Empirical Studies on Central Banks' Expectations Management

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Diese Dissertation besteht aus drei Arbeitspapieren, von denen zwei in Zusammenarbeit mit jeweils einem Koautor entstanden sind.

- Winkelmann, Lars (2013):
  "Quantitative forward guidance and the predictability of monetary policy: a wavelet based jump detection approach",
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- Winkelmann, Lars und Bibinger, Markus (2013):
  "ECB monetary policy surprises: identification through cojumps in interest rates",
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Contents

General introduction and results

The last two decades have seen a tremendous change in both the conduct and the understanding of monetary policy. While still in the 1990s central banks were well known for their secrecy and often cryptic communication, nowadays central banks around the world prefer a clear and comprehensive communication that sets the basis for a transparent policy implementation.

A prime example for the trend towards greater transparency is the communication policy of the Federal Reserve (FED). It was until 1994 that the FED did not even announce its decisions on its key policy rate. Today, the FED publishes press releases about policy rate changes, releases minutes of decision taking meetings and started to publish projections of the key interest rate more than two years into the future.

Reasons for the dramatic change in central banking are often discussed in the context of improved information processing technologies (e.g. Woodford, 2001) and increased political demands for accountability and transparency of public institutions (e.g. Geraats, 2002). Furthermore, Dynamic Stochastic General Equilibrium (DSGE) models that emphasize the forward-looking nature of the economy have become the standard tool for macroeconomic analysis, see e.g. Goodfriend (2005) and Galí (2008).

In this new framework, the efficiency of monetary policy is no longer determined by central banks' ability to surprise markets but by their ability to guide markets. Monetary policy aims at *managing expectations* in the economy. As put forward by Morris and Shin (2008), monetary policy describes a strategic problem where instruments under the direct control of central banks are less important than the messages central banks send out. But how easy is it to use communication to manage expectations and what are the costs and benefits of doing so? An extensive literature, partly reviewed by Blinder et al. (2008), has made several advances. However, significant questions remain open: Can transparency go too far? How sensitive is the success of the expectations management during an economic crisis?

The present thesis comprises three individual papers that all provide new empirical evidence to recent questions of the expectations management literature. Considering time periods around 2001 to 2012, a challenge faced in all three papers is to adequately consider effects of the recent global financial and European sovereign debt crisis. To that aim, powerful econometric tools are developed that evaluate central bank guidance and market expectations before and during crisis periods. Throughout the thesis, measures of market expectations are derived from the term structure of interest rates. While the first two papers focus on instantaneous effects of policy announcements, the third paper focusses on the duration of these effects, i.e. the long run dynamics. Main contributions of the present thesis can be summarized as follows:

- ***Paper 1***: "Quantitative forward guidance and the predictability of monetary policy: a wavelet based jump detection approach"

  In the first paper, a new wavelet technique is proposed to assess the link between central banks' interest rate projections and the predictability of monetary policy. Referring to the Norwegian example, the study compares jump probabilities on central bank announcement days before and after the introduction of the interest rate projections. The main result indicates that the projections significantly improve the predictability of monetary policy.

  This result gains in importance due to the fact that more and more central banks introduce interest rate projections, but often with different implementation modalities. While currently there is little empirical evidence about significant benefits of interest rate projections, the Norwegian approach appears as a successful example.

- ***Paper 2***: "ECB monetary policy surprises: identification through cojumps in interest rates"

  In the second paper, a test for cojumps is introduced to evaluate markets' perceptions of monetary policy announcements. Based on announcements of the European Central Bank, the test detects the occurrence of a surprise and identifies whether interest rates reflect adjustments to news about the state of the economy or reflect adjustments to changes of policy preferences. Empirical evidence suggests that markets' perceptions about policy preferences have been remarkably stable.

  The result indicates a sufficiently transparent and credible communication of policy preferences – particularly during crisis times. The result also suggests that enhanced communication about future economic conditions may further increase the effectiveness of monetary policy.

- ***Paper 3***: "Assessing the anchoring of inflation expectations"

  The third paper proposes a smooth-transition model to assess the anchoring of inflation expectations. A new data set of daily inflation expectations is derived for the United States, United Kingdom, European Monetary Union and Sweden. Results suggest that inflation expectations are well anchored in all countries under investigation. Expectations in the United Kingdom during a crisis period indicate signs of instability.

  Empirical evidence suggests that expectation formation processes are successfully controlled by central banks. The relevance of this finding is emphasized by the fact that the traditional approach to assess the anchoring of inflation expectations suggests that expectations have become equally distorted since the outbreak of the global financial crisis in 2008.

The overall goal of the present thesis is to contribute to a thorough understanding of key economic concepts behind the expectations management of central banks. I hope that the empirical results, policy conclusions and econometric tools are helpful when rethinking or monitoring current policy strategies. Besides the practical value, I hope that the thesis motivates future research. Explicit suggestions for future research are given at the end of each paper.

Allgemeine Einleitung und Resultate

In den vergangenen zwei Jahrzehnten haben sich sowohl das Verständnis von Geldpolitik als auch die Art und Weise, wie Geldpolitik implementiert wird, extrem gewandelt. Während noch in den 1990er Jahren Zentralbanken für ihr hohes Maß an Geheimhaltung und eine kryptisch erscheinende Kommunikation bekannt waren, folgen sie heutzutage klaren und umfassenden Kommunikationsstrategien, die die Grundlage für eine transparente Geldpolitik bilden.

Ein Paradebeispiel für den Trend zu mehr Transparenz ist die Kommunikationsstrategie der Federal Reserve (FED), der Zentralbank der Vereinigten Staaten von Amerika. Bis 1994 hat die FED nicht einmal ihre Entscheidungen über den Leitzins verkündet. Heute veröffentlicht die FED Pressemitteilungen über Leitzinsänderungen, Protokolle von entscheidungstreffenden Sitzungen und Projektionen des Leitzinses mehr als zwei Jahre in die Zukunft.

Als Gründe für den dramatischen Wandel in der Kommunikation von Zentralbanken werden oft die revolutionären Entwicklungen der Informationstechnologien (z.B. Woodford, 2001) und die verstärkten politischen Forderungen nach Rechenschaftspflicht und Transparenz öffentlicher Institutionen (z.B. Geraats, 2002) genannt. Des Weiteren sind Dynamisch Stochastisch Allgemeine Gleichgewichtsmodelle (DSGE Modelle), die den in die Zukunft gerichteten Charakter der Wirtschaftssubjekte betonen, zum neuen Standard makroökonomischer Analysen geworden, siehe z.B. Goodfriend (2005) und Galí (2008).

In diesem neuen Rahmen ist die Effizienz von Geldpolitik nicht durch die Fähigkeit von Zentralbanken bestimmt, Märkte mit ihren Entscheidungen zu überraschen, sondern durch ihre Fähigkeit, Markterwartungen über zukünftige Entscheidungen zu leiten. Die Geldpolitik von Zentralbanken verfolgt das Ziel, Erwartungen von Wirtschaftssubjekten zu managen. Wie von Morris und Shin (2008) zum Ausdruck gebracht, beschreibt Geldpolitik damit ein strategisches Problem, bei dem Instrumente unter der direkten Kontrolle von Zentralbanken weniger bedeutsam sind als die Nachrichten, die Zentralbanken senden. Aber wie einfach ist es, mit Hilfe von Kommunikationsstrategien Erwartungen zu steuern und was sind die Kosten und der Nutzen dieser Strategien? Eine umfangreiche Literatur zum Erwartungsmanagement, die teilweise durch Blinder et al. (2008) zusammengefasst wird, widmet sich dieser zentralen Frage und hat bereits große Fortschritte erzielt. Dennoch bleiben wichtige Fragen offen: Kann Transparenz zu weit gehen? Wie anfällig ist der Erfolg des Erwartungsmanagements während einer Wirtschaftskrise?

Die vorliegende Arbeit besteht aus drei einzelnen Arbeitspapieren, die alle neue empirische Ergebnisse zu aktuellen Fragen des Erwartungsmanagements liefern. Basierend auf Untersuchungszeiträumen von 2001 bis 2012 sind alle drei Papiere mit der Herausforderung konfrontiert, die jüngste globale Finanzkrise und europäische Staatsschuldenkrise angemessen zu berücksichtigen. Zu diesem Zweck werden in dieser Arbeit ökonometrische Werkzeuge entwickelt, die den Zusammenhang von Zentralbankkommunikation und Markterwartungen vor und in Krisenzeiträumen auswerten. In allen drei Papieren werden Markterwartungen aus der Zinsstrukturkurve abgeleitet. Während die ersten beiden Papiere den sofortigen bzw. unmittelbaren Einfluss von Zentralbankkommunikation auf Markterwartungen untersuchen, fokussiert das dritte Papier auf die Dauer der Wirkung solcher unmittelbaren Effekte. Die wichtigsten Beiträge der vorliegenden Arbeit können wie folgt zusammengefasst werden:

- ***Paper 1***: "Quantitative forward guidance and the predictability of monetary policy: a wavelet based jump detection approach"

  Im ersten Papier wird ein neues Wavelet-Verfahren für die Untersuchung des Zusammenhangs zwischen Zinsprojektionen von Zentralbanken und der Vorhersagbarkeit von geldpolitischen Entscheidungen vorgeschlagen. Auf Grundlage der Geldpolitik in Norwegen werden Sprungwahrscheinlichkeiten an Geldpolitiktagen vor und nach der Einführung von Zinsprojektionen verglichen. Das entscheidende Ergebnis zeigt, dass die Projektionen die Vorhersagbarkeit geldpolitischer Entscheidungen signifikant verbessern.

Dieses Ergebnis ist besonders bedeutsam, da aktuell mehr und mehr Zentralbanken Zinsprojektionen einführen, jedoch häufig mit unterschiedlichen Umsetzungsmodalitäten. Da wenig empirische Evidenz über signifikante Vorteile der Projektionen vorliegt, erscheint der norwegische Ansatz als ein erfolgversprechendes Beispiel.

- ***Paper 2***: "ECB monetary policy surprises: identification through cojumps in interest rates"

  Im zweiten Beitrag wird ein Test für Kosprünge eingeführt, um zu bewerten, wie Märkte geldpolitische Ankündigungen wahrnehmen. Basierend auf Meldungen der Europäischen Zentralbank (EZB) deckt der Test zum einen das Auftreten einer unerwarteten geldpolitischen Entscheidung auf, zum anderen unterscheidet der Test, ob die Zinsstruktur Anpassungen an Neuigkeiten über den Zustand der Ökonomie oder Veränderungen geldpolitischer Präferenzen widerspiegelt. Die empirischen Ergebnisse deuten darauf hin, dass die Märkte die Präferenzen der EZB als bemerkenswert stabil empfinden.

  Die Ergebnisse zeigen, dass geldpolitische Präferenzen ausreichend transparent und glaubwürdig kommuniziert werden. Dies gilt insbesondere in Krisenzeiten. Die Ergebnisse implizieren auch, dass eine verstärkte Kommunikation über die zukünftige wirtschaftliche Entwicklung die Effektivität der Geldpolitik weiter erhöhen kann.

- ***Paper 3***: "Assessing the anchoring of inflation expectations"

  Das dritte Papier schlägt ein Smooth-transition Modell vor, durch das die Verankerung von Inflationserwartungen bewertet werden kann. Ein neuer Datensatz täglicher Inflationserwartungen für die Vereinigten Staaten, Großbritannien, die Europäische Währungsunion und Schweden wird erzeugt und untersucht. Die Ergebnisse legen nahe, dass die Inflationserwartungen in allen untersuchten Ländern gut verankert sind.

Die Inflationserwartungen in Großbritannien während einer Krisenperiode zeigen Anzeichen von Instabilität.

Die Ergebnisse zeigen, dass Erwartungsprozesse von Zentralbanken erfolgreich gesteuert werden. Die Relevanz dieses Befundes wird durch die Tatsache hervorgehoben, dass der traditionelle Ansatz zur Messung der Verankerung von Inflationserwartungen gleichermaßen verzerrte Erwartungen seit dem Ausbruch der globalen Finanzkrise im Jahr 2008 impliziert.

Das übergeordnete Ziel der vorliegenden Arbeit ist es, zu einem umfassenden Verständnis wichtiger Konzepte des Erwartungsmanagements von Zentralbanken beizutragen. Ich hoffe, dass die empirischen Ergebnisse, Schlussfolgerungen und ökonometrischen Werkzeuge hilfreich beim Überdenken oder Überwachen aktueller Kommunikationsstrategien sind. Über den praktischen Wert hinaus hoffe ich, dass diese Arbeit zukünftige Forschung motiviert. Explizite Vorschläge für bedeutende Fragestellungen werden am Ende jedes Papiers gegeben.

1 Quantitative forward guidance and the predictability of monetary policy: a wavelet based jump detection approach

1.1 Introduction

Guiding expectations about future policy decisions has become a standard practice of central banks around the world. Beside setting a very short term interest rate, i.e. the key rate, the expectations management about future key rate settings is an important instrument of monetary policy. However, specific techniques to manage expectations are remarkably different, see Blinder et al. (2008). Most central banks, including the Bank of England and the European Central Bank, give only *qualitative* signals about the likely direction of the next few policy decisions. In contrast, a small but increasing number of central banks implement a *quantitative* strategy by publishing numerical projections of key rates up to three years into the future.[1]

[1] Central banks that guide quantitatively are the Reserve Bank of New Zealand (since 1997), the Norges Bank (since 2005), the Swedish Riksbank (since 2007), the Czech National Bank (since 2008), the Sedlabanki Islands (since 2007) and, in a slightly different way, the Federal Reserve (since 2012).

From both a theoretical and empirical perspective, there is a controversy about *quantitative* guidance. Mishkin (2004) addresses the concern that markets misinterpret the projections as a commitment to future policy decisions. Morris and Shin (2002) and Rudebusch and Williams (2008) show that central banks' projections may crowd out private forecasts which results in even worse outcomes relative to the case of no central bank guidance. While empirical papers such as Detmers and Nautz (2012), Ferrero and Secchi (2009) and Moessner and Nelson (2008) find significant responses of market interest rates to a published policy path, advantages of *quantitative* guidance compared to *qualitative* guidance are not established yet. A cross-country, event-study by Kool and Thornton (2012) suggests that adjustments of interest rates on monetary policy announcement days do not depend on the guidance regime. In the same vein, the GARCH approach of Andersson and Hofmann (2009) indicates equally likely policy surprises irrespective of whether forward guidance involves the publication of an own interest rate path or not.

The current paper proposes a jump detection approach to investigate whether a change in the guidance strategy from *qualitative* to *quantitative* guidance increases the predictability of monetary policy. We follow the analogy of Das (2002) and Piazzesi (2005), and identify monetary policy surprises through jumps in interest rates on policy announcement days. Due to relatively short sample periods of quantitative guidance, combined with occasional, extraordinary market responses to central bank announcements, it appears beneficial to avoid inference on magnitudes of policy surprises. Parameter estimates of conventional event-study approaches are usually dominated by a small fraction of extreme values. Applying standard distributional assumptions renders it difficult to find any statistically significant difference between sample estimates. Therefore, we focus on a binary jump variable. The relative number of jumps within a *qualitative* and *quantitative* guidance period serves as a statistic to test the main hypothesis of less policy surprises during the period of key rate projections.

Estimation and testing for jumps in financial data usually refers to semimartingales which constitute a wide class of continuous time, stochastic processes. In the literature on non-parametric inference on semimartingales, several approaches have been proposed to separate a diffusion and jump part given discrete observations. Estimates of both components refer to the quadratic variation made up as the sum of the integrated volatility and the jump variation, see e.g. Aït Sahalia and Jacod (2012) and Dumitru and Urga (2012). However, most methods like the bi-power variation of Barndorff-Nielsen and Shephard (2004) are not meant to localize the exact timing of jumps. To localize jumps, Lee and Mykland (2008) and Andersen et al. (2007) propose a t-test-type approach performed on each return standardized by the bi-power variation. Similarly, Mancini (2009) and the extension of Podolskij and Ziggel (2010) rely on the realized volatility and bi-power variation and utilize a thresholding technique on squared return series to locate jump points. Instead of thresholding returns directly, Fan and Wang (2007) propose a more comprehensive approach and use coefficients of a discrete, decimated wavelet transform. With the wavelet transform the information on jump locations and variation is stored at high-resolution levels (fine scales) while useful information for integrated volatility is captured by low-resolution levels (coarse scales). The variance of the integrated volatility estimator benefits from the orthogonality of the decimated transform. However, the orthogonality came at the price of localizing jumps at dyadic locations only. Furthermore, no straightforward expression for increments in the quadratic variation can be derived.

The methodology proposed here extends the wavelet approach of Fan and Wang (2007) to the discrete, non-decimated wavelet transform. We establish a pointwise decomposition of the quadratic variation, which we finally use to detect jump points. The decomposition is considered in the context of Locally Stationary Wavelet (LSW) process of Nason et al. (2000) and van Bellegem and von Sachs (2008). Given the link between a discretely sampled semimartingale and the class of LSW processes, we derive a representation of the quadratic variation in terms of a wavelet spectrum. Since the local regularity of a semimartingale translates to its wavelet spectrum, jump points of an observed process can be detected via wavelet spectrum estimates. A smooth version of the adaptive threshold estimator of von Sachs and MacGibbon (2000) applied to the spectrum localizes jumps of the underlying semimartingale.

Empirical evidence refers to the Norwegian example. The case of Norway provides a sufficiently long history of six years of key rate projections. Furthermore, it allows observations of a 2001 to 2011 sample to be partitioned into a qualitative and quantitative guidance period. The main results on daily short and long term interest rates indicate: First, quantitative guidance does not further improve the predictability of current policy decisions. Second, switching from qualitative to quantitative guidance significantly decreases revisions of markets' expectations about future policy decisions. Since a qualitative guidance strategy already implies a high level of short term guidance, we conclude that quantitative guidance significantly enhances the transparency about the decision making process of monetary policy and improves the longer-term predictability of central banks.

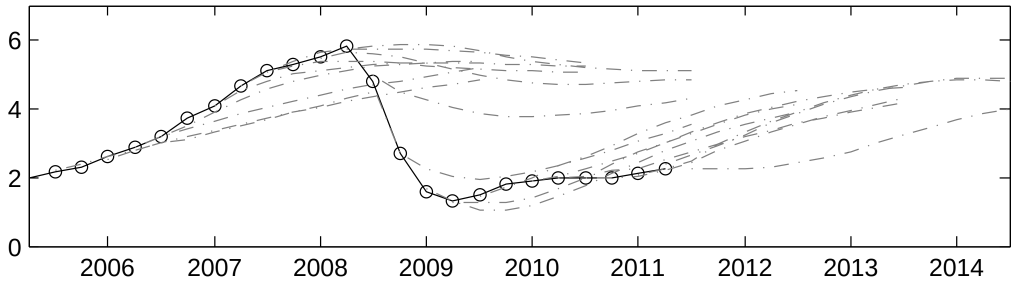
The remainder of the paper proceeds as follows. Section 1.2 highlights the rational of central banks' forward guidance and provides examples of qualitative and quantitative guidance. The Norwegian interest rate data is introduced in the context of target and path surprises in Section 1.3. The economic hypotheses are formulated in Section 1.4. Section 1.5 introduces the jump detection approach and the estimator of jump probabilities. Section 1.6 contains the empirical part. We show estimates of wavelet spectra and jump probabilities as well as results of the hypothesis tests. Section 1.7 concludes.

1.2 Monetary policy guidance: the Norwegian example

Central Banks' main instrument to reach the goal of price stability is a very short term interest rate, i.e. the key rate.[2] It is, however, not the short end of the term structure but a longer rate that affects economic conditions. Therefore, the transmission of monetary policy to longer-term rates is of crucial importance. Relations between short and longer-term interest rates are usually discussed in

[2] In Norway, the key rate is the overnight deposit rate. Decisions on the key rate are made on monetary policy announcement days every sixth week, see Norges Bank (2009).

Figure 1.1: The Norges Bank's key rate projections.



Notes: Quarterly average of the actual key rate (black, solid line) and projections in the baseline scenario (gray, dashed lines) from Nov. 2005 to Dec. 2011. Circles highlight projection days. The key rate is given in percentage points.

the context of the expectations hypothesis. Its simplest, linearized form is given by:

$$R_t^{(n)} = \frac{1}{n}\left(r_t + \sum_{i=1}^{n-1} \mathbb{E}_t(r_{t+i})\right), \tag{1.1}$$

where $R_t^{(n)}$ denotes the interest rate at time t and maturity $n > 1$, r_t is the short term rate with $n = 1$ and $\mathbb{E}_t$ is the expectations operator with respect to information available at t. The expectations hypothesis highlights that steering the very short end of the term structure, r_t, has only minor effects on longer-term yields, $R_t^{(n)}$. What matters is the path of expected future short rates, $\sum_{i=1}^{n-1} \mathbb{E}_t(r_{t+i})$. Therefore, central banks have implemented communication strategies to manage expectations about a future policy path.

Most central banks adopt a qualitative guidance strategy. The technique provides hints on the most likely direction of the next few key rate changes. An example of qualitative guidance is given in a talk of the Norges Bank's governor, Gjedrem (2003): "We have experienced a period of monetary policy easing. This period is not over." While this statement is precise about the sign of the next policy move, its magnitude and implications for subsequent key rate changes remains vague. From 2001 to 2005 such qualitative hints within speeches, interviews and press conferences constitute the Norges Bank's guidance strategy.

A relatively new strategy, that has gained in importance in recent years, is quantitative guidance. Central banks that guide quantitatively are much more explicit about their future policy assessments. They provide a path of numerical values of future key rates on pre-announced publication days. In November 2005 the Norges Bank has replaced its qualitative guidance strategy by quantitative guidance. Since then numerical values of a projected path of future key rates are published at every third monetary policy announcement day. Figure 1.1 illustrates the Norges Banks's history of quantitative guidance. Each dashed line belongs to a projected path that reflects quarterly averages of the key rate up to three years into the future.[3]

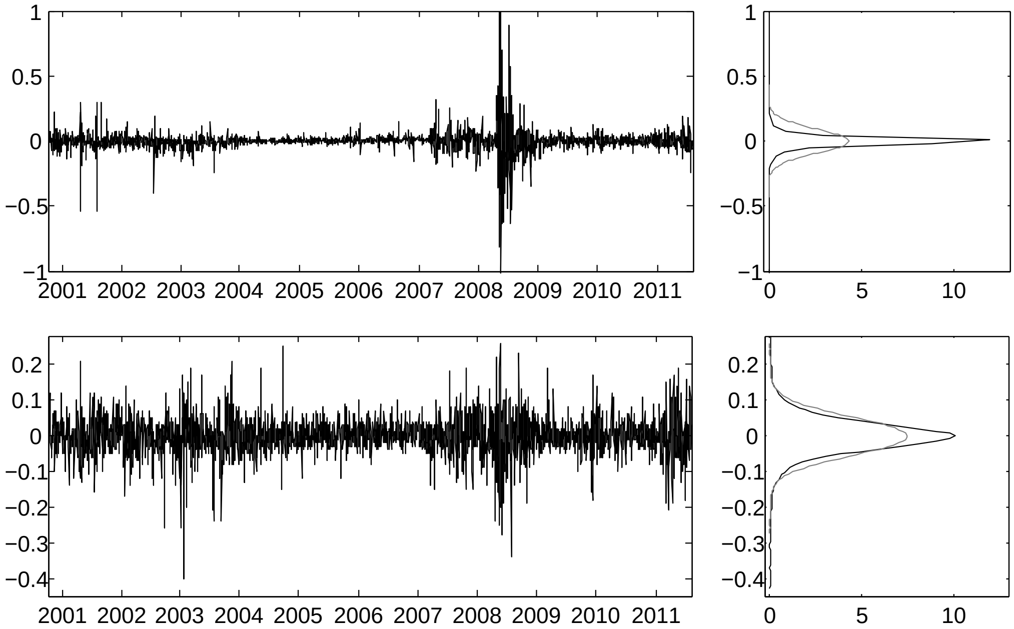
The main goal of quantitative guidance is to enhance the efficiency of monetary policy. As highlighted by Svensson (2006), given a path of expected future key rates along with forecasts of major macroeconomic variables, a central bank's reaction function becomes more explicit. Consequently, under stable central banks' preferences, quantitative guidance should reduce the need of market adjustments on policy announcement days, thus, enhance the predictability of monetary policy.

1.3 Target and path surprises

We distinguish between the short term and long term predictability of monetary policy by referring to the target and path surprise framework introduced by Gürkaynak et al. (2005). With respect to the expectations hypothesis (1.1), target and path surprises are based on the driving forces behind short and longer-term interest rates. A target surprise is defined as an unexpected key rate change. According to (1.1), the key rate is a major component of shorter-term interest rates. Since decisions on the Norges Bank's key rate are made every sixth week, we define jumps in 1 month Norwegian money market rates on monetary policy announcement days as an indicator of unexpected policy decisions. In contrast

[3]Projections are published in Monetary Policy Reports. Further information about the underlying model and additional criteria are provided in Brubakk et al. (2006) and Qvigstad (2006).

Figure 1.2: 1 month and 3 year interest rates and return density functions.



Notes: Daily changes in 1 month (upper part) and 3 year (lower part) interest rates in percentage points. The right hand plots show the estimated probability density function (black) and a corresponding normal density (grey).

to shorter-term rates, longer-term rates are mainly driven by expectations about future key rates. Therefore, the path surprise measures the degree to which market participants revise their expected monetary policy path following the actual decision or aspects of policy guidance. We interpret jumps in a 1 year money market rate and a 3 and 5 year Norwegian government bond rate on monetary policy announcement days as evidence about revisions in market's expectations about future policy decisions.[4]

We assess target and path surprises for a sample period from March 2001 to December 2011. The starting date of our sample is marked by the introduction of inflation targeting in Norway. The sample includes a total of 2721 daily obser-

[4]See Gürkaynak et al. (2007a) for an overview of different surprise measures.

vations, including 94 policy announcement days.[5] Figure 1.2 gives an example of the data. The figure depicts day to day changes of the 1 month and 3 year Norwegian interest rates in conjunction with estimates of the respective return probability density function. Norwegian interest rates reflect the well known and often cited stylized facts of financial return series: the sample mean is close to zero, the marginal distribution is slightly skewed and heavily tailed, volatility is clustered while the autocorrelation of adjacent returns appears to be small. In particular, the leptokurtic shape of the density functions indicates the presence of jumps. We aim at detecting these jumps to assess the predictability of monetary policy.

1.4 Economic hypotheses

To assess the impact of the guidance strategy on the predictability of monetary policy, we define three economic hypotheses. Each hypothesis refers to a specific classification of monetary policy announcement and non-announcement (all other days) days. In particular, we distinguish between a qualitative and a quantitative guidance period. The criterion to assess the predictability are jump probabilities.

News-hypothesis: *Monetary policy announcements contain relevant news. The announcements induce significant target and path surprises.*

We call target and path surprises significant if jump probabilities on announcement days are significantly larger than on non-announcement days. The verification of the News-hypothesis across the qualitative and quantitative guidance samples already provides a first indication about an impact of the guidance strategy. However, shifts in target and path surprises can be driven by a change of jump probabilities on non-announcement days. Therefore, our main focus is on the predictability across the qualitative and quantitative guidance periods.

[5]The data is available on the Norges Bank's web page: http://www.norges-bank.no.

Guidance-hypothesis: *Quantitative guidance enhances the predictability of monetary policy. Quantitative guidance induces significantly less target and path surprises than qualitative guidance.*

Less target surprises imply a decrease in jump probabilities of the 1 month rate. A significant decrease determines improvements in the short term predictability of monetary policy. In contrast, less path surprises are identified by a decrease in jump probabilities of the 1, 3 and 5 year interest rates. A significant decrease enhances the longer-term predictability of monetary policy. As a control for an overall decrease of jump probabilities, we state the Jump-level-hypothesis.

Jump-level-hypothesis: *The overall level of jump probabilities of interest rates is constant across the qualitative and quantitative guidance sample.*

We evaluate the Jump-level-hypothesis via jump probabilities on non-announcement days. The three hypotheses are further formalized in Table 1.2. If both, the Guidance- and Jump-level-hypothesis hold true, we deduce that quantitative guidance significantly increases the short and longer-term predictability of monetary policy.

Important for a valid analysis of our hypothesis: Since 2003 the Norges Bank provides hints about future policy decisions on policy announcement days only, see Holmsen et al. (2008). Thus, monetary policy surprises are not artificially reduced by information given between announcement days.

In the next section we propose a jump detection approach for the daily interest rate data. The jump detection provides a first step in the estimation of jump probabilities.

1.5 Methodology

1.5.1 Semimartingales and Locally Stationary Wavelet processes

Following the standard literature on asset price modeling (see e.g. Aït Sahalia and Jacod 2012), we assume the yield $X = (X_t)_{t\in[0,1]}$ of a specific maturity to be a semimartingale.

$$dX_t = \mu_t dt + \sigma_t dB_t + dJ_t, \quad t \in [0,1] \tag{1.2}$$

For the present empirical investigation, the $t \in [0,1]$ interval refers to the whole sample period from 2001-2011. The terms on the right hand side of (1.2) correspond to the drift, diffusion and jump part of X. B_t is a standard Brownian motion and the diffusion variance σ_t^2 is called the spot volatility. To detect jumps in X which reflect surprise elements, it is informative to consider a compound Poisson jump part. Hence, we assume J_t to consist of a Poisson process N_t, that counts the number of jumps up to time t. The jump size at time t is $\Delta J_t = J_t - J_{t-}$. Estimates of the quantities in (1.2) are usually build on the quadratic variation,

$$QV_t = \int_0^t \sigma_s^2 ds + \sum_{\ell=1}^{N_t} (\Delta J_\ell)^2, \quad t \in [0,1], \tag{1.3}$$

including the integrated volatility and the jump variation. The focus of our investigation is on the process N_t. In particular, we are interested in daily time intervals on $[0,1]$ where N_t increases by one.

With daily data at hand, we approximate the semimartingale at T equally spaced, discrete time points $t_i = i/T, i = 1, ..., T$. The sampling of the increments of the semimartingale gives a (mean zero) sequence $\Delta X = (\Delta X_{t_i})_{t_i\in(0,1]}$, with daily differences $\Delta X_{t_i} = X_{t_i} - X_{t_{i-1}}$, $i = 1, ..., T$. Following the definition of Locally Stationary Wavelet (LSW) processes of Nason et al. (2000) and the generalization of van Bellegem and von Sachs (2008), we can write the sampled increments of the semimartingale in terms of a LSW process. The mean-square representation of the sampled increments from (1.2) is given by:

$$\Delta X_{t_i} = \sum_{j=-\infty}^{-1} 2^{j/2} \sum_{k=-\infty}^{\infty} W_j(t_k) \psi\left(\frac{t_k - t_i}{2^j}\right) \xi_{j,t_k}, \quad t_i = i/T,\ i = 1, ..., T, \tag{1.4}$$

with a scale j and location t_i dependent transfer function $W_j : (0,1] \to \mathbb{R}$, a non-decimated wavelet system $\left(2^{j/2}\psi(\cdot)\right)_{j,t_k}$ generated via dilation (j) and translation (t_k) of a mother wavelet ψ and a zero mean orthonormal identically distributed random process ξ_{j,t_k}. For ease of presentation, LSW processes are usually build on the simplest discrete non-decimated system, called the Haar system. However, in general any function that satisfies time-frequency localization properties can be used as a mother wavelet, compare Fryzlewicz and Nason (2006) and the admissibility conditions in Daubechies (1992, Sec. 1.3).[6] Out of (1.4), the quantity of interest is the wavelet spectrum

$$S_j(t_i) = W_j^2(t_i), \quad j = -1, -2, \dots \,. \tag{1.5}$$

Paralleling classical Fourier spectral analysis, the wavelet spectrum provides a decomposition of the process' variance. The larger the wavelet spectrum at scale j and time point t_i, the more dominant is the contribution of scale j in the variance at time t_i. In the present context of semimartingales, the spectrum $S_j(t_i)$ is considered a decomposition of the quadratic variation. Given (1.4), from Proposition 1 of van Bellegem and von Sachs (2008) and the wavelet integrated volatility of Høg and Lunde (2003) and Fan and Wang (2007), a representation of the quadratic variation in terms of the LSW spectrum carries over:

$$\mathrm{QV}_{t_i}^{(LSW)} = \sum_{s=1}^{i} \sum_{j=-\infty}^{-1} S_j(t_s), \quad t_i = i/T,\ i = 1, ..., T. \tag{1.6}$$

The LSW representation transmits the local regularity of X to the wavelet spectrum $S_j(t_i)$ at scale $j = -1, -2, ...$ and time point t_i. Since the jump part J_t constitute a high frequent characteristic of the underlying process, it materializes at the fine scales of the wavelet spectrum. Lower-resolution levels capture the integrated volatility. The different decay orders of wavelet coefficients of the Brownian and jump part formulated by Fan and Wang (2007) translate to the wavelet spectrum and allow the jump detection via thresholding.

[6] Small scales j correspond to low frequencies, while scales approaching -1 correspond to high frequencies. For an introduction to wavelets see Daubechies (1992) and Vidakovic (1999). In our application, ΔX outside the $(0,1]$ interval are captured by the reflection boundary condition. However, to ease notation, in the following boundaries are treated in the sense of zero padding.

1.5.2 Jump localization on wavelet spectrum estimates

As introduced by Nason et al. (2000), the expansion of an observed process ΔX, on a non-decimated wavelet system $\left(2^{j/2}\psi(\cdot)\right)_{j,t_k}$ defines an estimator of the wavelet spectrum. The wavelet periodogram at time point t_i and resolution level j is given by:

$$I_j(t_i) = 2^j \left(\sum_{k=1}^{T} \Delta X_{t_k} \psi \left(\frac{t_k - t_i}{2^j} \right) \right)^2, \quad j = -J, ..., -1,\ t_i = i/T,\ i = 1, ..., T, \tag{1.7}$$

with $-J = \lfloor -\log_2 T \rfloor$ the coarsest scale. As in the Fourier case, the periodogram is not a consistent estimator of the spectrum (1.5). For fixed scales j, its expected value is $\mathbb{E}\left(I_j(t_i)\right) = \sum_{\ell=-J}^{-1} A_{j\ell} S_\ell(t_i)$, where $A_{j\ell}$ are elements of the invertible, inner product matrix of the autocorrelation wavelets, see van Bellegem and von Sachs (2008).[7] Compared to the decimated wavelet transform, the bias is the price to pay for the better time resolution of the non-decimated transform.[8] However, as the expected value of the periodogram suggests, (asymptotic) unbiasedness can be achieved by pre-multiplying (1.7) with the elements of the inverted, inner product matrix:

$$\hat{S}_j^{(UB)}(t_i) = \sum_{\ell=-J}^{-1} A_{j,\ell}^{-1} I_\ell(t_i) \tag{1.8}$$

is the unbiased spectrum estimator. The consistent estimator of the spectrum is an appropriately smoothed version of (1.8) across time, denoted by $\hat{S}_j(t_i)$, see e.g. Fryzlewicz and Nason (2006).

We simply deduce, since $\hat{S}_j(t_i)$ is a consistent estimator of the local variation for each scale j and time point t_i, $\sum_j \hat{S}_j(t_i)$ is a consistent estimator of the increment in the quadratic variation of X at t_i. Additional summation across time, $\sum_{t_i} \sum_j \hat{S}_j(t)$, provides the LSW estimator of the quadratic variation (1.6). The

[7] Note that A is not simply the identity matrix since the non-decimated system is not orthogonal.

[8] The use of the decimated wavelet transform gives values of I_j at dyadic time points $t_i 2^j$, $i = 1, ..T, j = -J, ..., -1$, only. The decimated transform does not allow the local variance to be written as a wavelet spectrum, see van Bellegem and von Sachs (2008).

estimator parallels the expression of the wavelet realized volatility in Fan and Wang (2007). However, in contrast to Fan and Wang (2007), the summation object $\hat{S}_j(t_i)$ has the crucial advantage of a more detailed time resolution and a direct statistical meaning as a consistent decomposition of the quadratic variation. In particular, the detailed time resolution of $\hat{S}_j(t_i)$ allows for a pointwise localization of jumps.

To detect the jumps, we define an upper bound of a spectrum $\tilde{S}_j(t_i)$ at time point t_i and scale j that contains the drift and diffusion part of (1.2) only, i.e. $\tilde{S}_j(t_i)$ belongs to a process without jumps. Focusing on high resolution levels $j \to -1$, we localize jumps in X by

$$\hat{N}_{j,t_i} = \sum_{s=1}^{i} \mathbb{1}\left(\hat{S}_j(t_s) \geq \tilde{S}_j(t_s)\right), \quad t_i = i/T,\, i = 1, ..., T. \tag{1.9}$$

At fine resolution levels j, the indicator function $\mathbb{1}(\cdot)$ equals one whenever the estimated spectrum $\hat{S}_j(t_i)$ exceeds the upper bound of the spectrum $\tilde{S}_j(t_i)$ without jumps. $\tilde{S}_j(t_i)$ can be considered a smooth version of the time varying threshold of von Sachs and MacGibbon (2000).

$$\tilde{S}_j(t_i) = (n+1)^{-1} \sum_{k=-n/2}^{n/2} \hat{S}_j(t_{i-k})\delta^2(n), \tag{1.10}$$

with $n << T$ a positive, even number and $\delta(n)$ a reasonable threshold criterion. One choice of criterion is that of the universal threshold, i.e. $\delta(n) = \sqrt{2 \log n}$, see e.g. Wang (1995). Since the threshold $\tilde{S}_j(t_i)$ is time varying and depends on the spectrum, the number of detected jumps is not artificially increasing on local time intervals where the integrated volatility is high. The adaptiveness appears as an advantage compared to usually employed global tuning parameters. In the empirical application we do not consider a comparison of different scales j, see the discussion of Raimondo (1998), but follow Wang (1995) and Fan and Wang (2007) and refer to the finest scale $j = -1$. Thus, we detect a jump at t_i if $\hat{N}_{-1,t_i} - \hat{N}_{-1,t_{i-1}} = 1$.

Based on the spectrum estimates, we are now in the position to localize the jump points of the observed interest rate data. In order to test the economic hypotheses formulated in Section 1.4, we next define an estimator of jump probabilities.

1.5.3 Jump probabilities

The main statistic to test for an impact of increased forward guidance are jump probabilities $p_{\mathcal{M}}$ on different subsets of the date vector, $\mathcal{M} \subset [t_1, ..., t_T]$. The sets belong to either policy announcement days or days without policy announcements. Furthermore, we distinguish between a qualitative and a quantitative guidance period. Table 1.1 gives a precise formulation of the different sets $\mathcal{M}$. To estimate the jump probabilities for each set, we localize the jumps from the daily interest rate data via wavelet spectrum estimates. The number of jumps for the whole observation period is given by $\hat{N}_{j=-1,t_T=1}$ from (1.9). Restricting the detected number of jumps to sets $\mathcal{M}$, provides the jump probability estimator

$$\hat{p}_{\mathcal{M}} = h^{-1}\hat{N}^{\mathcal{M}}_{-1,1}, \tag{1.11}$$

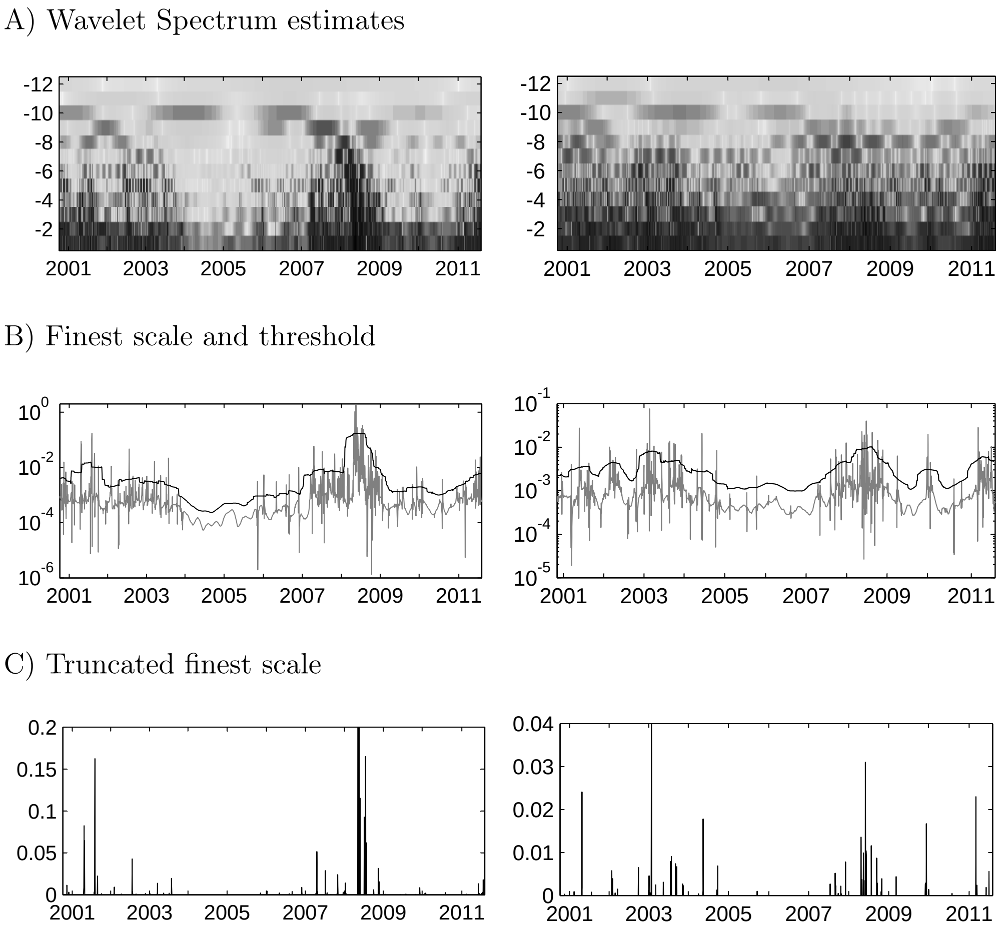
with h the number of days that belong to $\mathcal{M}$. Since the counting process $(N_{-1,t_i})_{t_i \in (0,1]}$ is defined as a Poisson process, we approximate the occurrence of jumps at a particular day by the Bernoulli distribution. The estimated variance of (1.11) is, therefore, given by $\hat{\mathrm{Var}}(\hat{p}_{\mathcal{M}}) = \hat{p}_{\mathcal{M}}(1 - \hat{p}_{\mathcal{M}})/h$. As a natural choice, we build the hypothesis tests on the principles of a simple t-test.

1.6 Empirical results

1.6.1 Wavelet spectra of Norwegian interest rates

In order to get deeper insights into the variation and jump characteristics of the observed processes, we estimate wavelet spectra of the interest rates as described in Section 1.5.2. Computational steps closely follow Nason et al. (2000). Results are based on Daubechies' least asymmetric wavelets, i.e. Symmlets, and a minimax threshold criterion, see Vidakovic (1999, Sec 3.4.5 and 6.4) for further details. In contrast to the differencing operations of Haar wavelets, Symmlets are closer related to averaging filter functions, thus, can be considered to provide local averages of the return series. We chose a bandwidth of 12 days at the finest scale, i.e. six vanishing moments, to achieve some degree of smoothness. We apply

Figure 1.3: Wavelet spectrum estimates for 1 month and 3 year interest rates.



Notes: Spectrum estimates of 1 month (left) and 3 year (right) interest rates based on Symmlets with six vanishing moments and a wavelet shrinkage method (hard thresholding). Part A depicts estimates of wavelet spectra from the finest scale $j = -1$ up to the coarse scale $j = -12$ (color code: the darker the shading the stronger the impact of the particular scale and time point). Part B highlights the finest scale $j = -1$ (gray line) and the minimax threshold with a window width of six month (black line). Part C shows values at $j = -1$ above the threshold.

the minimax threshold criterion since it is less conservative than the universal threshold. As a robustness check, Appendix 1.B reports results on Haar wavelets and the universial threshold. We also consider results for different numbers of vanishing moments.

Figure 1.3 depicts estimated spectra of the 1 month (left column) and the 3 year (right column) interest rates. Part A shows wavelet spectrum estimates on a time-scale plane. Non-surprisingly, the color code of the plots indicates that most of the return variation can be attributed to fine scale components (dark shading). On average, the finest scale $j = -1$ accounts for more than 50 percent of the total variation (1.6). Coarser resolution levels gain in importance around 2008. The darker shading displays the volatility increasing effects of the global financial crisis. However, due to the local adaptiveness of the threshold, we do not distinguish between crisis and non-crisis periods. As Part B of Figure 1.3 shows, the threshold (black line) adjusts to the local increase of the variation (gray line). Since spectrum estimates at scale $j = -1$ above the threshold localize jumps, the number of detected jumps is not artificially increasing during times of financial stress. Truncated estimates of the finest scale above the threshold are shown in Part C of Figure 1.3. The truncated estimates indicate the heterogeneity of squared jump sizes across time. Our focus on jump probabilities avoids handling this heterogeneity.[9]

To analyze changes in target and path surprises we now focus on jump probabilities and the hypotheses formulated in Section 1.4.

1.6.2 Quantitative guidance and monetary policy surprises

In the previous subsection we estimate spectra of the different interest rate series and detect jump points according to the thresholding rule presented in Section 1.5.2. We now take advantage of the localized jump points to verify the economic hypotheses discussed in Section 1.4. We simply compare different jump probabilities by a standard approximation of the t-test. Tests are titled

[9]See further assessments of the jump points in Appendix 1.A.

according to their respective hypothesis. The estimated jump probabilities are presented in Table 1.1. Table 1.2 reports the test results.

During the period of qualitative guidance Norwegian interest rates show a pronounced response to monetary policy announcements. On average, jumps on policy announcement days are three times more likely than on all other days. For example, Table 1.1 shows that the three year rate jumps on announcement days with an estimated probability of 12.5%, i.e. five jumps out of 40 policy days. In contrast, on non-announcement days the probability is 3.45%, corresponding to 39 jumps out of 1129 non-policy days. As the p-values of the News-tests in Table 1.2 indicate, at a confidence level of 10%, all maturities have significantly larger jump probabilities on monetary policy announcement days. This suggests significant target and path surprises during the period of qualitative guidance.

In the quantitative guidance period jump probabilities of the 1 and 5 year maturities are no longer larger on policy announcement days than on non-announcement days. In general, the difference between jump probabilities is much smaller than during the period without key rate projections. For the example of the three year rate, the probability of a jump on policy announcement days has decreased to 3.70%. With a total number of 54 policy days this implies halving the absolute number of jumps and a decline by 8.8 percentage points. At the same time, jumps on non-announcement days decline by 0.5 percentage points only. p-values of the News-tests show that jump probabilities are no longer significantly larger on monetary policy days. Consequently, no significant target and path surprises can be observed during the period of quantitative guidance.

Since we find significant policy surprises during the qualitative guidance period but non-significant policy surprises since key rate projections are published, evidence so far suggests that quantitative guidance increases the predictability of monetary policy. Utilizing the Guidance- and Jump-level-test, we now test across the qualitative and quantitative guidance sample to verify whether target and path surprises decrease significantly.

Table 1.1: Jump probabilities on policy announcement and non-announcement days.

Guidance period	Sets	Obs.	$\hat{p}_{\mathcal{M}_i}$ 1 month	12 month	3 year	5 year
Qualitative (2001-2005)	$\mathcal{M}_1 = \{\text{Announcement days}\mid\text{Qual}\}$	40	15.0 (5.65)	12.5 (5.23)	12.5 (5.23)	10.0 (4.74)
	$\mathcal{M}_2 = \{\text{Non-announcement days}\mid\text{Qual}\}$	1129	3.90 (0.58)	4.87 (0.64)	3.45 (0.54)	3.28 (0.53)
Quantitative (2005-2011)	$\mathcal{M}_3 = \{\text{Announcement days}\mid\text{Quant}\}$	54	9.26 (3.94)	3.70 (2.57)	3.70 (2.57)	1.85 (1.83)
	$\mathcal{M}_4 = \{\text{Non-announcement days}\mid\text{Quant}\}$	1498	4.94 (0.56)	4.00 (0.51)	2.94 (0.44)	3.40 (0.47)

Notes: Estimates of jump probabilities $p_{\mathcal{M}_i}$ of set $i = 1, 2, 3, 4$, and corresponding standard deviations are given in percent. Jump detection refers to (1.9) and Symmlets with six vanishing moments and an adaptive, six month minimax threshold.

Table 1.2: Results of hypothesis tests.

Test	Hypothesis	p-values 1 month	12 month	3 year	5 year
News-test(Qual)	$H_0 := \hat{p}_{\mathcal{M}_1} \leq \hat{p}_{\mathcal{M}_2}$, $H_1 := \hat{p}_{\mathcal{M}_1} > \hat{p}_{\mathcal{M}_2}$	0.03	0.07	0.04	0.08
News-test(Quant)	$H_0 := \hat{p}_{\mathcal{M}_3} \leq \hat{p}_{\mathcal{M}_4}$, $H_1 := \hat{p}_{\mathcal{M}_3} > \hat{p}_{\mathcal{M}_4}$	0.14	0.95	0.38	0.71
Guidance-test	$H_0 := \hat{p}_{\mathcal{M}_1} \leq \hat{p}_{\mathcal{M}_3}$, $H_1 := \hat{p}_{\mathcal{M}_1} > \hat{p}_{\mathcal{M}_3}$	0.20	0.07	0.07	0.05
Jump-level-test	$H_0 := \hat{p}_{\mathcal{M}_2} = \hat{p}_{\mathcal{M}_4}$, $H_1 := \hat{p}_{\mathcal{M}_2} \neq \hat{p}_{\mathcal{M}_4}$	0.19	0.29	0.46	0.86

Notes: Jump probabilities $\hat{p}_{\mathcal{M}_i}$ of set $i = 1, 2, 3, 4$ are taken from Table 1.1. p-values refer to the approx. normally distributed test statistic $z_{ij} = (\hat{p}_{\mathcal{M}_i} - \hat{p}_{\mathcal{M}_j})/\sqrt{Var(\hat{p}_{\mathcal{M}_i}) + Var(\hat{p}_{\mathcal{M}_j})}$. We reject the Null hypotheses at a confidence level of 10%.

Regarding the short term predictability of monetary policy, the Guidance-test applied to the 1 month rate indicates no significant reduction in target surprises. The jump probabilities on policy announcement days decline from 15% to 9.26%. However, with a p-value of 0.2, the guidance-test suggests no further improvements in the predictability of current policy decisions. In contrast, the Guidance-tests for longer-term maturities of 1, 3 and 5 years reflect significantly less jumps on monetary policy announcement days. Jumps of the 1 and 3 year rates decline from 12.5% to 3.70%. With the introduction of quantitative guidance, path surprises became significantly less likely, implying that market participants revise their expected path of future key rates less frequent. Quantitative guidance consequently enhances the longer-term predictability of monetary policy.

Finally, results of the Jump-level-test strengthen the outcomes of our empirical study. The Jump-level-test indicates no significant changes in jump probabilities on non-announcement days between the two guidance samples. Thus, the outcome of the Guidance-test is not driven by an overall decline in jump probabilities. We rule out an overall structural break of jump intensities between the two guidance periods and interpret changes on policy announcement days as driven by changes in policy guidance.

1.7 Conclusion

This paper's contributions are twofold: First, we introduce a new methodology to detect jumps in time series data. We propose to formulate Locally Stationary Wavelet processes in the context of semimartingales. The connection allows a decomposition of the quadratic variation of semimartingales by means of a wavelet spectrum. We detect jumps on wavelet spectra via an adaptive thresholding rule. The pointwise time resolution and a direct statistical meaning as a consistent decomposition of the quadratic variation appear as benefits of the spectrum estimator. Second, based on the Norwegian example, we provide new evidence in favor of quantitative guidance compared to qualitative guidance. While our empirical results suggest that quantitative guidance does not improve the predictability of actual policy decisions, we find that switching from qualitative to quantitative guidance stabilizes expectations about future policy decisions. We conclude that key rate projections improve the longer-term predictability of monetary policy.

Extension of the present work appear promising. We already indicate that the jump detection approach can be easily extended to define estimates of the jump variation and integrated volatility. Furthermore, the formulation of semimartingales under additive noise appears as a simple extension since the wavelet transform can be considered a smoothing operator and a further de-noising step is involved in the spectrum estimate. For empirical investigations, longer histories of key rate projections would be helpful. Studying market adjustments to central bank's revisions at particular projection horizons would further increase the understanding about central banks' ability to drive markets' expectations. The analysis of common jumps (cojumps) of particular interest rate maturities appears as a promising technique to investigate that relation.

1.A Evaluation of jump days

Based on the data introduced in Section 1.3 and the setup of Section 1.5, we investigate the size of returns on days where jumps occur (jump days). On average, the absolute change in interest rates should be relatively large on jump days. Table 1.2 reports these sample averages and contrasts jump days with returns of the whole data set.

Table 1.2: Average absolute changes in interest rates.

Sample	1 month	1 year	3 year	5 year
Whole data set	3.75	3.09	3.69	3.60
Jump days	19.42	12.3	13.3	11.9
Announcement-days	3.54	3.10	2.33	4.97
Jump announc.-days	15.60	10.4	24.0	19.6

Notes: The average of absolute changes in interest rates for different maturities are given in basis points. The whole sample includes 2721 observations and 94 policy announcement days. Announcement days that induce jumps range from 5 jumps (5 year rate) to 11 jumps (1 month rate), compare Table 1.

1.B Robustness analysis

We document the sensitivity of our main results with respect to the specific choice of wavelets and thresholds. Table 1.3 shows estimated jump probabilities for the different subsets $\mathcal{M}$ of the date vector as defined in Table 1.1. We present results for the Haar wavelet and Symmlets. The tuning-parameter is the threshold criterion and its specific window size (i.e. six month and three month). We also tried different numbers of vanishing moments for Symmlets (4 and 8), however the impact on jump probabilities is rather negligible, thus, we do not report these results here.

Non-surprisingly, our study shows that the different setups have an impact on the number of detected jumps. Thus, jump probabilities depend on the chosen threshold and wavelet. However, the choice of setup has only a small impact on the relative frequency of jumps between the different sets of the date vector (e.g. comparing the qualitative guidance and quantitative guidance period). Since our economic hypotheses are defined to elucidate relations between jump probabilities (given one specific setup), our empirical conclusions do not crucially depend on the chosen setup.

Table 1.3: Jump probabilities for different estimation setups.

	Set	Minimax(6)				Universal(6)			
		1 month	1 year	3 year	5 year	1 month	1 year	3 year	5 year
Haar	$\hat{p}_{\mathcal{M}_1}$	22.5 (6.60)	30.0 (7.25)	17.5 (6.01)	10.0 (4.74)	12.5 (5.23)	20.0 (6.32)	12.5 (5.23)	10.0 (4.74)
Haar	$\hat{p}_{\mathcal{M}_2}$	4.52 (0.62)	8.59 (0.83)	5.93 (0.70)	5.76 (0.69)	2.04 (0.42)	3.37 (0.54)	2.92 (0.50)	3.01 (0.51)
Haar	$\hat{p}_{\mathcal{M}_3}$	24.1 (5.82)	20.4 (5.48)	7.41 (3.56)	9.26 (3.49)	7.41 (3.56)	12.9 (4.57)	3.70 (2.57)	3.70 (2.57)
Haar	$\hat{p}_{\mathcal{M}_4}$	7.88 (0.70)	6.54 (0.64)	5.87 (0.61)	6.01 (0.61)	2.94 (0.44)	2.54 (0.41)	2.87 (0.43)	3.94 (0.50)
		Minimax(3)				Universal(6)			
		1 month	1 year	3 year	5 year	1 month	1 year	3 year	5 year
Symmlet	$\hat{p}_{\mathcal{M}_1}$	15.0 (5.65)	12.5 (5.23)	15.0 (5.65)	10.0 (4.74)	10.0 (4.74)	7.50 (4.16)	10.0 (4.74)	7.50 (4.16)
Symmlet	$\hat{p}_{\mathcal{M}_2}$	5.31 (0.67)	5.93 (0.70)	3.72 (0.56)	5.61 (0.59)	2.57 (0.47)	3.01 (0.51)	1.15 (0.32)	1.42 (0.35)
Symmlet	$\hat{p}_{\mathcal{M}_3}$	14.8 (4.83)	5.56 (3.12)	3.70 (2.57)	3.70 (2.57)	5.56 (3.12)	1.85 (1.83)	1.85 (1.83)	0 (0.00)
Symmlet	$\hat{p}_{\mathcal{M}_4}$	4.07 (0.59)	5.14 (0.57)	3.87 (0.50)	4.21 (0.52)	3.88 (0.50)	2.40 (0.40)	1.00 (0.26)	0.93 (0.25)

Notes: Estimates of jump probabilities and standard errors in parentheses are given in percent. Sets $\mathcal{M}_i$ refer to $i = 1, 2, 3, 4$ different subsets of the date vector: $\mathcal{M}_1$: Policy announcement days during the qualitative guidance period, $\mathcal{M}_2$: Non-announcement days during the qualitative guidance period, $\mathcal{M}_3$: announcement days during the quantitative guidance period, $\mathcal{M}_4$: Non-announcement days during the quantitative guidance period.

2 ECB monetary policy surprises: identification through cojumps in interest rates

2.1 Introduction

Understanding market responses to monetary policy announcements is of great interest for policy makers, financial market participants and academia alike. Since the first link in the transmission of monetary policy is from a central bank's key rate to longer-term interest rates, the issue has been studied mostly in the context of the term structure of interest rates.

The predominant approach to investigate the response pattern of the yield curve traces back to Cook and Hahn (1989) and Kuttner (2001) and is based on a simple linear regression where changes in interest rates of single maturities are regressed on a monetary policy surprise variable.[1] While such regressions have established that the shorter-end of the yield curve consistently moves in the direction of the policy surprise, the regressions do not provide a consistent answer for the longer-end of the yield curve. In fact, the direction of responses of a 10 year maturity are rather mixed across countries and sample periods, compare e.g. Goldberg and Leonard (2003), Gürkaynak et al. (2005) and Beechey and Wright (2009).

[1] The surprise is usually the unexpected changes in the key rate. Popular measures of monetary policy surprises include derivative prices on interest rates (Kuttner, 2001), survey expectations (Ehrmann and Fratzscher, 2003) and jumps in short term interest rates (Winkelmann, 2013).

Models of Ellingsen and Söderström (2001) and Rudebusch and Wu (2008) provide explanations for varying effects of monetary policy on the term structure of interest rates. They stress that it is not the occurrence and size of a policy surprise but its *source* that determines the response pattern of the yield curve. By showing that policy surprises regarded as providing news about economic conditions shift interest rates of all maturities in the same direction (*level shift* of the yield curve), while surprises driven by perceived adjustments in central bank preferences move the short and long end in opposite directions (*rotation* of the yield curve), the authors give structural reasons for the mixed empirical findings.

The present paper studies the role of *level shifts* and *rotations* empirically. We propose a new approach based on cojumps of a short and long term interest rate to disentangle the two distinct response patterns of the yield curve. We reformulate the recently proposed test for cojumps of Bibinger and Winkelmann (2013) and provide a test to discriminate between *level shifts* and *rotations* of the yield curve. We detect level shifts through unidirectional jumps and rotations by cojumps where the short and long end of the yield curve jump in opposite directions. Drawing on the structural interpretations of level shifts and rotations, the two distinct response patterns identify markets' perceptions about the *sources* of monetary policy surprises. The empirical application refers to 133 policy announcements of the European Central Bank (ECB) in the period from 2001 to 2012.

Our paper is closely linked to two different kind of recent empirical studies. First, with Schmidt and Nautz (2012) we share the goal of disentangling the *sources* of monetary policy surprises. Based on ECB policy decisions and qualitative survey data of financial market experts, the authors confirm the existence and the time varying nature of the two distinct sources. However, they do not consider effects on the yield curve and their regression framework does not allow to study single policy announcement days. The second close connection refers to the analysis of *level shifts* and *rotations* of the yield curve by Claus and Dungey (2012). The authors extend a standard term structure model to classify particular policy announcements of the Federal Reserve (FED) into yield curve shifting and rotating announcements. The clear distinction to the present paper is given by the econometric approach. In contrast to a factor modeling of daily interest rates, we refer to intraday observations and high-frequency statistics. Our cojump approach particularly benefits from its high-frequency perspective. Besides localizing the instantaneous response on policy announcement days, in the vein of Ehrmann and Fratzscher (2009), the high-frequency data allows us to perform the test of level shifts and rotations for each policy day independently. Thus, the day-wise testing procedure enables a real time policy analysis.

The detection of monetary policy surprises through cojumps builds on Dungey et al. (2009), Lahaye et al. (2011) and Evans (2012), among others, who establish (co)jumps in high-frequently recorded asset prices as a measure for information arrivals. In contrast to the predominant modeling approach of high-frequency data, in the context of directly observable, independent semimartingales, we generalize the assumptions and explicitly take microstructure frictions (see Aït-Sahalia et al., 2005 and Zhang, 2011) and the correlation structure in a multivariate setting into account. The robustness to microstructure frictions avoids the down-sampling to e.g. 5 or 10 minute returns and, thereby, the waste of a tremendous amount of data. Observations at the tick-frequency crucially increase the information content of intraday time intervals where markets are affected by news announcements. Furthermore, the setting of a multivariate semimartingale captures (spot)covariations which are the foundations of our test for level shifts and rotations of the term structure. The natural choice of a cojump estimator in a multivariate, noisy setting is the spectral estimator of Bibinger and Winkelmann (2013). We consider the bivariate case and apply the estimator to tick-data of interest rate futures.

Our main result indicates that ECB policy surprises induce almost exclusively level shifts. Tests at a 5% significance level detect 35 announcement days that shift the level of the term structure. We find only one case where a significant rotation occurs and 97 policy announcement days without significant surprises. Inline with simple linear regressions in the context of ECB policy announcements (e.g. Andersson et al., 2009 and Brand et al., 2009), our finding suggests an average response pattern where all yields along the maturity structure move in the direction of the policy surprise. We confirm this connection by regressing our test results on a conventional monetary policy surprise variable.

Through the detected level shifts and rotations we draw conclusions about the perceived sources of policy surprises. We find that 26% of ECB policy announcements are interpreted by market participants to provide news about the current state of the economy. In contrast, less than 1% can be considered to be driven by perceived adjustments in ECB policy preferences. The rare yield curve rotations on policy announcement days reflect a credible and stable policy implementation and communication.

The paper is arranged in six upcoming sections. Section 2.2 reviews the link between monetary policy surprises and level shifts and rotations of the yield curve. Section 2.3 introduces the high frequency data of the yield curve and studies its microstructure. The modeling framework and the test for level shifts and rotations are described in Section 2.4. Empirical results are presented in Section 2.5. Section 2.6 concludes.

2.2 Sources of policy surprises and the yield curve

Following the path breaking work of Taylor (1993), Clarida et al. (1998) and Clarida et al. (1999), an extensive theoretical and empirical literature has studied interest rate settings by central banks. A brought consensus has emerged that monetary policy can be described by a simple rule that connects changes in a central bank's key interest rate Δr_t with changes in main economic variables, i.e. in inflation $\Delta\pi_t$ and output Δy_t:

$$\Delta r_t = \lambda \Delta\pi_t + (1-\lambda)\Delta y_t, \quad \lambda \in [0,1]. \tag{2.1}$$

The rule simply implies that central banks increase (decrease) their key rate when inflation rises (falls) or when output expands (weakens), in order to reduce (induce) future inflationary pressure.[2] Although rules like (2.1) are remarkably adept

[2]In accordance with Taylor (1993), rules like (2.1) are called Taylor-rules.

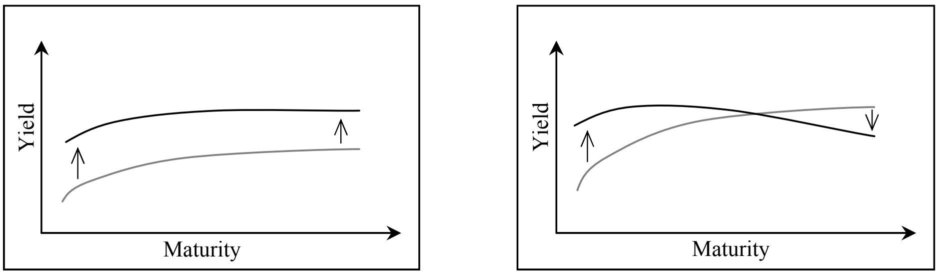
at describing central banks' interest rate decisions empirically, the implementation of reaction functions is not officially confirmed by central banks. Therefore, interest rate rules remain rather implicit and markets' expectations about future policy decisions depend on individual assessments about the future economic variables as well as the central banks' preference parameter λ, see Schmidt and Nautz (2012). In this context, monetary policy surprises can be triggered by two distinct sources: First, news about π_t and y_t, such that markets readjust expectations about current and future economic conditions. Second, changes in the preference parameter, such that markets change the weighting of the economic variables in their individual interest rate rules. In both cases markets update their expectations about future key rates and price the changes into the yield curve.

The stylized macroeconomic model of Ellingsen and Söderström (2001) suggests the identification of the market perceived sources of policy surprises through the particular response pattern of the yield curve.[3] They extend a dynamic version of a simple aggregate supply - aggregate demand model by the expectations hypothesis of interest rates. An interest rate rule like (2.1) determines the optimal strategy of monetary policy in that framework. Inducing information asymmetries between market participants and the monetary policy authority, they find two distinct response patterns of the yield curve that disentangle the two sources of monetary policy surprises. First, in the case where markets interpret the policy surprise to provide news about current and future economic conditions, changes in expected future key rates shift all yields of the maturity structure in the same direction (level shift). Second, if markets perceive the policy surprise to reflect changes in policy preferences, revisions of expected future key rates drive the short and long end of the yield curve in opposite directions (rotation).

In economic terms, level shifts and rotations can mainly be explained by the connection of interest rates and markets' inflation expectations, compare Ehrmann et al. (2011). While changes in shorter-term rates are mostly driven by the current

[3] We focus here on Ellingsen and Söderström (2001). However, similar conclusions can be drawn from a standard DSGE model (Ellingsen and Söderström, 2006) and, with a slightly different terminology, from a macro-finance model (Rudebusch and Wu 2008).

Figure 2.1: Upward level shift (left) and a rotation (right) of a yield curve.



key rate, responses of longer-term interest rates are determined by policy effects on future inflation. Due to relatively strong inflation persistence, documented in e.g. Hassler and Wolters (1995) and Meller and Nautz (2012), news that significantly affect the current rate of inflation translate to revisions of inflation expectations along *all* maturity horizons, see also the discussion in Gürkaynak et al. (2007b).[4] Therefore, a positive (negative) policy surprise that reflects significant news about an increase (decrease) in current inflation and output increases (decreases) inflation expectations at every expectation horizon. As illustrated by the left hand plot of Figure 2.1, in this case, the yield curve shifts upwards (downwards). In contrast, a positive (negative) policy surprise observed to increase (decrease) the weight on inflation, decreases (increases) inflation persistence. Consequently, shocks to inflation decay faster (slower) and longer-term inflation expectations drop (move up).[5] The right hand plot of Figure 2.1 displays a resulting rotation of the yield curve.

In the following, we provide a test for level shifts and rotations of the yield curve. To distinguish between the two distinct response patterns, we utilize high-frequency data of interest rates on monetary policy announcement days.

[4]Note that the joint movements appear as a necessary condition of level shifts and rotations. Consequently, the analysis excludes policy surprises that induce idiosyncratic movements at either the short or long end of the term structure.

[5]This argument requires the increase (decrease) of the weight on inflation to be taken during times where inflation is above (underneath) a target or steady state value.

2.3 Yield curve data

In this section we present the high-frequency data of our empirical study. We particularly address its microstructure to motivate our econometric setting introduced in Section 2.4.

2.3.1 Tick-data

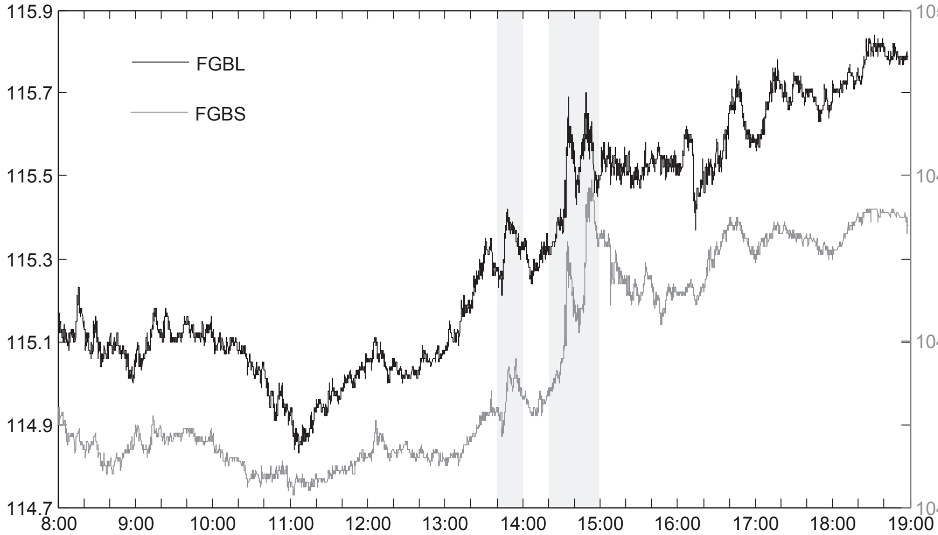
To study the response pattern of the yield curve to monetary policy announcements of the ECB, we refer to tick-data on German government bonds. We assume that yields along the term structure of interest rates are related via some general form of the expectations hypothesis. The shape of the yield curve can, therefore, be captured by a short and long term interest rate. Instead of picking actually traded bonds, we utilize futures data from the derivative exchange EUREX.[6] Compared to bonds, futures usually have the advantages to be traded more frequently and to represent constant maturity prices. As evidenced by Dungey and Hvozdyk (2012), government bond futures share very closely related dynamics with the underlying bond market.

The short end of the term structure is represented by the Euro-Schatz Futures (FGBS), whose underlying is a fictive German government bond maturing in about 2 years having a coupon of six percent. The FGBS closely captures the medium term policy horizon of the ECB. While the 2 year maturity is sufficiently long to prevent a close control via monetary policy, it is sufficiently short to be consistent with the direction of money market responses to monetary policy announcements.[7] The long end of the term structure is captured by the Euro-Bund Futures (FGBL), which calls for the delivery of a fictive 10 year German government bond with a coupon of six percent. The 10 year horizon of FGBL is

[6]The data is provided by the "Research Data Center" of the CRC 649.

[7]E.g. Gürkaynak et al. (2005) and Brand et al. (2010) report a positive relation between monetary policy surprises and a 2 year rate. By using a short term bond maturity we also avoid dealing with effects of money market turmoils during the global financial crisis. We use the 2 year maturity also for data availability reasons.

Figure 2.2: Government bond futures on 2.10.2008.



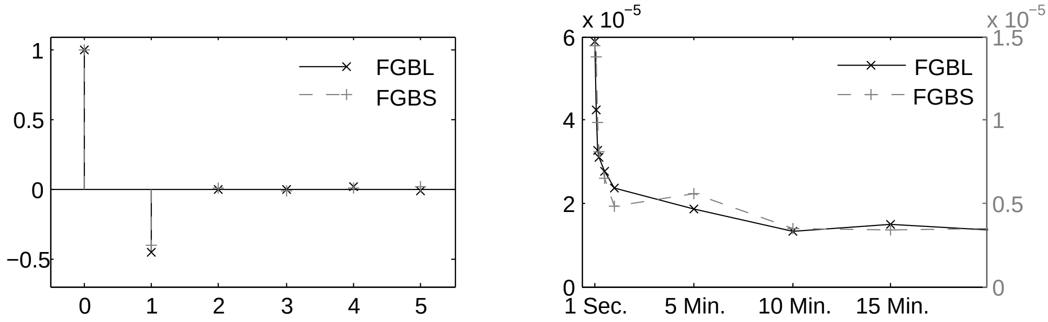
Notes: Price notation. FGBS (grey) represents the 2 year maturity, FGBL (black) the 10 year maturity. Number of ticks: FGBL 7,710; FGBL 14,849. Intervals where the ECB communicates with markets are emphasized.

important for investment and saving decisions, however, not explicitly triggered by monetary policy.

Our sample includes tick-data of FGBS and FGBL from January 2001 to August 2012. For both futures we take the most frequently traded contract month, which is the three month expiring horizon. Allowing for recurring response patterns, we focus on 133 scheduled ECB policy announcements, which typically take place on the first Thursday of each month. On each announcement day the ECB follows a fixed communication scheme. The decision on the key rate is published via a press release at 13:45 CET and is further explained in a subsequent press conference starting at 14:30 CET. Besides the announcement days, we take 458 Thursdays without ECB policy announcements to contrast the two response patterns. We fix the trading time from 8:00 CET to 19:00 CET. The average number of trades per day is around 10,000 for the FGBL series and around 5,000 for FGBS.

Figure 2.2 provides an example of the tick-data for October, 2. 2008. The figure reflects common dynamics of the 2 and 10 year prices. Particularly around the

Figure 2.3: Autocorrelation (left) and signature plot (right) on 2.10.2008.



Notes: The autocorrelation up to five lags is based on tick-data. The signature plot refers to the realized volatility (sum of squared returns) computed for each sampling frequency (x-axis) separately.

shaded time intervals where the ECB communicates with markets, both series appear to be tied together more closely than during the rest of the day. Due to decreasing yields (increasing prices) at either the short and long end of the term structure, this policy day most likely induces a level shift. Particularly the strong movements around 14:20 to 15:00 CET may reflect the arrival of new information during the press conference. The test for level shifts and rotations proposed in Section 2.4 evaluates whether the comovements are sufficiently strong to identify a policy surprise.[8]

2.3.2 The role of microstructure noise

In this paper we identify policy surprises via cojumps in tick-data of the FGBS and FGBL series. However, due to the imperfections of trading processes, tick-data is widely known to be very noisy, see Hautsch (2012) for a comprehensive discussion. The noise comes from a vast array of issues collectively known as market microstructure, including price discreteness, infrequent trading and bid-ask bounce effects. If microstructure frictions are present, single transaction prices no longer reflect the true price process. In this case, large observed returns do not consistently localize (co)jumps. Thus, it is of crucial importance that the

[8]In Appendix 2.A, we study the example of October, 2. 2008 in more detail.

econometric approach to estimate and test for cojumps explicitly accounts for the microstructure.

The observed processes in Figure 2.2 do not directly display a noise perturbation. As shown by Aït-Sahalia et al. (2005), the presence of microstructure frictions can be detected by a negative first order autocorrelation and an exponentially increasing realized volatility (sum of squared returns) the higher the sampling frequency. Therefore, Figure 2.3 depicts the autocorrelation structure and the signature plot of the observed processes. For both the FGBL and FGBS data a significant first order autocorrelation around -0.4 and a strongly increasing realized volatility, for sampling frequencies of tick size to 15 minute intervals, are evident.

To distinguish between level shifts and rotations of the yield curve in the context of the noisy interest rate futures, we utilize the spectral estimator and test for cojumps of Bibinger and Winkelmann (2013). In the next section we introduce the cojump estimator for the bivariate case and provide the test for level shifts and rotations.

2.4 Methodology: detection of level shifts and rotations of the yield curve

In this section we introduce the test for level shift and rotations of the yield curve. The approach is based on cojumps of the short and long term interest rate futures presented in Section 2.3. First, we describe the standard setting of continuous time processes to model high frequently recorded asset prices. We refer to noisy and non-synchronous observations and highlight the estimation problem. Second, we review the spectral estimator of cojumps of Bibinger and Winkelmann (2013) in the bivariate case. Third, based on the spectral estimator, we adapt the wild bootstrap type of test for cojumps and define a test for level shifts and rotations of the yield curve.

2.4.1 Non-parametric volatility model

As demonstrated in the previous section, the high-frequency data of the short (FGBS) and long (FGBL) end of the term structure is affected by market microstructure noise. A common modeling framework for noise perturbation in high-frequency data is to treat the microstructure as observation error, see e.g. Aït-Sahalia et al. (2005). In the following, the notation $t \in [0,1]$ refers to the trading time of a single day. Thus, we aim at presenting cojump statistics for each day separately.

Let $Y^{(q)} = (Y_i^{(q)})_{i=0,..,T^{(q)}}$ denote the log of discretely observed high-frequency prices with $q = 1$ the short end and $q = 2$ the long end of the maturity structure. The index $i = 0, ..., T^{(q)}$ counts respective intraday observations. The observed processes are then expressed as the latent, true log-price processes $X^{(q)} = \left(X^{(q)}_{t_i^{(q)}}\right)_{t_i^{(q)} \in [0,1]}$ plus market microstructure noise $\varepsilon_i^{(q)}$.

$$Y_i^{(q)} = X^{(q)}_{t_i^{(q)}} + \varepsilon_i^{(q)}, \quad q = 1, 2\,,\ t_i^{(q)} \in [0,1]\,,\ i = 0, 1, ..., T^{(q)} \tag{2.2}$$

The microstructure noise is a mean zero, i.i.d. sequence with standard deviation $\eta^{(q)}$ and independent of $X^{(q)}$. The time index of $X^{(q)}$ allows the modeling of non-synchronous observations of the two processes, with $t_i^{(1)} \neq t_i^{(2)}$ for $i = 0, ..., T^{(q)}$. In accordance with term structure models of e.g. Duffie and Kan (1996) and Dai and Singleton (2000), we utilize the class of semimartingales to model the true bond price processes $X^{(q)}$. The short and long end of the maturity structure evolves as

$$dX_t^{(q)} = \mu_t^{(q)} dt + \sigma_t^{(q)} dW_t^{(q)} + dJ_t^{(q)}\,, \quad q = 1, 2\,,\ t \in [0,1]\,, \tag{2.3}$$

where $\mu_t^{(q)}$ is a drift, $\sigma_t^{(q)}$ the spot volatility, $W_t^{(1)}$ and $W_t^{(2)}$ correlated standard Brownian motions with $d[W^{(1)}, W^{(2)}]_s = \rho_s\, ds$ and $J_t^{(1)},\ J_t^{(2)}$ possibly correlated pure jump processes.

The main goal of the econometric approach is to provide an estimator of simultaneous jumps under (2.2). The general idea to achieve this goal stems on the non-noisy case and considers occasions where the product of jump sizes $\Delta J_t^{(1)} \Delta J_t^{(2)}$

is different from zero, compare Mancini and Gobbi (2012). Therefore, the cojump estimation is usually based on the quadratic covariation between the true log-prices:

$$[X^{(1)}, X^{(2)}] = \int_0^1 \rho_t \sigma_t^{(1)} \sigma_t^{(2)} dt + \sum_{0 \leq t \leq 1} \Delta J_t^{(1)} \Delta J_t^{(2)}, \quad t \in [0,1]. \tag{2.4}$$

The covariation comprises two parts, the integrated covolatility and the cojumps. The integrated covolatility is made up of the spot volatilities $\sigma_t^{(q)}$ and the correlation ρ_t between the two Brownian semimartingale parts. The cojumps are given by the sum of cross products between simultaneous jumps. To estimate the two parts in (2.4) under noisy and non-synchronous observations, we utilize the spectral cojump estimator of Bibinger and Winkelmann (2013).

2.4.2 Spectral estimator of cojumps

The spectral estimator of cojumps by Bibinger and Winkelmann (2013) is build on Reiß (2011) and Bibinger and Reiß (2013). It provides an efficient cojump estimator via thresholding increments of the quadratic covariation (2.4). Estimation in the spectral domain benefits from the orthogonality of the transform, hence, reduces the estimator's variance. To localize the cojumps, the trading time $t \in [0,1]$ is split into h^{-1} partitions. Thus, up to the time length h of a block, we are able to detect the cojumps.

The block-wise map of observed returns $\Delta_i Y^{(q)} = Y_i^{(q)} - Y_{i-1}^{(q)}$, $i = 1, ..., T^{(q)}$, $q = 1, 2$, in the frequency domain is accomplished via the sine basis. The spectral statistic for block $k = 0, ..., h^{-1} - 1$ and frequency $j = 1, ...J$ is given by

$$S_{jk}^{(q)} = \frac{\sqrt{2h}}{j\pi} \sum_{i=2}^{T^{(q)}} \Delta_i Y^{(q)} \sin\left(j\pi h^{-1}(t_i^{(q)} - kh)\right) \mathbb{1}_{[kh,(k+1)h]}(t_i^{(q)}), \tag{2.5}$$

where the indicator function $\mathbb{1}$ evaluates the transform on block k. The map in the frequency domain results in independent statistics $S_{jk}^{(q)}$, $j \geq 1$. Information from non-synchronous intraday returns within each block k is translated to the synchronous spectral statistics $S_{jk}^{(1)}, S_{jk}^{(2)}$, $k = 0, ..., h^{-1} - 1$. The expansion (2.5) can be considered a linear combination of weighted (with the sine) pre-averages of the return series.[9] Higher frequencies contain diminishing information about the process (2.3), thus, we discard frequencies above a spectral cut-off J.

Block-wise increments in the quadratic covariation (2.4) between FGBS and FGBL are provided by the **SP**ectral **E**stimator of the **C**o**V**olatility

$$\Delta_k \mathbf{SPECV}(Y^{(1)}, Y^{(2)}) = h \sum_{j=1}^{J} w_{jk} \frac{\pi^2 j^2}{h^2} S_{jk}^{(1)} S_{jk}^{(2)}, \quad k = 0, ..., h^{-1} - 1, \quad (2.6)$$

such that on $t \in [0,1]$ for $T^{(q)} \to \infty$

$$\sum_{k=0}^{h^{-1}-1} \Delta_k \mathbf{SPECV}(Y^{(1)}, Y^{(2)}) \xrightarrow{\mathbb{P}} [X^{(1)}, X^{(2)}].$$

The quadratic covariation between the true price processes $X^{(q)}$ is consistently estimated by appropriately scaled cross products of spectral statistics of the observed processes $Y^{(q)}$, $q = 1, 2$. The optimal weights w_{jk}, with $\sum_j w_{jk} = 1$, are proportional to local Fisher information and minimize the estimator's mean square error, see Bibinger and Winkelmann (2013) for their explicit form. Under vanishing microstructure noise all frequencies are weighted equally and the estimator reduces to the realized covolatility, the natural choice in this situation.

From (2.4) it follows that the absolute value of increments of quadratic covariation (2.6) are much larger on blocks k where the product of jump sizes is different from zero. Therefore, cojumps can be detected and estimated via thresholding the increments of the quadratic covariation. The daily **SP**ectral **E**stimator of **C**o**J**umps of FGBS and FGBL based on a locally adaptive threshold u_k is given by

$$\mathbf{SPECJ}(Y^{(1)}, Y^{(2)}, u_k) = \sum_{k=0}^{h^{-1}-1} \Delta_k \mathbf{SPECV}(Y^{(1)}, Y^{(2)}) \mathbb{1}_{\{|\Delta_k \mathbf{SPECV}(Y^{(1)}, Y^{(2)})| > u_k\}}, \quad (2.7)$$

with $T^{(q)} \to \infty$ on $t \in [0,1]$ satisfying

$$\mathbf{SPECJ}(Y^{(1)}, Y^{(2)}, u_k) \xrightarrow{\mathbb{P}} \sum_{0 \le t \le 1} \Delta J_t^{(1)} \Delta J_t^{(2)}.$$

[9] Or equivalently a pre-average of the price process with the cosine, see Bibinger and Reiß (2013).

If an increment in quadratic covariation estimates on a given block k is below the threshold u_k, it contributes to the integrated covolatility. In contrast, increments above the threshold localize and consistently sum up to cojumps. Since increments of the Brownian components in (2.3) are normally distributed, extreme value theory provides a supremum of block-wise increments of the integrated covolatility. Thus, the universal threshold $\hat{u}_k = 2\log(h^{-1})h\sigma_k^{(1,2)}$, with $k = 0, ..., h^{-1} - 1$ and $\sigma_k^{(1,2)}$ a pilot estimator of the spot covolatility, separates the integrated covolatility and cojumps. To obtain a feasible pilot estimator, we refer to local averages of (2.6) in the neighborhood of k with equally weighted spectral statistics.

The sign of the spectral estimator of cojumps (2.7) can be interpreted like the sign of a correlation coefficient. It reflects whether the relation between the short and long end of the term structure is positive or negative. Thus, up to the blocklength h we can detect cojumps and also verify whether they are unidirectional or point in different directions. Next, we propose a test to detect level shifts and rotations of the yield curve.

2.4.3 The test for level shifts and rotations

Based on the spectral estimator of cojumps (2.7) for noisy and non-synchronous tick-data of a short and long term interest rate, we provide a test for level shifts and rotations of the term structure. For a single trading day, the test evaluates the direction of simultaneous jumps. We formalize the hypotheses as follows:

Level shift hypothesis: $H_1^L := \left(\sum_{0\leq t\leq 1} \Delta J_t^{(1)} \Delta J_t^{(2)}\right) > 0$

- The short end ($q = 1$) and long end ($q = 2$) of the yield curve jump in the same direction. Significant cojumps lead to a parallel shift of the term structure.

Rotation hypothesis: $H_1^R := \left(\sum_{0\leq t\leq 1} \Delta J_t^{(1)} \Delta J_t^{(2)}\right) < 0$

- The short end ($q = 1$) and long end ($q = 2$) of the yield curve jump in opposite directions. Significant cojumps tilt the term structure.

The null hypothesis stresses that no cojump occurs, i.e. $H_0 := \left(\sum_{0\leq t\leq 1} \Delta J_t^{(1)} \Delta J_t^{(2)}\right) = 0$. To test the hypotheses, we utilize one-sided alternatives of the wild bootstrap type of test proposed by Bibinger and Winkelmann (2013). The wild bootstrap principle avoids that the test statistic degenerates under H_0 by disturbing its block-wise increments in the case of no cojumps. Similar to the cojumps estimator (2.7), the test statistic is based on the increments in quadratic covariation (2.6):

$$\mathcal{T}(Y) = T_{\min}^{\frac{1}{4}} \sum_{k=0}^{h^{-1}-1} \Delta_k \mathbf{SPECV}(Y^{(1)}, Y^{(2)}) \left(1 - \zeta_k \mathbb{1}_{\{|\Delta_k \mathbf{SPECV}(Y^{(1)},Y^{(2)})| \leq u_k\}}\right), \tag{2.8}$$

where $\mathbb{1}$ is the indicator function and ζ_k the i.i.d. noise term on each intraday block k. With ζ_k a Binomial process, satisfying $\mathbb{P}(\zeta_k = 0.9) = 0.5 = \mathbb{P}(\zeta_k = 1.1)$, and an appropriately scaled test statistic $\widetilde{\mathcal{T}}(Y)$, Bibinger and Winkelmann (2013) establish a central limit theorem under the null of no cojumps. Thus, the standard normal distribution and its critical values can be used to distinguish between the hypotheses. Since cojumps dominate the value of the test statistic, the sign of $\widetilde{\mathcal{T}}(Y)$ enables the discrimination between the Level shift and Rotation hypothesis. The test for shifts and rotations is summarized by the following diagram.

$$\begin{cases} H_1^L := \left(\sum_{0\leq t\leq 1} \Delta J_t^{(1)} \Delta J_t^{(2)}\right) > 0 & \text{if} \quad \widetilde{\mathcal{T}}(Y) > c_{1-\alpha} & \Leftrightarrow & \text{level shift} \\ H_1^R := \left(\sum_{0\leq t\leq 1} \Delta J_t^{(1)} \Delta J_t^{(2)}\right) < 0 & \text{if} \quad \widetilde{\mathcal{T}}(Y) < c_{\alpha} & \Leftrightarrow & \text{rotation} \\ H_0 := \left(\sum_{0\leq t\leq 1} \Delta J_t^{(1)} \Delta J_t^{(2)}\right) = 0 & \text{if} \quad |\widetilde{\mathcal{T}}(Y)| \leq c_{1-\alpha} & \Leftrightarrow & \text{no cojump} \end{cases}$$

The test can be seen as a mixture of two one-sided tests. Since both are based on the same test statistic and differ by their sign only, we take them as a single test. The practical implementation works as follows: We choose a significance level α and compute the test statistic. If $\widetilde{\mathcal{T}}(Y)$ is positive, we compare the test statistic with the upper critical value $c_{1-\alpha}$. In the case where the test statistic is larger then $c_{1-\alpha}$, we detect a level shift of the yield curve. If $\widetilde{\mathcal{T}}(Y)$ is negative, we take the lower critical value c_α. A test statistic smaller than c_α, detects a rotation. If both critical values are not exceeded, we find no significant shift or rotation of the yield curve.[10]

Using the high-frequency prices presented in Section 2.3, we now test ECB announcement days for shifts and rotations of the yield curve.

2.5 Empirical evidence: shifts and rotations on ECB policy announcement days

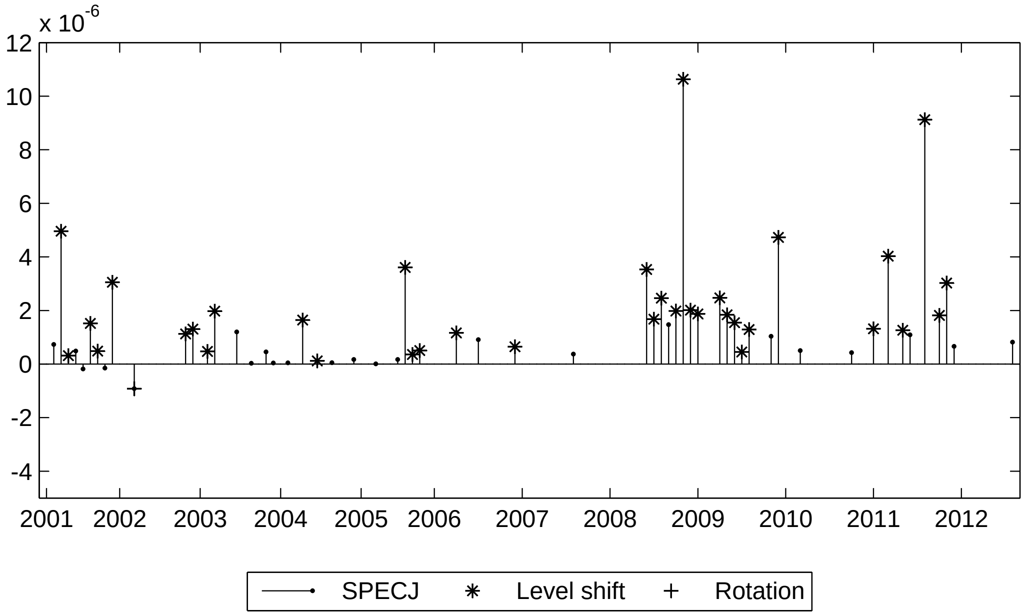
This section provides empirical evidence about level shifts and rotations of the German yield curve in response to ECB policy announcements. First, we apply the cojump estimation and testing procedure introduced in Section 2.4. The focus is on daily statistics, thus, we determine for each policy announcement day independently whether a level shift, a rotation or no significant joint movement prevails. As discussed in Section 2.2, we utilize the response pattern of the yield curve to identify the market perceived source of a policy surprise. Second, we evaluate the daily results by studying the intradaily occurrence of shifts and rotations. Regressions establish a link between the test results and a survey based monetary policy surprise variable.

2.5.1 Day-wise tests

In this subsection we present the main results of our test for level shifts and rotations of the term structure. Since the test is based on cojumps, we also report cojump estimates (2.7) for each of the 133 ECB announcements from 2001 to 2012. For the daily estimates, we refer to the noisy and non-synchronous tick-data of government bond futures presented in Section 2.3. We set $h^{-1} = 33$, thus, detect cojumps on 20 minutes time intervals (33 blocks per day). Blocks of 20 minutes appear as a reasonable number to study the timing of shifts and rotations to the ECB's press releases (13:45 CET) and press conferences (starting

[10] Note that the null hypothesis includes disjoint jumps at either the short or long end of the term structure.

Figure 2.4: Shifts and rotations of the yield curve on ECB announcement days.



Notes: SPECJ is the cojump estimator (2.7). The detection of level shifts and rotations are based on the cojump test (Section 2.4) and a 5% significance level. Daily estimates and tests refer to tick-data of the short (2 year) and long (10 year) term interest rate.

14:30 CET). We set the frequency cut-off $J = 35$ and refer to a 5% significance level. We find that our economic conclusions do not critically depend on the specific values of these parameters.

Figure 2.4 summarizes the main results. The bars display the value of the cojump estimator (2.7) at respective policy announcement days. Since the cojump estimator equals zero in the case where none of the intradaily increments in quadratic covaration exceed the threshold, the majority of the policy announcement days indicate no cojump activity. On 58 out of the 133 ECB announcements, the cojump estimator is different from zero. The larger the absolute size of the estimate, the stronger is the effect of the cojump on the yield curve.[11] However, if on a

[11] Quantifying the yield curve movement in terms of basis points from the covariance type of estimator is difficult. The square root of the SPECJ estimator can be taken as a rough approximation of the percentage change in prices.

particular day the intradaily variation is very high, it is possible that even larger estimated cojumps are non-significant. In the same way, relatively small cojumps can be statistically significant if the intradaily variation is very low. The test for level shifts and rotations of the yield curve detects significant cojumps.

First, we take the negative cojump estimates and verify whether they imply yield curve rotations. The test reveals that only one out of three negative cojump estimates rotates the yield curve. In Figure 2.4 the rotation is highlighted by a plus sign. Interestingly, policy announcements associated with negative cojump estimates occur in the beginning of the sample around late 2001 and early 2002 only. In terms of identification, the negative cojumps suggest that markets tend to interpret the policy announcements to reflect revisions in ECB policy preferences during that time. The finding matches with the assessments of Schmidt and Nautz (2012). For a period before 2003, they find that markets were particularly uncertain about the role of inflation within the interest rate rule of the ECB. The weaker perceived stability goes hand in hand with a strategy debate about policy preferences during that time. The clarification in ECB (2003), including a more precise definition of price stability (inflation should be below but close to 2%) and a de-emphasizing of the role of monetary aggregates for short term policy decisions, is find by Schmidt and Nautz (2012) as an important step towards a more transparent interest rate rule. The test for level shifts and rotations confirms this finding. Since the policy clarification in 2003, cojump estimates on policy announcement days are exclusively positive. Thus, monetary policy surprises no longer reflect perceived changes in ECB's policy preferences.

Our second focus is on the positive cojump estimates. Significant cojumps that shift the level of the term structure are marked by stars in Figure 2.4. In total, out of 55 positive cojump estimates 35 are evaluated as level shifts. Level shifts occur more regularly during the global financial crisis (starting around late 2008) and the European sovereign debt crisis (since 2011). As put forward in Section 2.2, level shifts identify policy surprises perceived to provide news about the current and future state of the economy. Since deep financial turbulences usually reflect uncertain macroeconomic conditions, the state of the economy is more difficult to evaluate during times of financial stress. The more frequent and stronger level shifts around 2008 and 2011 appear as a natural consequence.

The investigation of eleven years of ECB monetary policy from 2001 to 2012 shows that 73% of the policy announcements are well-predicted by market participants. 26% are interpreted to provide significant news about the state of the economy, while less than 1% of the announcements induce adjustments in perceived policy preferences. The results suggest a reliable, stable and well-communicated policy implementation. In particular, the policy communication during the global financial and European sovereign debt crisis appears to be successful, since we observe no adjustments in markets' perceptions about policy preferences during the crisis periods. This implies that financial markets do not perceive the non-standard or unconventional measures, summarized by Eser et al. (2012) and the reference therein, to change the ECB's policy preferences.[12]

2.5.2 Intraday response patterns

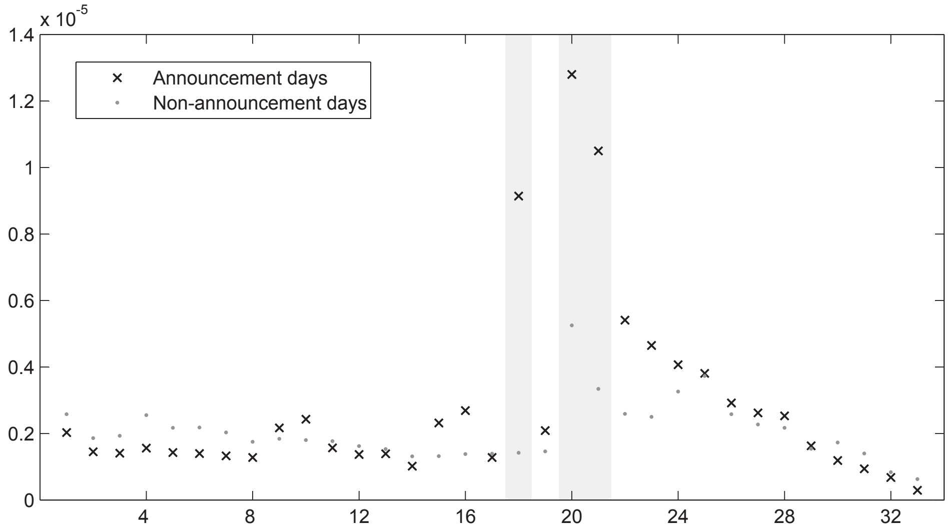
In this subsection we provide evidence that the test for level shifts and rotations consistently detects monetary policy surprises. First, a descriptive approach locates the average intradaily occurrence of shifts and rotations. Second, regressions provide a direct link between the test results and a survey measure of monetary policy surprises.

2.5.2.1 Localization

If level shifts and rotations of the yield curve are driven by monetary policy surprises, they should occur within time intervals where the ECB communicates with markets. To study this relation, we decompose the cojump estimator and refer to average absolute increments in quadratic covariation estimates on the 20 minutes intraday blocks. According to (2.8), large increments locate significant shifts and rotations of the yield curve.

[12] Note that the majority of non-standard or unconventional measures were announced in press conferences on policy announcement days.

Figure 2.5: Block-wise averages of increments in quadratic covariation estimates.



Notes: The figure depicts average increments of SPECV on each intraday block for the 133 policy announcement and 458 non-announcement days from 2001 to 2012. The x-axis refers to the 33 20 minute intraday blocks. Blocks where the ECB communicates with markets are emphasized.

Figure 2.5 shows the average increment for each of the 33 intraday blocks. Increments (cross) within the shaded intervals clearly indicate that press releases (block 18) and press conferences (block 20, 21) have on average a strong impact on the yield curve. In contrast, the intraday pattern on non-announcement days (gray dots) is rather flat.[13] Thus, the detected level shifts and rotations occur instantaneously in response to the ECB's communication.[14]

The relative size of increments in Figure 2.5 reflects that the press conferences have on average a larger effect on the maturity structure than the actual decision on the key rate. Inline with regressions of EURIBOR futures by Ehrmann and Fratzscher (2009), this emphasizes the meaning of press conferences to communicate intentions of the policy decisions. In the context of the structural explana-

[13]The spike on non-announcement days on block 20 can be explained by the publication of weekly US jobless claims on Thursdays at 14:30 CET.

[14]Appendix 2.A provides further details. We show deaggregated examples of two distinct policy announcements.

Table 2.1: Upward and downward level shifts.

Block	Press release ($k = 18$)	
Period	pre crisis	crisis
Policy surprise	0.48 * (0.22)	0.61 * (0.27)
Pseudo R^2	0.30	0.27

Notes: Ordered probit regressions refer to a normal error distribution. Huber, White robust standard errors are given in parenthesis. * indicates significance at the 5% level. Results are based on 78 monetary policy announcement days in the pre-crisis period (2001-2007) and 55 in the crisis period (2008-2012).

tions for level shifts and rotations, press conferences help market participants to infer the source of policy surprises and to adjust expectations about future policy decisions appropriately.

2.5.2.2 The link to survey expectations

We study the link between the test results on level shifts and rotations and a survey based monetary policy surprise variable. Regressions of the two variables aim at establishing our test for level shifts and rotations as a consistent measure to detect monetary policy surprises.

We focus on upward and downward level shifts that occur in response to the press release. Upward and downward level shifts are classified through the sign of average returns on the respective intraday block. The difference between the actual decision on the key rate and median expectations serves as a monetary policy surprise variable. Expectations are taken from the Bloomberg survey.

Regression results of the ordered variable on the survey measure are reported in Table 2.1. The significant coefficient estimates indicate that the test for level shifts and rotations consistently detects monetary policy surprises. If markets overestimate (underestimate) the decision on the key rate, the whole yield curve shifts downwards (upwards).

The test results on level shifts and rotations in Section 2.5.1 in conjunction with Table 2.1 provide a link to the standard linear regression literature of Cook and Hahn (1989) and Kuttner (2001). As documented in e.g. Andersson et al. (2009) and Brand et al. (2009), responses of single maturities to ECB policy surprises are uniformly positive. Our test for level shifts and rotations confirms that finding and suggests that the majority of yield curve responses are simultaneous adjustments at both the short and long end of the maturity structure.

2.6 Conclusion

This paper contributes to the literature on yield curve responses to monetary policy announcements. We propose an empirical test to distinguish between *level shifts* and *rotations* of the yield curve. The test is based on daily high-frequency statistics and discriminates the response patterns through cojumps of a short and long term interest rate. The cojump approach is consistent with the traditional regression studies of Cook and Hahn (1989) and Kuttner (2001), however, allows to zoom in to single monetary policy announcements and to study the response pattern of the yield curve for each announcement day independently.

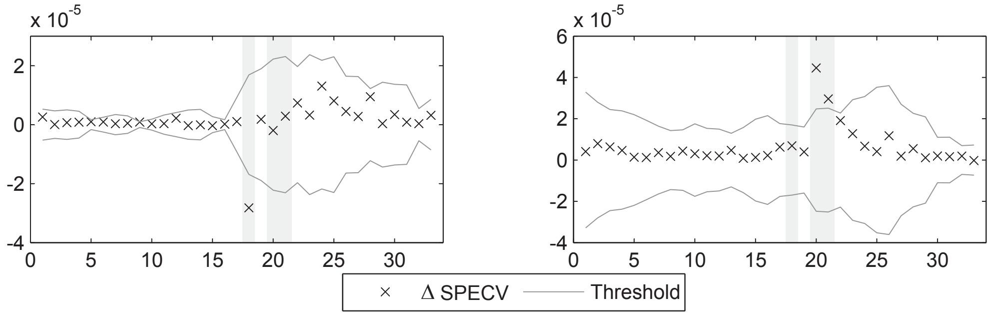
The practical value of the new test is motivated by the theoretical work of Ellingsen and Söderström (2001) and Rudebush and Wu (2008). The response of the yield curve on a particular monetary policy announcement day *i*) detects the occurrence of a policy surprise and *ii*) identifies markets' perceptions about the *source* of the surprise. Thus, the test enables central banks to monitor markets' understanding about monetary policy and to learn whether intentions of a policy decision are well-communicated.

The empirical example of ECB monetary policy from 2001 to 2012 suggests a reliable, stable and well-communicated policy implementation. Ever since the ECB's clarification of the monetary policy strategy in 2003, we find that markets' perceptions about policy preferences have been remarkably stable. This finding includes the global financial and European sovereign debt crisis. The communication of non-standard and unconventional measures during crisis times were not perceived to soften the ECB's main mandate of price stability.

None the less, our results suggest that the efficiency of monetary policy can be further increased. Approx. 26% of the policy announcements are interpreted by market participants to provide news about macroeconomic conditions. Besides the publication of official projections about current and future states of the economy, the availability of guidelines to produce appropriate economic forecasts appears as a possible step towards further enhancements in effectiveness.

2.A Examples of level shifts and rotations

Figure 2.6: Detection of a rotation on 07.03.2002 (left) and level shifts on 02.10.2008 (right).



Notes: Cojump estimates are given by the sum of increments in SPECV (2.6) outside the threshold bands. The x-axis displays the 33 20 minute intraday blocks. Blocks where the ECB communicates with markets are emphasized.

This appendix illustrates how the day-wise estimation of cojumps works and provides news related arguments for particular shifts and rotations of the yield curve. We highlight two different examples of monetary policy announcement days. Based on the test results in Section 2.5.1, we pick the rotation of the yield curve on March, 7. 2002 and the level shift of the yield curve on October, 2. 2008. In Section 2.4.3 we define negative cojump estimates as rotations and positive estimates as level shifts of the yield curve. Figure 2.6 depicts increments in quadratic covariation estimates (2.6) and respective thresholds. The cojump estimator (2.7) shows that increments outside the threshold bands localize cojumps and sum up to the cojump estimate.

On March, 7. 2002, the negative cojump estimate is determined by the increment on block 18. Thus, the publication of the press release triggered a policy surprise on that day. With an unchanged key rate at 3.25%, some Bloomberg survey participants expected lower interest rates to boost the economic recovery after the 2000-2001 recession (average expectations were slightly below 3.25%). However, with annual inflation above 2%, the ECB emphasized with its interest rate decision the role of inflation more strongly than expected. Markets adjusted to that new information about policy preferences such that the yield curve rotated. The press conference (block 20 and 21) did not provide further significant surprises on that day.

In terms of policy response, the right hand plot of Figure 2.6 displays the exact opposite compared to the left hand plot. On October, 2. 2008 the positive cojump estimate is determined by the increments on block 20 and 21. According to the Bloomberg survey, on that day the decision on the key rate (unchanged at 4.25%) was fully expected. However, strong pronouncements of downside risks due to the intensification of the global financial crisis during the press conference lead to revisions of markets' economic outlook. The news about the economic conditions triggered level shifts of the yield curve.[15]

[15] The wording of the introductory statement and the question and answer session can be find on the ECB webpage: http://www.ecb.int/press/pressconf/2008/html/index.en.html .

3 Assessing the anchoring of inflation expectations

3.1 Introduction

Expectations play a key role in the conduct of modern monetary policy. In particular, the New-Keynesian Phillips curve stresses the importance of inflation expectations for the rate of actual inflation. Central banks' ability to achieve price stability is thus directly linked to its ability to anchor inflation expectations at their target. Major central banks, including the Federal Reserve, the Bank of England and the European Central Bank, monitor inflation expectations as an indicator of inflation pressure. The quote "inflation expectations are well anchored" is a frequently used phrase in press conferences and monetary policy reports. Yet, in spite of their prominent role in monetary policy, inflation expectations are still under-researched. Specifically, it is not clear how the degree of anchoring of inflation expectations should be defined and measured empirically.

In monetary policy practice it is often argued that inflation expectations are well anchored if their distance to a more or less explicit inflation target is sufficiently small, see BoE (2010) and ECB (2011). More sophistically, the empirical literature employs news regressions and a pass-through criterion. The news regression approach exploits the idea that anchored inflation expectations should be insensitive to economic news, compare Levin et al. (2004) and Gürkaynak et al. (2010b). Similarly, the pass-through criterion of Jochmann et al. (2010) and Gefang et al.

(2012) defines inflation expectations as anchored if longer-term expectations do not respond to changes in shorter-term expectations. Both approaches restrict their attention to first differences of the inflation expectations measure.

In the present paper, we argue that differencing leads to a loss of valuable information and imposes implausible dynamics of inflation expectations. Firstly, a regression in first differences implies a unit root for the level of expected inflation, i.e. shocks to the level never die out. Such extreme persistence appears hardly compatible with the idea of anchored expectations. Secondly, within a first difference regression any information about the level of expected inflation is lost. However, even if the central bank does not announce an explicit inflation target, the level of inflation expectations should be of crucial importance.

We propose an exponential smooth transition autoregressive (ESTAR) model to assess the degree of anchoring. Nobay et al. (2010) recently showed that the ESTAR model captures the dynamics of the actual rate of US inflation remarkably well.[1] As a natural extension, we apply this model to inflation expectations data. The distinguishing feature of the ESTAR approach is given by its flexible dynamics. On the one hand, the model accounts for the locally high persistence typically observed in expectations data, while on the other hand it implies global stationarity, i.e. shocks to the level die out eventually.

The ESTAR model allows inflation expectations to return to some long-run equilibrium value or *anchor*. This value will be interpreted as the *market-perceived* inflation target, which may well deviate from an officially announced inflation target of a central bank. The transition speed within the exponential function determines how fast the reversion to the perceived target takes place and therefore provides a natural measure of the *strength* of the anchor. The transition function of the ESTAR model implies an increasing incentive to revise expectations the more they deviate from the market-perceived target. These characteristics appear suitable and also intuitive in view of anchored inflation expectations generated by credible monetary policy. We include macroeconomic news variables as controls

[1] The ESTAR approach is also used to model the dynamics of other macroeconomic time series as, for instance, exchange rates (Kilian and Taylor 2003).

in the ESTAR model. Therefore, our approach represents an extension of the news regression of Gürkaynak et al. (2010b) which is nested as a special case. The crucial difference is, however, that even if economic news affect inflation expectations, they might still be well anchored. The main aspect of our criterion is, how fast the impact of a shock decays.

We investigate the degree of anchoring of inflation expectations in the United States (US), the European Monetary Union (EMU), the United Kingdom (UK) and Sweden (SW). The expectations measure under consideration is the so called break-even inflation (BEI) rate that is the most prominent measure of inflation expectations within the news regression and the pass-through literature. BEI rates can be derived from the spread of nominal and real government bond yields, i.e. inflation-indexed bonds. Although the considered countries have highly liquid nominal and real bond markets, constant maturity yields of real bonds derived from term structure estimates are usually not readily available. In order to avoid distortions triggered by different data sources and estimation techniques, we closely follow the methodology of Gürkaynak et al. (2010a) and construct a homogeneous data set of BEI rates for the countries under investigation.

With respect to the macroeconomic news variables, we find significant influence in all countries, suggesting equally distorted inflation expectations. The different mean-reverting properties of the expectations series, however, reveal that the degree of anchoring of inflation expectations varies substantially across countries and expectations horizons. We find that shorter-term expectations are anchored more firmly than longer-term expectations, meaning that shocks of a given magnitude die out faster in shorter-term expectations. Among the four countries, the anchoring of expectations is strongest in the EMU, along with a perceived target close to the ECB's implied inflation target of 2%. In contrast, UK inflation expectations exhibit the weakest degree of anchoring, reflecting very high persistence. This is accompanied by a high market-perceived target of up to 4.3%. In view of inflation expectations in the US, a comparison of a pre- and post-Lehman period shows that the strength of the anchor of shorter-term expectations decreases, while it increases for longer-term expectations.

The remainder of the paper is structured as follows. Section 3.2 introduces the anchoring criterion based on the ESTAR model. The measure of inflation expectations, i.e. BEI rates, are introduced in Section 3.3. Furthermore, Section 3.3 comprises a preliminary data analysis. Estimation results, including an impulse response analysis, are discussed in Section 3.4, and Section 3.5 concludes.

3.2 Assessing the degree of anchoring

We analyze the degree of anchoring by means of an exponential smooth transition autoregressive (ESTAR) model. Similar ESTAR specifications are prominently used in literature on purchasing power parity, and also to model the actual rate of inflation, see among others Kilian and Taylor (2003) and Nobay et al. (2010), respectively.[2] The model is given by

$$y_t = c + \exp\left(-\gamma(y_{t-1} - c)^2\right)\left(\sum_{i=1}^{p} \alpha_i y_{t-i} - c\right) + \beta X_t + \varepsilon_t \ , \tag{3.1}$$

where y_t represents the measure of inflation expectations, i.e. the BEI rate, and c is a constant. The sum of autoregressive parameters is restricted to $\sum_{i=1}^{p} \alpha_i = 1$ and X_t constitutes a vector of economic news variables, with β as the corresponding coefficient vector and ε_t as a zero mean white noise process. The dynamics of y_t are determined by the exponential smooth transition function $\exp(-\gamma(y_{t-1} - c)^2)$ which is the source of non-linearity in this model. The transition function is bounded between zero and one, and depends on the transition variable y_{t-1}, the smoothness parameter $\gamma > 0$, and a location parameter c. Given the restriction of the sum of autoregressive parameters, model (3.1) behaves locally like a random walk if the lagged expectations measure y_{t-1} equals c. If y_{t-1} departs from c, the process is stationary and the degree of mean reversion at time t depends on the squared difference between y_{t-1} and c. As shown in Kapetanios et al. (2003), the ESTAR model is globally stationary despite its local non-stationarity.

In economic terms, the equilibrium value c can be interpreted as the *market-perceived* inflation target. If the BEI rate was close to c in the last period, a shock

[2]The adequacy of the ESTAR specification in the present context of inflation expectations is evidenced by linearity tests as presented in Appendix 3.B.

to inflation expectations would have a long lasting impact. That is, the model allows for local high persistence when deviations from the target are so small that they are economically negligible. However, when shocks drive the BEI rate further away from the target, the anchoring pulls expectations back to c. Due to the non-linearity of the model, the persistence of inflation expectations decreases in the distance to the market-perceived target, i.e. the larger the gap between y_{t-1} and c, the stronger the mean reversion. For a given distance, the parameter γ controls the shape of the exponential function and hence the transition speed towards c. Therefore, estimates of γ are considered a natural measure for the *strength of the anchoring* of inflation expectations: the larger the γ, the stronger the anchor. Apart from γ, the market-perceived inflation target c provides further important information, namely the level of expectations, which may or may not be close to the announced central bank's inflation target.

Following the news regression literature, we also include major macroeconomic and monetary news as control variables; compare Gürkaynak et al. (2010b). The crucial difference between our econometric approach and the standard news regression is that model (3.1) allows the expectations measure to mean revert. In fact, the news regression given by

$$\Delta y_t = \beta X_t + \varepsilon_t \tag{3.2}$$

implies a unit root in the level of y_t. The ESTAR extension of (3.2) mitigates this implausible assumption. It provides more flexible inflation expectations dynamics and nests the news regression for the special case $p = 1$ and $\gamma = 0$. Furthermore, the news regression approach in (3.2) is likely to suffer from an omitted variable bias, i.e. due to data availability, the selection of news variables might be incomplete. In contrast, our approach does not rely on the completeness of the X_t vector since the consistently estimated γ reflects the adjustment speed to a shock of any nature, be it a shock in X_t or in ε_t.

3.3 Break-even inflation rates

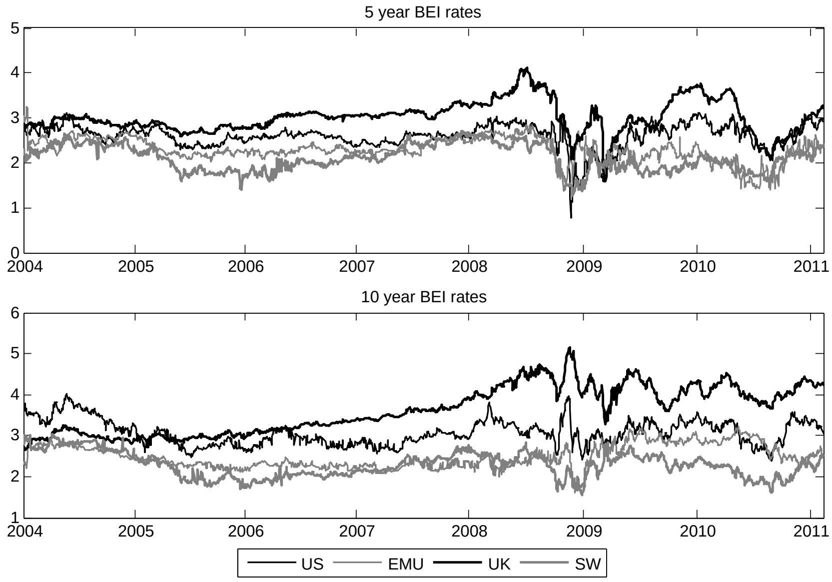
The expectations data are extracted from nominal and inflation-indexed government bond yields. According to the Fisher equation, the spread between nominal and real yields provides a measure of inflation expectations, i.e. the break-even inflation (BEI) rate. In contrast to a holder of a real bond, the investor of a nominal bond faces inflation risk. Hence, BEI rates are not a pure measure of inflation expectations. In fact, break-even inflation rates consist of inflation expectations and an inflation risk premium. Christensen et al. (2010) show, however, that the average risk premium is virtually zero within an affine term structure model for the US. Furthermore, given our interest in the anchoring of inflation expectations, including the premium as a part of the relevant variable provides important information. More specifically, a central bank that aims to stabilize inflation expectations should also aim to minimize the inflation risk premium. Therefore, we rely on BEI rates to evaluate the anchoring of inflation expectations.[3]

We investigate the degree of anchoring in the United States (US), the European Monetary Union (EMU), the United Kingdom (UK) and Sweden (SW). This selection is consistent with the former anchoring literature and is narrowed by data availability. We investigate daily data from January 2004 to February 2011. By starting in 2004, we ensure that the countries have highly liquid nominal and real bond markets across a wide range of maturities. We follow the methodology of Gürkaynak et al. (2007c) and Gürkaynak et al. (2010a) and estimate nominal and real Nelson-Siegel-Svensson yield curves to obtain coherent term structures of BEI rates across the different countries under investigation.[4] The inflation expectations measure is the one-year forward break-even inflation rate. We consider two different expectations horizons: the five-year horizon and the ten-year

[3]In order to disentangle the two components, affine term structure models of e.g. Adrian and Wu (2009) and Christensen et al. (2010) are available. Such a filtered inflation measure, however, strongly depends on the choice of the model and, of course, is subject to estimation uncertainty.

[4]By building a coherent dataset, we intend to minimize the risk of distortions induced by using different data sources that rely on different methodologies. For instance, the FED uses the Nelson-Siegel approach while the Bank of England applies a spline method; the criteria for choosing the specific bonds also differ between different data sources. For details on our methodology see Appendix 3.A.

Figure 3.1: Five- and ten-year BEI rates



Notes: Calculated via nominal and real forward rates from Nelson-Siegel-Svensson yield curves. The five-year rate reflects expectations in five years for one year, the ten-year rate expectations in ten years for one year.

horizon. The one-year forward in five years captures the ability of central banks to anchor inflation expectations within the often defined policy horizon of three to five years. The ten-year horizon is commonly used in the anchoring literature and represents longer-term expectations, compare Gürkaynak et al. (2010b) and Beechey et al. (2011).

Figure 3.1 depicts the five-year (upper graph) and ten-year (lower graph) expectations horizons of the different countries. The figure indicates that market participants expect inflation around two and three percentage points. As expected, revisions of expectations are rather small on a daily basis, such that the depicted series behave very persistently. The degree of anchoring over time is not obvious but an impact of the global financial crisis is clearly visible. Therefore, both a pre-crisis and a crisis period are considered. We follow a standard treatment of dating the crisis by defining the bankruptcy of Lehman Brothers on 15 September

Table 3.1: Descriptive statistics of inflation expectations

		pre-crisis			crisis		
	Horizon	mean	std.	d	mean	std.	d
US	5Y	2.63	0.16	0.75 [0.64,0.86]	2.54	0.40	0.56 [0.40,0.73]
	10Y	3.05	0.32	0.87 [0.76,0.98]	3.11	0.29	0.63 [0.47,0.80]
EMU	5Y	2.40	0.18	0.77 [0.66,0.88]	2.09	0.28	0.52 [0.36,0.67]
	10Y	2.37	0.19	0.63 [0.53,0.74]	2.71	0.31	0.93 [0.76,1.10]
UK	5Y	3.04	0.29	0.90 [0.80,1.02]	2.96	0.46	0.90 [0.74,1.08]
	10Y	3.35	0.48	0.68 [0.57,0.79]	4.15	0.30	1.03 [0.87,1.22]
SW	5Y	2.20	0.28	0.64 [0.54,0.75]	1.93	0.22	0.76 [0.58,0.91]
	10Y	2.33	0.32	0.70 [0.59,0.80]	2.20	0.26	0.82 [0.66,0.99]

Notes: Mean and standard deviation in percentage point and d the order of fractional integration.Pre-crisis sample Jan 2004 - Sep 2008 ($\sim$ 1200 obs.), crisis sample Sep 2008 - Feb 2011 ($\sim$ 630 obs.).

2008 as its starting point. Note that our crisis period lasts until 2011 and thus incorporates the European sovereign debt crisis as well.

Descriptive statistics of the break-even rates before and after the Lehman bankruptcy are presented in Table 3.1. BEI rates across the different countries and expectations horizons are on average well above the two percent mark. The two percent mark is often viewed as an inflation target in the EMU, the UK and Sweden and very recently in the US as well. The means and standard deviations of most countries are larger for the ten-year horizon than for the five-year horizon. A clear pattern of how the crisis affects the expectations measure is not evident.

To get a first impression of the mean reversion properties of inflation expectations we follow the literature on inflation persistence (e.g., Hassler and Wolters 1995, Meller and Nautz 2012) and estimate the order of fractional integration, d. All estimates lie within the interval $(0.5, 1)$, where processes are still mean reverting but non-stationary.[5] However, it is well-known that estimates of the order of fractional integration are misleading if non-linearities of the true underlying process are not considered, see e.g. Ohanissian et al. (2008) and Kruse and Sibbertsen (2011). In line with this interpretation, we conducted the Kapetanios et al. (2003) and Teräsvirta (1994) linearity tests against ESTAR. These test results provide strong evidence in favor of the ESTAR model (see Appendix 3.B).

3.4 Empirical results on the anchoring of inflation expectations

3.4.1 Strength and level of the anchor

The effect of at least one macroeconomic news variable is statistically significant in all countries under investigation (see Appendix 3.C.2). Strictly applying the news regression criterion, we would conclude, that inflation expectations in the EMU, the US, Sweden and the UK are equally deanchored. Instead, our extended ESTAR model allows to further analyze shocks to inflation expectations. Specifically, we estimate how long their effect lasts.

The empirical analysis focuses on the two model parameters γ and c in equation (3.1) that provide information on the strength and level of the anchor. Since the ongoing crisis potentially changes the degree of anchoring, we account for parameter shifts within our ESTAR specification (3.1). Specifically, a Lehman step dummy LEH that takes the value one from 9/15/2008 until the end of the sample captures breaks in c and γ.[6] Estimation results on the anchoring of inflation expectations, given in Table 3.2, are interpreted with respect to three perspectives: across the five- and ten-year expectations horizons; across countries; and across the pre-crisis and the crisis period.[7]

[5]The non-stationarity is caused by an unbounded variance of the process.

[6]Note that we found estimation results of the time series dynamics to be robust against a sample split, i.e. separate estimation of the pre-crisis and crisis sample.

[7]Note that the γ and c estimates are robust against the exclusion of the news variables.

Table 3.2: Anchoring of inflation expectations

	US		EMU		UK		SW	
	5Y	10Y	5Y	10Y	5Y	10Y	5Y	10Y
c	**2.613** (0.029)	**3.233** (0.059)	**2.416** (0.021)	**2.491** (0.035)	**3.113** (0.108)	**3.463** (0.140)	**2.169** (0.049)	**2.310** (0.066)
LEH	−0.181 (0.100)	**−0.181** (0.075)	**−0.370** (0.048)	0.162 (0.096)	0.102 (0.532)	**0.830** (0.180)	**−0.217** (0.092)	−0.140 (0.082)
γ	**0.294** (0.086)	**0.055** (0.016)	**0.531** (0.188)	**0.189** (0.059)	0.021 (0.014)	0.011 (0.007)	**0.074** (0.026)	**0.057** (0.025)
LEH	**−0.250** (0.088)	**0.152** (0.071)	−0.023 (0.188)	−0.113 (0.071)	−0.015 (0.017)	0.020 (0.019)	0.047 (0.073)	0.108 (0.067)
p	1	4	2	3	2	3	2	2
Q(5)	0.59	0.26	0.95	0.28	0.08	0.05	0.23	0.58
Q(10)	0.60	0.41	0.97	0.35	0.01	0.14	0.18	0.75
ARCH(1)	0.58	0.00	0.86	0.02	0.01	0.10	0.63	0.22
ARCH(5)	0.67	0.11	0.89	0.29	0.07	0.47	0.24	0.56

Notes: ML estimation of $y_t = c + c\,\mathrm{LEH} + \exp\left(-(\gamma + \gamma\,\mathrm{LEH})(y_{t-1} - (c + c\,\mathrm{LEH}))^2\right)\left(\sum_i \alpha_i y_{t-i} - (c + c\,\mathrm{LEH})\right) + \beta X_t + \varepsilon_t$. $y_t :=$ daily BEI rates are measured in percentage points in the sample period Jan 2004 to Feb 2011. Numbers in bold indicate significance at the 5% level. Bollerslev-Wooldrige heteroskedasticity consistent standard errors of the estimated coefficients are given in parentheses. LEH:= step dummy that takes the value one from 9/15/2008 until 2/14/2011 and zero elsewhere. Estimation results for the news variables can be found in Appendix 3.C.2. The lag length p is determined by standard autocorrelation tests. The p-values of Q-statistics $Q(5)$ and $Q(10)$ illustrate that no significant autocorrelation up to order 10 is left in the residuals. ARCH LM test results reflect that, apart from a few exceptions, the GARCH(1,1) ensures no remaining ARCH effects.

Anchoring across expectations horizons

Estimates of γ are given in the third and fourth row of Table 3.2. The larger the γ, the stronger the anchoring of inflation expectations. Our results indicate a stronger anchoring of five-year BEI rates for all countries under investigation (the US crisis sample excepted). One explanation of this finding might be that the often defined policy horizon of central banks consists of a period between three and five years. This reflects that markets expect a more active role of central banks against medium term inflationary pressure. As a consequence, shocks to longer-term expectations are more persistent. Results on the strength of the anchor are confirmed by estimated market-perceived targets that, on average, take values around 2.5 percentage points for five-year and close to 3 percentage points for ten-year expectations horizon. Deviations of market-perceived targets from a central bank target of two percent can in part be explained by a positive risk premium. In line with Christensen et al. (2010), our findings reflect that markets associate longer-term expectations with higher uncertainty about inflation and thus with a larger premium.

Anchoring across countries

For a given level of the market-perceived target, our point estimates of γ suggest that EMU expectations are anchored most firmly, followed by US, Sweden and finally the UK. The transition speed of UK expectations is by far the slowest, reflecting a very high degree of persistence. For the five-year horizon in the UK, for instance, γ equals 0.02. In shorter-term expectations in the EMU, however, we find $\gamma = 0.53$, which indicates a much lower degree of persistence. Considering the location of the anchor, the cross-country comparison reveals that inflation expectations are anchored around the smallest values (between 1.94 and 2.31) in Sweden. For the EMU and US the level of the anchor is located between roughly 2.5 and 3.2 percent. In the UK data on the other hand, we find market-perceived targets of up to 4.29 percent.

Anchoring and the financial crisis

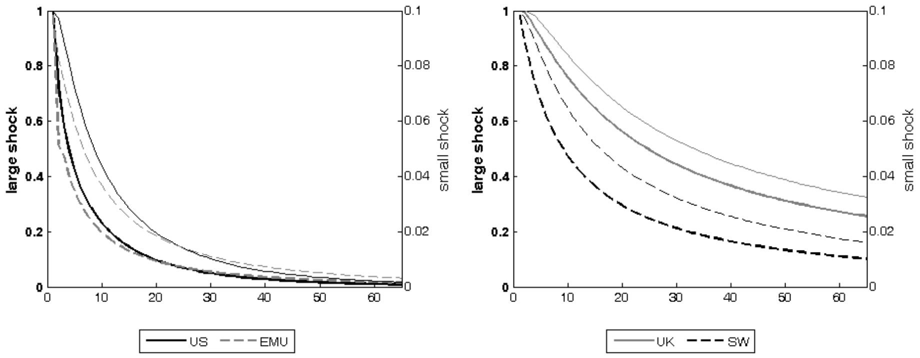
The impact of the crisis does not point in a unique direction. Market-perceived targets, however, change significantly in all countries. In the US and Sweden, c decreases for both expectations horizons, indicating a decrease in inflation pressure. In contrast, the market-perceived target strongly increases by 0.83 percentage points in longer-term UK expectations. In the EMU the term structure of BEI rates steepens due to a decreasing perceived target at the shorter-term horizon (from 2.42 to 2.05) and a non-changing target of longer-term expectations. Unlike the level, the strength of the anchor did not change significantly in most of the countries during the crisis. An exception is given by the US BEI rates. While the transition speed decreases for the medium-term horizon, it increases for the longer-term horizon. This reflects an increasing degree of anchoring of longer-term horizons and a declining degree of shorter horizons.

3.4.2 Impulse response analysis

In order to reveal what estimates of γ actually imply for the persistence of inflation expectations, we compute impulse response functions. Since standard techniques for linear processes are not applicable to the ESTAR model, we make use of generalized impulse response functions (GIRFs) as suggested by Koop et al. (1996).[8] The analysis allows us to investigate the anchoring strength for the different countries and time horizons with respect to shocks of different magnitudes. Specifically, non-linear dynamics of inflation expectations are highlighted by two different shock sizes: a *small* shock of 10 basis points (bp) and a *large* shock of 100 bp. Given the estimated standard deviations of the BEI rates in Table 3.1, the small shock roughly represents one half of a standard deviation, while the large shock is approximately four times a standard deviation. In addition to the impulse responses, we calculate half-lives that indicate the number of days an initial shock needs to be absorbed by 50 percent.

[8]See Appendix 3.D for further details on computational steps.

Figure 3.2: Impulse response functions of 5 year BEI rates



Notes: Generalized impulse response functions are based on ESTAR estimates of the pre crisis as given in Table 3.2. Detailed simulation steps are described in Appendix 3.D. Magnitudes of the shocks are set to 10 bp ("small shock", indicated by thin lines, right axis) and 100 bp ("large" shock, indicated by bold lines, left axis). The x-axis reflects the number of days after the initial shock.

Figure 3.2 depicts the impulse response functions of the five-year expectations. The figure clearly indicates the nature of the non-linear model: Impulse responses of the large shock decrease much stronger than responses to the small shock. While the initial impact of the large shock drives expectations far away from the perceived target, the anchoring of inflation expectations results in a fast absorption of the shock. In other words, the larger the initial shock, the stronger revisions of expectations in the direction of the perceived target. This effect becomes more pronounced when γ is larger. Half-lives, as reported in Table 3.2, confirm results from the previous subsection. We elaborate along the same three perspectives: across expectations horizons, across countries and through pre-crisis and crisis sample.

Half-lives indicate the better anchoring of shorter-term expectations. In comparison to the five-year horizon, a shock to inflation expectations at the ten-year horizon needs, on average, about one week more to be absorbed by 50%.

Turning to the cross-country comparison, half-lives of up to 4 weeks mirror the strong anchoring of EMU, Sweden and US expectations. In contrast, the time to absorb 50% of a shock is 5 to 10 weeks in the UK. The overall impression from

Table 3.3: Half-lives in days

		pre-crisis		crisis	
	Horizon	10 bp	100 bp	10 bp	100 bp
US	5Y	9	4	19	12
	10Y	19	16	9	5
EMU	5Y	7	3	6	2
	10Y	11	7	9	5
UK	5Y	34	25	28	24
	10Y	43	40	49	42
SW	5Y	16	10	17	11
	10Y	16	11	18	10

Notes: Reported values represent the absorption time measured in days for 50% of the initial shock size of 10 bp ("small shock") and 100 bp ("large shock"), respectively.

Table 3.3 is, however, that shocks are absorbed fairly rapidly in all four countries, which expresses a substantial degree of anchoring.

In view of the pre-crisis and crisis period, half-lives of US inflation expectations reflect the significant break in the anchoring strength. The break reverses the absorption time of longer- and shorter-term expectations in that shorter horizons appear less anchored during the crisis. Since the expectations data for the EMU, the UK and Sweden display no significant break in γ, the slight changes in half-lives simply result from the particular set of histories used to compute impulse responses in each subsample.

In sum, the decay of the impulse responses illustrates the main idea of the proposed anchoring measure: well-anchored inflation expectations should display stationary characteristics and should therefore always tend to return to some long-run equilibrium value.

3.5 Conclusion

In this paper we propose a non-linear time series approach to determine the degree of anchoring. We build on a well-known analytical framework for investigating this topic, namely the news regression, wherein first differences of an expectations measure are regressed on macroeconomic news. Specifically, the implicit unit root assumption of the news regression approach is relaxed as we allow anchored inflation expectations to follow a globally stationary ESTAR process. This generalization permits a shift in focus from the immediate news effect to the dynamics of inflation expectations. Model parameters are economically interpretable as a market-perceived inflation target and as the strength of the anchor that drives expectations back to the target.

Macroeconomic news variables turn out to have a significant impact on inflation expectations in the US, EMU, UK and Sweden. While in the news regression context this result suggests equally distorted and non-stationary expectations, the proposed ESTAR extension reveals mean-reversion and thus well anchored inflation expectations in all countries under investigation. The ESTAR estimates show, firstly, that shorter-term inflation expectations are anchored more firmly than longer-term expectations. Secondly, expectations appear best anchored in the EMU, followed by the US, Sweden and the UK. Thirdly, in most countries the average level of inflation expectations decreases during the crisis.

Given central banks' mandate to stabilize the actual rate of inflation, our results support the view of credible policy strategies that anchor inflation expectations in all countries investigated here. Apart from the UK, the market perceived inflation targets are close to the usually imposed inflation targets of around 2 percent. Moreover, expectations vary around these targets in a stationary manner. This leads to the conclusion that expectation formation processes are successfully controlled by central banks.

So far, the univariate setup implies that shocks to inflation expectations are uncorrelated across countries. Of course, for many cases, such as oil price shocks, the uncorrelatedness assumption might be too rigid. A multivariate extension of the present approach would therefore provide an interesting path for future research.

3.A Term structure estimation

This appendix describes how the constant maturity series were estimated as well as which and how many bonds were used. Our data set is based on bond yields downloaded from the Bloomberg database (for an overview see Table 3.4). We take all outstanding, standard government bonds (e.g. no callables) with more than two years time to maturity into account. Bonds with less than 24 months to maturity are cut out because real bonds' indexation lags erraticate the yields of these securities, as shown in Gürkaynak et al. (2010a).

Table 3.4: Nominal and real bonds - overview

Short name	indexation	$\#'04$	$\#'10$	Obs.
US TREASURY N/B	-	124	204	1792
TSY INFL IX	US CPI	12	31	
FRANCE O.A.T.	-	31	34	1858
FRANCE O.A.T.I/L	EMU HICP	4	6	
UK TREASURY	-	26	35	1856
UK TSY I/L	UK CPI	9	17	
SWEDEN GOVT	-	12	9	1837
SWEDEN I/L	CPI Sweden	5	5	

Notes: $\#'04$, $\#'10$ report the number of outstanding bonds in June 2004 and 2010, Obs. is the number of daily observations within the time span of January 2004 until February 2011. EMU HICP refers to the harmonized index of consumer prices of the European Monetary Union.

For each day where yields for more than three bonds are available, we follow the approach of Gürkaynk et al. (2007c), and estimate constant maturity yields. The standard parametric yield curve specification is based on a functional form that was proposed by Nelson and Siegel (1987) and extended by Svensson (1994):

$$\hat{z}_t(\tau) = \beta_1 + \beta_2 \left[\frac{1 - e^{-\frac{\tau}{\lambda_1}}}{\frac{\tau}{\lambda_1}} \right] + \beta_3 \left[\frac{1 - e^{-\frac{\tau}{\lambda_1}}}{\frac{\tau}{\lambda_1}} - e^{-\frac{\tau}{\lambda_1}} \right] + \beta_4 \left[\frac{1 - e^{-\frac{\tau}{\lambda_2}}}{\frac{\tau}{\lambda_2}} - e^{-\frac{\tau}{\lambda_2}} \right].$$

The observed zero coupon yield for maturity τ is given by $z(\tau)$, whereas the model-implied yield is $\hat{z}(\tau)$. We minimize $\sum(\hat{z}(\tau) - z(\tau))^2$ with respect to the parameters β_1, β_2, β_3, β_4, λ_1 and λ_2 by the Differential Evolution approach proposed by Storn and Price (1997). Forward rates are derived from zero-coupon yield curves via

$$f_t(n,m) = \frac{1}{m}((n+m)\hat{z}_t(n+m) - n\hat{z}_t(n)) \ , \tag{3.3}$$

in which $f_t(n,m)$ is the forward rate at time t for a period of m years, beginning n years in the future. The n-year BEI rate reflects today's expected inflation rate (plus an inflation risk premium) and is given by $\text{BEI}(n) = f_t^{\text{nom}}(n,m) - f_t^{\text{real}}(n,m)$.

3.B ESTAR specification tests

Table 3.5: Linearity tests against ESTAR

		H_0 : stationary AR(p)			H_0 : non-stationary AR(p)		
	Horizon	whole	pre-crisis	crisis	whole	pre-crisis	crisis
US	5Y	41.4^{***}	21.3^{***}	10.6^{***}	-5.19^{***}	-4.10^{***}	-3.16^{**}
	10Y	33.4^{***}	44.5^{***}	7.08	-4.01^{***}	-2.17	-2.91^{**}
EMU	5Y	59.5^{***}	65.2^{***}	6.70	-5.52^{***}	-10.8^{***}	-3.15^{**}
	10Y	44.9^{***}	44.9^{***}	16.9^{**}	-2.14	-2.11	-1.96
UK	5Y	33.4^{***}	44.5^{***}	5.34	-3.99^{***}	-1.32	-2.75^{*}
	10Y	46.6^{***}	44.2^{***}	42.9^{***}	-2.61	-1.37	-1.72
SW	5Y	11.9^{**}	21.9^{***}	7.41	-3.59^{***}	-3.11^{**}	-2.33
	10Y	38.4^{***}	30.6^{***}	33.4^{***}	-4.55^{***}	-3.43^{***}	-4.22^{***}

Notes: Test statistics of the LM test with the null hypothesis of a stationary autoregressive process and KSS with the null of a non-stationary autoregressive process. The lag length is chosen in that residuals are free from significant autocorrelation. The rejection of the respective null hypothesis at the 10% is indicated by *, at the 5% by ** and at the 1% level by ***. Sample periods: whole refers to January 2004 - February 2011; pre-crisis to January 2004 - September 2008; and crisis to September 2008 - February 2011.

For specification of the ESTAR model, we perform two different types of linearity tests. Both approximate the exponential function in (3.1) around $\gamma = 0$ to obtain an auxiliary regression. The t-test of Kapetanios et al. (2003) (KSS) tests the null of a linear non-stationary autoregressive process against ESTAR non-linearities. We also run the LM test of Saikkonen and Luukkonen (1988) and Teräsvirta (1994) to test the null of a linear, stationary autoregressive process against ESTAR non-linearities. Both tests are carried out since conventional autoregressive models are close to non-stationarity up to such a degree, that standard unit root tests show conflicting test results.

Table 3.5 shows the results of the two linearity tests. The LM test rejects the null across all countries and almost all sample periods. For a given country, an expectation horizon and a sample period, at least one of the two tests rejects the null in favor of the ESTAR model.[9] Consequently, we interpret these results as conclusive evidence that the true underlying processes can be well-approximated by an ESTAR model.

3.C News variables

3.C.1 News data

The news variables are calculated by the difference between the actual and the expected value. The expected value is represented by the mean prediction of the Bloomberg survey of professional economists, mostly consisting of bankers. They submit their forecast before or on the Fridays prior to the data release. The actual and forecasted values of the advanced estimate of the gross domestic product (GDP), industrial production (IP), consumer price index (CPI) and the producer price index (PPI) refer to the percentage yearly basis. The GDP, IP, CPI and PPI news measure the difference between the actual and forecasted value in percentage points. The unemployment rate (UMP) and the monetary policy

[9] The exception is the Swedish five-year BEI rate in the crisis sample. However, the test statistic of 7.41 corresponds to a p-value of 0.11 and the KSS test statistic of -2.33 falls above the 10% level of -2.66. Even though tests fail to reject the null at the 10% level, they point in the non-linear direction. In general, due to the sample split, linearity tests tend to suffer from low power, which may partly explain the failure of rejecting the null in a few cases.

rate (MP) are measured in percentages. The respective news variable reflects the unexpected component in percentage points. In line with the rational expectations assumption, mean forecast errors are close to zero, mostly uncorrelated and some do not reject the null of normality.[10]

3.C.2 Estimation results for news variables

While time series dynamics determine the degree of anchoring, surprise components of major economic announcements reveal potential sources of shocks that drive expectations away from the market-perceived target. Estimation results on the news coefficients are reported in Table 3.6. Numbers in bold reflect significance at the 10% level, indicating news announcements that lead to systematic revisions in inflation expectations. Monetary policy news, for example, show a significant impact in all countries. In general, for each country we observe at least one announcement that move markets' expectations significantly.

[10]We run the same type of regressions with median expectations. Qualitative results remain the same.

Table 3.6: Estimation results for news variables

	US		EMU		UK		SW	
	5Y	10Y	5Y	10Y	5Y	10Y	5Y	10Y
GDP	0.006	0.002	**0.088**	−0.013	0.025	−0.002	−0.004	−0.003
	(0.006)	(0.013)	(0.034)	(0.032)	(0.028)	(0.015)	(0.010)	(0.006)
IP	**0.023**	−0.019	0.002	−0.004	−0.002	−0.003	0.002	0.001
	(0.010)	(0.015)	(0.004)	(0.003)	(0.003)	(0.004)	(0.002)	(0.002)
UEM	**−0.070**	0.049	**−0.074**	−0.054	0.037	−0.007	0.001	0.051
	(0.037)	(0.031)	(0.045)	(0.047)	(0.030)	(0.048)	(0.016)	(0.043)
CPI	−0.023	−0.029	0.058	−0.110	0.085	**0.043**	**−0.050**	0.018
	(0.028)	(0.037)	(0.079)	(0.110)	(0.055)	(0.026)	(0.023)	(0.024)
PPI	0.006	0.001	0.023	0.028	−0.011	0.010	0.011	0.007
	(0.004)	(0.013)	(0.618)	(0.024)	(0.099)	(0.008)	(0.009)	(0.010)
MP	**−0.280**	**−0.469**	0.182	**0.657**	−0.021	**−0.048**	0.044	**0.167**
	(0.063)	(0.070)	(0.414)	(0.349)	(0.033)	(0.018)	(0.059)	(0.084)

Notes: ML estimation results for the news variables X_t in equation (3.1), $y_t = c + c\,\text{LEH} + \exp\left(-(\gamma + \gamma\,\text{LEH})(y_{t-1} - (c + c\,\text{LEH}))^2\right)\left(\sum_i \alpha_i y_{t-i} - (c + c\,\text{LEH})\right) + \beta X_t + \varepsilon_t$. Daily BEI rates, y_t, are measured in percentage points in the sample period January 2004 to February 2011. Bollerslev-Wooldrige heteroskedasticity consistent standard errors of the estimated coefficients are given in parentheses. Symbols in bold indicate significance at the 10% level. c and γ estimates are reported in Table 3.2.

3.D Generalized impulse response and X-life

In order to calculate the GIRFs, we follow Koop et al. (1996). The GIRF at $t+h$ is defined as the difference between the expected value of a stochastic process conditioned on an impulse ξ hitting the process at time t, and the conditional expectation that is obtained without such a shock:

$$\mathrm{GIRF}(h, \xi, \omega_{t-1}) = \mathbb{E}[y_{t+h}|y_t + \xi, \omega_{t-1}] - \mathbb{E}[y_{t+h}|y_t, \omega_{t-1}] \;, \tag{3.4}$$

where ω_{t-1} refers to one particular history of the process y_t. $\mathrm{GIRF}(h, \xi, \omega_{t-1})$ represents one realization of the random variable $\mathrm{GIRF}(h, \xi, \Omega_{t-1})$ and can be approximated via stochastic simulation. To calculate $\mathbb{E}[y_{t+h}|y_t + \xi, \omega_{t-1}]$ and $\mathbb{E}[y_{t+h}|y_t, \omega_{t-1}]$, we average over 1000 future paths, in which each y_{t+h} is created by iterating it on the ESTAR model with parameter values equal to those from the empirical estimates and with randomly drawn GARCH(1,1) errors with i.i.d. normal innovations. The impulse ξ is set to the size of one residual standard deviation, i.e. $\xi = \sigma_\varepsilon$. The aspect of interest of the random variable $\mathrm{GIRF}(h, \sigma_\varepsilon, \Omega_{t-1})$ is given by its unconditional mean:

$$\mathbb{E}[\mathrm{GIRF}(h, \sigma_\varepsilon, \Omega_{t-1})] = \mathbb{E}[y_{t+h}|y_t + \sigma_\varepsilon] - \mathbb{E}[y_{t+h}|y_t] \;\; . \tag{3.5}$$

We approximated equation (3.5) by averaging over all ω_{t-1} observed in the sample. Note that it is the unconditional mean of the GIRF that we refer to simply as GIRF or *impulse response* throughout the paper.

Following Dijk et al. (2007), X-lives are estimated by:

$$X\text{-life}(x, \sigma_\varepsilon) = \sum_{m=0}^{\infty} \left(1 - \prod_{h=m}^{\infty} \mathbb{1}(x, h, \sigma_\varepsilon) \right) \;\; \text{, with} \tag{3.6}$$

$$\begin{aligned} \mathbb{1}(x, h, \sigma_\varepsilon) = \mathbb{1} \Bigg(& \left| \mathbb{E}[\mathrm{GIRF}(h, \sigma_\varepsilon, \Omega_{t-1})] - \lim_{h \to \infty} \mathbb{E}[\mathrm{GIRF}(h, \sigma_\varepsilon, \Omega_{t-1})] \right| \\ & \leq x \left| \sigma_\varepsilon - \lim_{h \to \infty} \mathbb{E}[\mathrm{GIRF}(h, \sigma_\varepsilon, \Omega_{t-1})] \right| \Bigg) \;\; . \end{aligned}$$

$0 \leq x \leq 1$ refers to the chosen fraction of noise absorption ($x = 0.5$ and $x = 0.75$ in the application) and $\mathbb{1}(\cdot)$ is the indicator function.

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Ehrenwörtliche Erklärung

Ich habe die vorgelegte Dissertation selbst verfasst und dabei nur die von mir angegebenen Quellen und Hilfsmittel benutzt. Alle Textstellen, die wörtlich oder sinngemäß aus veröffentlichten oder nicht veröffentlichten Schriften entnommen sind, sowie alle Angaben, die auf mündlichen Auskünften beruhen, sind als solche kenntlich gemacht.

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