lambda}_0 = (\widehat{\beta}'\widehat{\beta})^{-1}\widehat{\beta}'(\widehat{a} + \frac{1}{2}(\widehat{B}^* vec(\widehat{\Sigma}) + \widehat{d}_e)) \tag{67}$$

$$\widehat{\lambda}_1 = (\widehat{\beta}'\widehat{\beta})^{-1}\widehat{\beta}'\widehat{c} \tag{68}$$

with $B^* = [vec(\beta^{(1)}\beta^{(1)\prime}), \ldots, vec(\beta^{(N)}\beta^{(N)\prime})]$ and $\widehat{d}_e = \widehat{\sigma}^2 i_N$. i_N is a Nx1 vector of ones. Beside affine excess returns, log bond prices also follow affine processes which depend on the state vector X_t and an error term u_t:

$$\ln P_{t+1}^n = A_n + B_n' X_{t+1} + u_{t+1}\,. \tag{69}$$

A reformulation of equation (69) leads to the following restrictions for bond pricing which can be solved recursive (see Adrian et al., 2012):

$$A_n = A_{n-1} + B_{n-1}'(\mu - \lambda_0) + \frac{1}{2}(B^{(n-1)\prime}\Sigma B^{(n-1)} + \sigma^2) - \delta_0 \tag{70}$$

$$B_n' = B_{n-1}'(\Phi - \lambda_1) - \delta_1 \tag{71}$$

$$A_0 = 0; B_0' = 0 \tag{72}$$

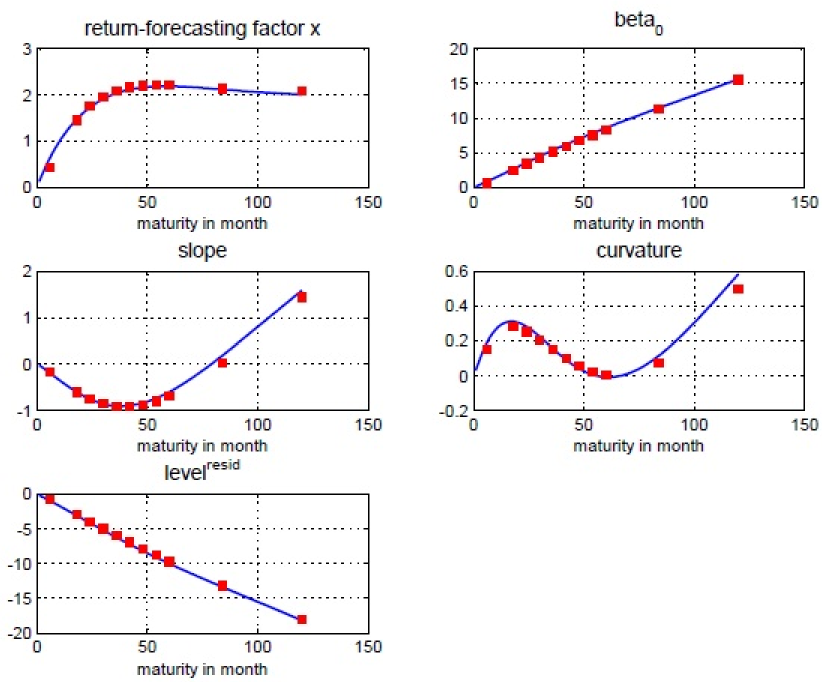
$$\beta_n' = B_n'\,. \tag{73}$$

Starting parameters $A_1 = -\delta_0$ and $B_1 = -\delta_1$ are derived from a linear projection of the log one-month interest rate, $y_t^{(1)}$, on a constant and X_t. δ_0 is the intercept coefficient and δ_1 the coefficient vector of X_t.

We test the holding of equation (73) by comparing estimated, β_n', and recursively solved, B_n', parameters (Figure 6). Both sets of parameters are nearly identical and the pattern of the coefficients consists with the literature. The slope of the return-forecasting factor x_t is comparable to Cochrane and Piazzesi (2008). $beta_0$ and $level_{0,t}$ own level effects

Figure 6: Regression coefficients $\beta^{(n)}$ and the recursively derived parameters B_n

These figures compare the regression coefficients $\beta^{(n)}$ from equation (66) with the model implied coefficients B_n from equation (71). The time period is 01/1995-08/2009. The blue line represents the regression coefficients for all considered maturities n=$\{1, \ldots, 120\}$. The red data points show the recursive estimated B_n coefficients. The return-forecasting factor x_t, $slope_t$ and $curvature_t$ are computed as suggested by Cochrane and Piazzesi (2008). The $level_t$ is modeled by the US zero-coupon parameter $beta_{t,0}$ derived from Gurkaynak et al. (2007). The residual of regressing the Cochrane and Piazzesi (2008) level factor on $beta_{t,0}$ is additionally considered.



and slope and curvature also load in a known pattern on interest rates.

Daily term premium estimation

To derive the daily term premium we follow Adrian et al. (2012) and Hellerstein (2011) and estimate the market prices of risk from end-of-month data and apply these coefficients to daily data. Figure 7 plots model implied and observed interest rates which underlines the good fit of the term structure model. Let the term premium be defined as the difference between model-implied and risk-free interest rates. We compute the latter ones by setting the market prices of risk in equations (70) and (71) to zero which returns

Figure 7: Model-implied and realized daily interest rates

These figures show daily yields derived from the Adrian et al. (2012) term structure model and implied by the Gurkaynak et al. (2007) data set with maturities of two-, five-, ten-years and average interest rates. The blue line represents realized interest rates and the blue line shows model-implied yields.

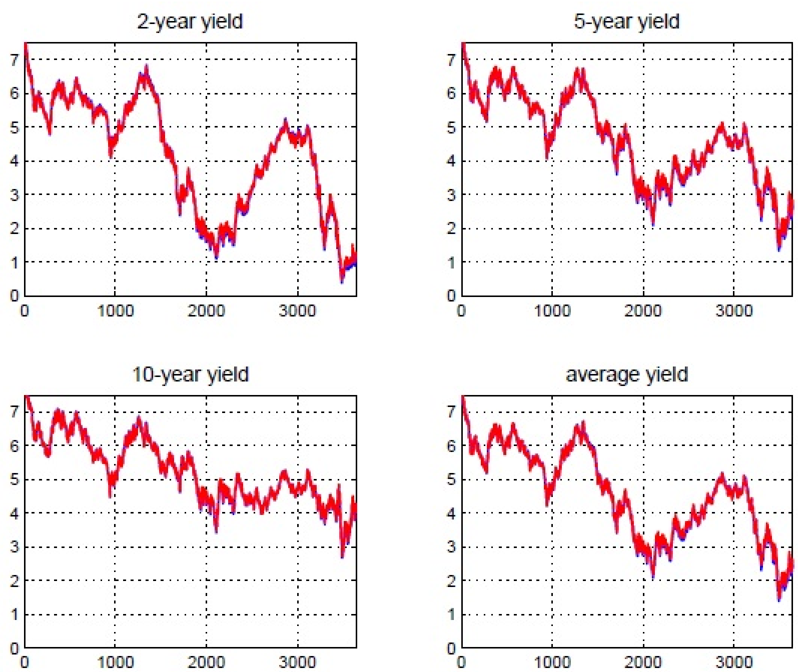
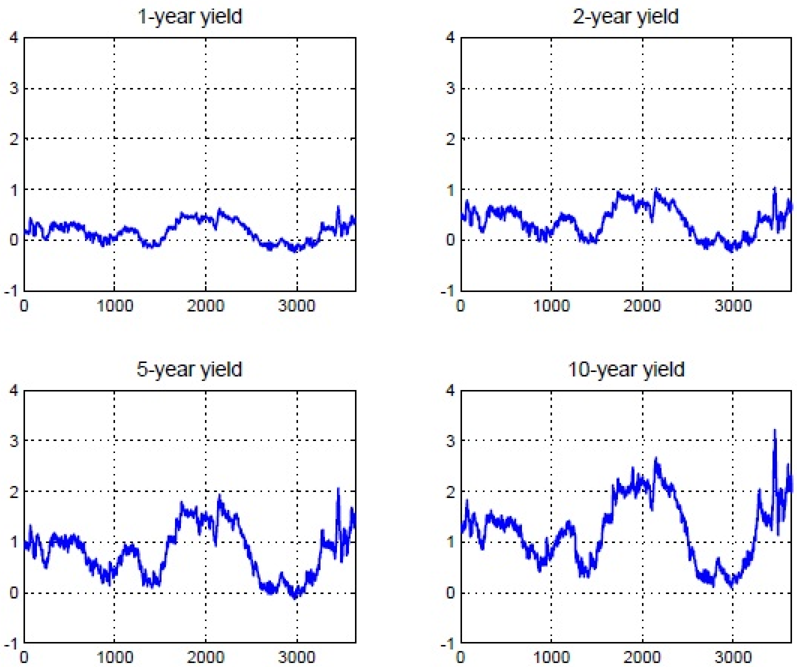


Figure 8: Term premium estimations

These figures show daily term premiums derived from the Adrian et al. (2012) term structure model for the period 01/1995-08/2009.



risk-neutral pricing parameters A_n^{RF} and B_n^{RF}. We fit these parameters into equation (69) and derive risk-neutral interest rates. Figure 8 shows the time-series pattern of the term premium for one-, two-, five- and ten-year maturity bonds.

4.5 Term premium determinants

This section identifies determinants of daily US term premium innovations which are the residuals of an AR(1)-process. We start with analyzing to which extent macroeconomic information influence risk premium innovations. This approach is comparable to Balduzzi and Moneta (2011) who document an economic risk premium related to macroeconomic announcements. Thereafter, we include market microstructure variables. Adrian et al. (2012) and Bollerslev et al. (2011) discuss the relation of volatility and the term premium. Li et al. (2009) suggest that information and liquidity risk are priced in the bond market. We proxy liquidity risk by the Amihud (2002)–liquidity measure[46] and proxy information risk by order flow (Fricke, 2012).

4.5.1 Macroeconomic announcements

We start with regressing term premiums on macroeconomic announcement dummies and a NBER recession dummy variable (see Table 28). Consistent with Ludvigson and Ng (2009) and Wright and Zhou (2009), the term premium owns a countercyclical pattern as the recession dummy is significant in all cases and suggests that return innovations are on average positive during recessions. Focussing on announcement releases reveals a negligible effect of macroeconomic releases. Only personal income and advanced GDP impact risk premium innovations. We see this as further evidence for a close relation between the bond risk premium and the economy (see Ludvigson and Ng, 2009, Wright, 2011 and Balduzzi and Moneta, 2011). However, R^2s near zero outline that macroeconomic announcements are not the appropriate candidates for explaining risk innovations.

4.5.2 Macroeconomic and market microstructure variables

The set of variables is enhanced by including market microstructure related variables. Order flow should be linked to risk premiums due to its "*level*"–effect (see Cochrane and Piazzesi, 2008 and Brandt and Kavajecz, 2004). The $Move$ index controls for the existence of a volatility risk premium and the Amihud (2002)–liquidity measure, $Illiq^{Amihud}$, for a pricing effect of liquidity.

[46] Results also hold for the consideration of changes of liquidity.

Table 28: Macroeconomic determinants of the term premium

This table reports regression results of the two-, five-, ten-year and average term premium on macroeconomic announcement dummies. $D^{rec.}$ represents a dummy variable which owns a value of one for each month which falls in a NBER recession period. The 10% (5%, 1%) significance level is marked with a * (**, ***). Robust standard errors (Newey and West, 1987) are used.

	maturity			
variable	**2-year**	**5-year**	**10-year**	**mean**
intercept	0.0015	-0.0012	-0.0040	-0.0012
US economic news				
GDP adv.	-0.0785*	-0.0915*	-0.0954*	-0.0834*
GDP pre.	-0.0319	-0.0421	-0.0436	-0.0371
GDP final	-0.0123	-0.0158	-0.0154	-0.0134
nonfarm payroll	0.0074	0.0010	-0.0121	0.0001
retail sales	-0.0255	-0.0302	-0.0295	-0.0269
ind. production	0.0275	0.0260	0.0142	0.0218
personal income	-0.0856***	-0.0872***	-0.0687**	-0.0770**
home sales	-0.0323	-0.0380	-0.0333	-0.0328
constr. spending	0.0205	0.0409	0.0936*	0.0471
factory orders	-0.0290	-0.0321	-0.0307	-0.0282
business inventories	-0.0373	-0.0440	-0.0468	-0.0404
housing starts	0.0416	0.0451	0.0364	0.0388
producer prices	-0.0441	-0.0415	-0.0230	-0.0347
consumer prices	-0.0240	-0.0308	-0.0328	-0.0269
FOMC	-0.0064	-0.0064	-0.0041	-0.0048
other variables				
$term\ premium_{t-1}$	-7.9991	-9.1955	1.9586	-5.4335
$D^{rec.}$	0.0518***	0.0676***	0.0683***	0.0592***
adj. R^2	0.0044	0.0039	0.0051	0.0048

Table 29: Macroeconomic announcements and market microstructure determinants of the term premium

This table reports regression results of the two-, five-, ten-year and average term premium on the first order flow factor, the Amihud (2002) liquidity measure, the Move index and several macroeconomic announcement dummies. $D^{rec.}$ represents a dummy variable which owns a value of one for each month which falls in a NBER recession period. The 10% (5%, 1%) significance level is marked with a * (**, ***). Robust standard errors (Newey and West, 1987) are used.

	maturity							
	2-year		5-year		10-year		mean	
variable	**Panel A**	**Panel B**	**Panel A**	**Panel B**	**Panel A**	**Panel B**	**Panel A**	**Panel B**
intercept	-0.0009	0.0006	-0.0013**	0.0002	-0.0015**	-0.0004	-0.0012**	0.0001
microstructure variables								
OF^{PC1}	-0.0126***	-0.0125***	-0.0138***	-0.0136***	-0.0123***	-0.0119***	-0.0122***	-0.0120***
$Move$		0.0292*		0.0444***		0.0750***		0.0461***
$Illiq^{Amihud}$		-8.5902**		-6.8666		-4.4589		-6.3568
US economic news								
GDP adv.		-0.0068*		-0.0079*		-0.0082		-0.0072*
GDP pre.		0.0017		0.0011		0.0002		0.0009
GDP final		-0.0021		-0.0024		-0.0021		-0.0021
nonfarm payroll		0.0014		0.0013		0.0011		0.0013
retail sales		-0.0019		-0.0023		-0.0022		-0.0020
ind. production		0.0026		0.0024		0.0012		0.0020
personal income		-0.0098***		-0.0101***		-0.0083***		-0.0090***
home sales		-0.0034		-0.0041		-0.0039		-0.0036
constr. spending		0.0027		0.0050		0.0104**		0.0055
factory orders		-0.0027		-0.0031		-0.0029		-0.0027
business inventories		-0.0022		-0.0027		-0.0031		-0.0025
housing starts		0.0047		0.0051		0.0043		0.0044
producer prices		-0.0041		-0.0038		-0.0017		-0.0031
consumer prices		-0.0022		-0.0028		-0.0029		-0.0024
FOMC		-0.0003		-0.0001		0.0007		0.0002
other variables								
$term\ premium_{t-1}$		-0.5930		-0.7153		0.3284		-0.3712
$D^{rec.}$	0.0051***	0.0048***	0.0067***	0.0065***	0.0069***	0.0066***	0.0059***	0.0056***
adj. R^2	0.1257	0.1319	0.1282	0.1338	0.1006	0.1078	0.1252	0.1315

Table 29, Panel A focusses on the effect of order flow. In contrast to macroeconomic announcements, order flow is a key driver of risk premium innovations. In all cases, the adj. R^2 jumps by more than 10%. Coefficients are highly significant (t-statistics between 17 and 19) and bear a clear interpretation from an asset-pricing and a market microstructure viewpoint.

Start with *asset-pricing*. Remember, that the pricing implications of order flow do not stem from a covariation of order flow with one of the pricing factors in the term structure model (see Section 4.4.2). Cochrane and Piazzesi (2008) point out that the bond risk premium is a compensation for bearing risk which is associated with the term structure's "*level*". As documented in Table 27, the commonality of order flow owns a level effect. What is the *macroeconomic* interpretation? We identify order flow as one main determinant. We interpret this effect in a market microstructure style. Evans and Lyons (2002) suggest that order flow stems from varying risk tolerance. Harvey (1989) argue that an expected economic downturn enforces investors to demand long-term bonds. These portfolio shifts will induce positive order flow. Moreover, order flow incorporates latent macroeconomic or private information (Brandt and Kavajecz, 2004, Green, 2004, Love and Payne, 2008 and Menkveld et al., 2012). Thus, the effect of order flow suggests that economic information determine bond risk premiums. However, these information are not primary related to macroeconomic announcements.[47]

4.6 Robustness

The results' robustness is checked by modifying *first* macroeconomic information and *second* the time period. The effect of order flow remains robust for all specifications.

[47]We also test the existence of an economic risk premium at announcement days which stems from order flow. Therefore, we split order flow into announcement and non-announcement days and find for both consistent signs and significance for both.

4.6.1 Modifying macroeconomic information

(i) *Macroeconomic announcement factor*

We construct a macroeconomic announcement factor which captures the pattern of the risk premium. Comparable to Ludvigson and Ng (2009) and Balduzzi and Moneta (2011), we regress the average risk premium on macroeconomic dummy variables and use the derived coefficients as weighting vector β:

$$F^{Macr.} = D^{Ann.}\beta \tag{74}$$

where D^{Ann} is the announcement matrix with an announcement dummy variable at each column. Table 30 documents significant coefficients of the macro factor for both with

Table 30: Macroeconomic factor and market microstructure determinants of the term premium

This table reports regression results of the average term premium on the first order flow factor, the Amihud (2002) liquidity measure, the Move index and the macroeconomic factor. The macro factor is weighted by the regression parameters derived from Table 28 and estimated as described in equation (74). $D^{rec.}$ represents a dummy variable which owns a value of one for each month which falls in a NBER recession period. The 10% (5%, 1%) significance level is marked with a * (**, ***). Robust standard errors (Newey and West, 1987) are used.

variable	**mean**	
	Panel A	**Panel B**
intercept	-0.0002	-0.0005
microstructure variables		
OF^{PC1}		-0.0120***
$Move$		0.0435***
$Illiq^{Amihud}$		4.6131
macroeconomic factor	0.9999***	0.9981***
other variables		
$term\ premium_{t-1}$	-0.5380	
$D^{rec.}$	0.0059***	
adj. R^2	0.0087	0.1327

and without microstructure variables. Nevertheless, the main driver of excess return innovations remains order flow as its inclusion lifts R^2s by more than 12%.

(ii) *Macroeconomic news*

Announcement dummies might be a crude measure for the flow of economic information. Balduzzi and Moneta (2011) show that an economic risk premium depends on the economic activity and propose to use of macroeconomic news as a more precise instrument. Available macroeconomic news are for the US the preliminary, advanced and final GDP, nonfarm payroll, unemployment, producer and consumer prices and additional for Germany the preliminary GDP and producer prices. Data are collected from MMS. Individual news are measured as the difference between the realized and the average forecasted value and is divided by the news' standard deviation over the whole sample (Balduzzi and Moneta, 2011).

Table 31 reports results with only macroeconomic news (Panel A) and additional with microstructure variables (Panel B). Considering macroeconomic news instead of announcement dummies does not improve the understanding of risk premium innovations. Order flow remains the driving factor.

Table 31: Macroeconomic news and market microstructure determinants of the term premium

This table reports regression results of the two-, five-, ten-year and average term premium on the first order flow factor, the Amihud (2002) liquidity measure, the Move index and several macroeconomic news. $D^{rec.}$ represents a dummy variable which owns a value of one for each month which falls in a NBER recession period. The 10% (5%, 1%) significance level is marked with a * (**, ***). Robust standard errors (Newey and West, 1987) are used.

	maturity							
	2-year		**5-year**		**10-year**		**mean**	
variable	**Panel A**	**Panel B**	**Panel A**	**Panel B**	**Panel A**	**Panel B**	**Panel A**	**Panel B**
intercept	-0.0010	-0.0011	-0.0014*	-0.0017**	-0.0015**	-0.0021***	-0.0012*	-0.0015**
microstructure variables								
OF^{PC1}		-0.0125***		-0.0137***		-0.0123***		-0.0121***
$Move$		0.0265*		0.0415**		0.0720***		0.0433***
$Illiq^{Amihud}$		1.0476		4.6448		8.1060		4.2581
US economic news								
GDP adv.	-0.0007	0.0000	0.0001	0.0008	0.0005	0.0012	-0.0001	0.0006
GDP pre.	0.0065	0.0076*	0.0052	0.0064	0.0014	0.0023	0.0043	0.0053
GDP final	0.0022	0.0025	0.0029	0.0032	0.0034	0.0037	0.0026	0.0029
nonfarm payroll	0.0056*	-0.0021	0.0035	-0.0052*	-0.0017	-0.0099***	0.0025	-0.0053*
unemployment	-0.0039	0.0003	-0.0033	0.0011	-0.0010	0.0026	-0.0026	0.0012
producer prices	0.0007	-0.0004	0.0016	0.0005	0.0034	0.0023	0.0017	0.0007
consumer prices	0.0025	0.0011	0.0025	0.0009	0.0017	0.0001	0.0021	0.0007
German economic news								
GDP pre.	-0.0097***	-0.0057	-0.0115***	-0.0071*	-0.0115**	-0.0074*	-0.0104***	-0.0063*
producer prices	-0.0007	-0.0001	-0.0010	-0.0003	-0.0013	-0.0008	-0.0010	-0.0004
other variables								
$term\ premium_{t-1}$	-0.9099	-0.5363	-0.9949	-0.6214	0.2033	0.4734	-0.6042	-0.2784
$D^{rec.}$	0.0054***	0.0052***	0.0069***	0.0068***	0.0069***	0.0069***	0.0061***	0.0059***
adj. R^2	0.0035	0.1251	0.0035	0.1293	0.0028	0.1078	0.0031	0.1273

4.6.2 Modifying the time period

During times of stress the "*flight-to-liquidity*" and "*flight-to-quality*" phenomenons might drive the here detected effect of order flow on risk premiums. We account for this possibility by splitting the sample into periods with and without financial stress. Financial stress is defined as the Russian default and the LTCM-crisis (1998–1999), the dot-com (2001–2002) and the subprime (2007–2009) asset price bubble.

Table 32 reveals only a marginal higher effect of order flow on bond risk. The adjusted R^2 increases above 15% and the corresponding t-statistic rises from 12 to 15 and suggests that order flow plays a more important role during financial stress periods. We note that during calm periods volatility innovations are priced in the risk premium but during times of stress this effect vanishes and liquidity conditions play an even higher role. This outcome might be a result of a search for liquidity and/or quality (Beber et al., 2009). However, the pricing effect of order flow is not affected by splitting the sample with respect to financial stress.

4.7 Conclusion

Possible components of the bond risk premium are economic-, inflation-, volatility-, jump-, liquidity- and information risk premiums. All of them are identified at a monthly or yearly frequency. The identification of determinants of daily risk premium innovations is scarce. Therefore, we apply the Adrian et al. (2012) term structure model and bring the search for determinants of bond risk premiums on a daily basis. Pricing factors are detached from possible risk premium determinants and are a mix of forward rates, -spreads (Cochrane and Piazzesi, 2008) and of the interest rate level (Balduzzi and Moneta, 2011). This paper merges macroeconomic- and finance-related aspects for an-

Table 32: Subsample analysis for boom and bust periods

This table reports regression results of the average term premium on the first order flow factor, the Amihud (2002) liquidity measure, the Move index and several macroeconomic news. Panel A reports results for the exclusion of financial stress periods which are defined as the years 1998–1999, 2001–2002 and 2007–2009. Panel B shows results for financial stress periods. The 10% (5%, 1%) significance level is marked with a * (**, ***). Robust standard errors (Newey and West, 1987) are used.

	maturity	
	mean	
variable	**Panel A** non-stress	**Panel B** stress
intercept	0.0000	0.0005
microstructure variables		
OF^{PC1}	-0.0114***	-0.0126***
$Move$	0.0577***	0.0307
$Illiq^{Amihud}$	-2.5140	16.0835**
US economic news		
GDP adv.	-0.0118**	-0.0025
GDP pre.	-0.0024	0.0053
GDP final	-0.0015	-0.0018
nonfarm payroll	-0.0010	0.0040
retail sales	-0.0012	-0.0033
ind. production	-0.0013	0.0053
personal income	-0.0110***	-0.0066*
home sales	-0.0034	-0.0041
constr. spending	0.0075	0.0043
factory orders	-0.0042	-0.0017
business inventories	-0.0001	-0.0048
housing starts	0.0039	0.0054*
producer prices	-0.0040	-0.0026
consumer prices	-0.0005	-0.0049
FOMC	0.0019	-0.0017
other variables		
$term\ premium_{t-1}$	-2.9242	5.2000**
adj. R^2	0.1108	0.1539

alyzing bond risk premiums by regressing risk premium innovations on macroeconomic and market microstructure variables.

Determinants of daily risk premiums look different to those which are documented at lower frequencies. Order flow dominates economic announcement releases for explaining risk premium innovations. This finding is new but should not surprise ex post as several hints suggest a link between the bond risk premium and order flow. Cochrane and Piazzesi (2008) work out that the bond risk premium is a compensation for bearing risk which is associated with the interest rate level. Order flow owns this level effect on yields (Brandt and Kavajecz, 2004) and is a determinant of monthly bond excess returns (Fricke, 2012).

At least, our results stand in contrast to Balduzzi and Moneta (2011) who document excess returns in the US bond future market at announcement days. We take the findings of Balduzzi and Moneta (2011) a step further and bring the focus on determinants of bond returns. These are macroeconomic announcements (Fleming and Remolona, 1997) and order flow (Brandt and Kavajecz, 2004, Green, 2004 and Pasquariello and Vega, 2007).

Does the dominating effect of order flow rules out an economic or inflation risk premium? We think not. Interpreting the order flow effect in its easiest way suggest that it stems from a changing risk tolerance of bond investors (see Evans and Lyons, 2002). Further, the majority of the market microstructure literature suggests that order flow incorporates latent/dispersed economic information (Menkveld et al., 2012, Pasquariello and Vega, 2007 and Green, 2004). Thus, our study does not rule out a relation of daily bond risk premium innovations to economic information. However, the link is not so clear as one might expect.

In sum, the documented link between bond risk and order flow reflects the outstanding role of order flow in financial markets. Order flow is linked to the above mentioned bond risk components: economic information (Pasquariello and Vega, 2007), volatility (Li et al., 2009), liquidity (Easley et al., 2011) and information risk (Li et al., 2009 and Easley et al., 2002).

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Final remarks

The European debt crisis, as the latest example in history, teaches us that sovereign bond investments bear substantial risk components. An insight which should be seen in a context with Sharpe (1964):

> "*..., the market presents him with two prices: the price of time, or pure interest rate ... and the price of risk, the additional expected return per unit of risk borne ...* "
>
> Sharpe (1964), p. 425.

With this background in mind, how should we understand the recent bond price rally of Northern European countries which led to zero or even negative interest rates? With central bank offer rates close to the zero-lower bound the price of time – the interest rate – becomes a negligible part. Thus, are sovereign bonds additional risk-free?

This thesis reveals that investors should be aware that even high-quality sovereign bonds bear substantial investment risks. As Section 2 reveals, even in the German bond future market, the most liquid market in Europe, investors are concerned about liquidity risk – even stronger since the collapse of Lehman Brothers. Further, investors care about order flow and its implied probability to trade with informed investors, which is also reflected in the term structure of interest rates. The effect is even more pronounced for term structure factors beside the classical pricing factors *level*, *slope* and *curvature*. These non-standard factors load on bond excess returns which can be understood as a compensation for bearing risk. Therefore, Section 3 and 4 especially link order flow to bond excess returns.

Be aware, that the financial press' explanation for the recent bond price rally is not related to underlying risk factors of the rallied bonds. Investors search relatively seen save assets which is known as the "*flight-to-liquidity*" and "*flight-to-quality* phenomenon (see Beber et al., 2009). It seems that during this ordinary time of financial stress investors fade out any risk components of government bonds of stable economies.

Therefore, let us hope that these bond markets which experienced several price rallies during the European debt crisis will own their liquidity and quality status in the future so that we will not see a "*flight-from-liquidity*"- and/or "*flight-from-quality*" phenomenon. History showed us the real-economy consequences of such a change of investors' risk perception – in recent times Greece, Ireland, Portugal, Spain and Italy.

The increasing importance of liquidity for pricing European peripheral bonds enforced the ECB to introduce the "*Outright Monetary Transactions (OMT)*" program.[48] The aim of this ECB program is to depress interest rates and the underlying risk premium by starting a bond buying program (see ECB, 2012a). Ex ante, the success of the OMT programm is questionable. Therefore, we try to evaluate the OMT program with the findings of this dissertation. For the US market, section 3 reveals nearly no pricing effect of liquidity on monthly bond excess returns – a crude measure of the bond risk premium. An increase of liquidity risk coincides with higher bond excess returns. However, the effect is limited to the short end of the yield curve which might also be a reason why the ECB conditions the OMT program to bonds with a maximum maturity of three years. When we regress expected excess returns on liquidity risk we do not find any effect which in sum might suggest that liquidity risk drives contemporaneous excess returns but is not such a strong concern such that it is priced in future excess returns through the expectation formation of future bond excess returns. For a deeper understanding of the relation of the bond risk premium to liquidity risk we compute daily bond risk premiums out of the US term structure (section 4). By sorting the sample for financial stress, we find a strong relation between liquidity risk and the bond risk premium. We see this as an indicator that liquidity risk is a possible driver of the risk premium of

[48]Note, that the Outright Monetary Transactions program will be started after the fulfilled condition that an European country is seeking aid from the ESM (see ECB, 2012a).

south Europe's and Ireland's stressed bond markets. As our findings are focused on one of the most liquid bond market, the results might be even stronger for the much more illiquid European peripheral bond markets.

In the short run the ECB's OMT might be successful in reducing interest rates be minimizing the bond risk premium which is associated with liquidity risk. However, section 3 reveals that long-run dynamics of bond markets are mainly driven by economic variables what should be kept in mind of politicians, economists and central bankers.

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