Essays on Monetary Policy and Asset Price Volatility

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Abstract

In Chapter 1 of this thesis, the importance of the term structure of interest rates is discussed in terms of reflecting the general economic stance and expectations.

In Chapter 2, I examine the predictive power of the Heterogeneous Autoregressive (HAR) model on government bond return volatility of major European government bond markets. The HAR-type volatility forecasting models show that short-term and medium-term volatility is a robust and statistically significant predictor of the term structure of intraday volatility. Also, I find the jump tail risk component contributes in forecasting the bond market volatility. Lastly, I show that almost half of the monetary policy announcement dates coincide with identified the jumps in bond returns, and the pre-announcement drift is present in the bond market. Hence, the monetary policy announcements are a crucial determinant of European bond market volatility.

Chapter 3 shows that the latent factors of the German government bond yield curve provide sufficient information in representing euro-area monetary policy dimensions. In this context, I identify three factors to encompass the multidimensional structure of the European Central Banks policies: target rate, monetary policy stance, and quantitative easing. Moreover, I measure the impact of monetary policy surprises on euro area asset prices and financial market indicators around the relevant announcement windows.

In Chapter 4, I examine whether the inclusion of yield curve volatility improves the stock market volatility forecasting. Using the foundations of the dividend growth model, I extend the model to incorporate and relate the shape of the yield curve that affects the transmission from bond markets to equity markets volatility. By including the risk premium and hedging premium, I show the shape of the yield curve is one of the determinants of equity market volatility and directly affects volatility through the transmission from bond volatility.

Chapter 5 concludes this thesis by highlighting significant remarks, limitations, and avenues for future research.

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Declaration

Chapter 2 of this study is based on the paper "Volatility Forecasting in European Government Bond Markets" coauthored by myself, Alexandros Kontonikas, and Athanasios Triantafyllou. This paper was published in International Journal of Forecasting in 2021. I am the primary author of the paper.

I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

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Chapter 1

Introduction

The term structure of interest rates carries crucial information on the current state of the economy as well as expectations regarding the future. Therefore, financial market participants, from investors to policymakers pay close attention to the interest rate developments in great detail. Since the risk-free interest rate is a primary input for asset pricing, analysing the risk-free rate developments is important not only for its significance in representing economic information but also for the asset pricing as a discount factor. Furthermore, the time variation of interest rates indicates the volatility in the economic agents' decision-making process. Thus, it is vital to develop models that reveal the dynamics of the interest rate volatility by generating reliable forecasts, and by exhibiting its representative power in major economic events, such as monetary policy and its transmissible nature.

Although volatility is generally perceived only as a risk measure, it yields much more information for financial decision-makers, as it shows the clustering in the returns.

There are many sources of volatility such as news' flows, macroeconomic fundamentals, and behavioral factors. In this perspective, the volatility of sovereign bonds is critical for being a direct recipient of macroeconomic news, from policy changes to data releases, and as a hedging instrument against downside risks. Thus, this study depends on government bonds in covering; volatility forecasting models to demonstrate the forecasting efficacy of well-exploited models in other asset classes, monetary policy effects to discover the market behavior before and after the policy changes, and the link between sovereign bonds and equity market volatility to show the importance of the term structure.

In Chapter 2 of this study, I fill a gap in the bond market volatility forecasting literature by analysing the predictive power of the Heterogeneous Auto-regressive model of Realized Volatility (HAR-RV) following Corsi (2009) by using European government bond market data in the high-frequency setting. The primary motivation to focus on the European bond markets is the increased turbulence in European economies, especially during the Global Financial Crisis period, which is then followed by the European debt crisis and raised major concerns by the distressed debt investors. During the crisis periods, the volatility of government bond markets surged to unprecedented levels. I focus on the euro-zone (France and Germany) and non-euro-zone markets (Switzerland and the UK) to control the debt crisis affects between 2005 and 2019. I apply a cascade type HAR model to capture short-, medium-, and long-term dynamics in the volatility forecasting structure. By utilizing the theoretical foundations of Barndorff-Nielsen &

Shephard (2002), the integrated variance of a price process is consistently approximated by realized variance, having sufficient intraday partitions in the price series. Therefore, the intraday term structure of volatility in the European government bond markets can be used to infer the diffusive and jump components of volatility. Those separate components are found to improve the forecasting power of the HAR model using bond market data.

Furthermore, I examine the role of monetary policy announcements within the HAR model of bond return volatility. These findings indicate that there is a common coincidence between the intraday jumps and monetary policy meetings. In addition, I extend the HAR models to incorporate the monetary policy meetings. In the literature (Lucca & Moench (2015)), the excess returns of US stock markets are reported before the FOMC decisions, which is called pre-FOMC drift, but this effect is found to be insignificant in the bond markets. I modify the HAR models so that models can be used to test for the presence of pre-meeting effect before the monetary policy decisions of the European Central Bank, Swiss National Bank, and Bank of England. Although the presence of pre-announcement drift in the bond market returns is refused in the literature, my findings show the pre-announcement drift is present in the volatility. In addition, I report that the pre-announcement drift appears through the continuous part of the volatility, integrated variation, not the jump variation.

My contributions to the extant literature have three-fold. Firstly, this is the first study that indicates the efficacy of HAR models in forecasting the European bond markets' volatility. Secondly, I contribute to the existing literature by showing the importance of intraday jumps in bond volatility forecasting (Andersen, Bollerslev & Diebold (2007)). Thirdly, I provide evidence of the significant pre-announcement effect in the bond market from the volatility perspective.

In Chapter 3 of this study, I quantify ECB's monetary policy shocks using the term structure of German government bonds. During and after the Global Financial Crisis, central banks cut the policy rates to historically low levels. The monetary policymakers started to use unconventional monetary policy tools extensively as forward guidance and large-scale asset purchase programs. Since the central bank policy rates rarely changed due to zero lower bound, measuring the impact of monetary policy on the economy via asset prices became a major challenge.

In the literature, there are other attempts to use fixed income securities in extracting policy shocks (Kuttner (2001); Gürkaynak et al. (2005); and Gürkaynak et al. (2007) for FOMC, and Altavilla et al. (2019); Andrade & Ferroni (2021); and Leombroni et al. (2021) for ECB). In this context, I use the foundations on fixed-income securities for being the representative of the monetary policy surprises around the monetary policy announcement windows. I show that the term structure of German bonds is a robust indicator of ECB policy surprises, even without the information on short-term securities. The surprises extracted from the bond market have a notable effect on the euro-zone financial markets: core and peripheral yields, exchange rate, credit costs, and inflation expectations. In addition, I find that quantitative easing (QE) shocks have more potency in affecting yield spreads and inflation expectations than target rate and forward guidance shocks.

The contribution of Chapter 3 lies in both my approach and empirical results. This study contributes to the literature on the high-frequency identification of the ECB's monetary policy shocks. Besides contributing relatively scarce existing literature on the impact of ECB policy surprises, to my knowledge, this is the first attempt to extract the information using intraday government bond yield curve fitting factors to represent the target rate, forward guidance, and QE shocks of the ECB policies around the scheduled policy announcement windows. Furthermore, this approach shed new light on the significant financial market effects of ECB policy surprises on euro area asset prices.

Since the changes in the term structure have the potential to reflect the macroeconomic stance and expectations of financial decision-makers, the transmission of bond volatility to other markets carries crucial information. Therefore, in Chapter 4, the impact of government bond market volatility on the stock market volatility is examined conditional on the shape of the yield curve.

In the discounted cash flow model, the changes in the interest rates affect the equity prices through two channels; expected cash flows and discount rates, which are challenging to decompose. In this context, I try to link interest rate volatility and stock market volatility in the high-frequency setting. This approach enables us to focus only on the impact from the lens of the discount rate channel on stock prices by eliminating the factors stemming from long-term shocks. In a high-frequency setting, I assume that the expected cash flows are unchanged, and discounted cash flow structure is simplified by linking the impact of interest rate shock to equity prices generated solely from the discount rates. Also, it is well-known that although the macroeconomic policies affect the term structure, especially in the short term, market participants' expectations are the main driver of the term structure. Therefore, I modify the discounted cash flow model by appending the growth expectations and risk premium. Following Cieslak & Pang (2021), I separate the risk premium into two parts: the (common) risk premium and hedging premium, which have a diverse set of effects on the term structure.

Results indicate that the shape of the yield curve, whether it is bull steepener, bull flattener, bear steepener, or bear flattener, determines the degree of transmission of volatility from bond markets to equity markets. I theoretically and empirically show that the bull steepener shift in the yield curve increases the sensitivity of equity market volatility to bond market volatility, on the contrary, the bear flattener yield curve reduces this sensitivity. In addition, I find that extending the HAR model in stock market volatility forecasting with term structure volatility, conditional on the shape of the yield curve, improves the forecasting capacity.

To my knowledge, this is the first attempt to provide a theoretical background on the transmission of bond market volatility to stock market volatility from the yield curve's shape perspective in a testable framework. By extending the Gordon growth model using the risk premium and hedging premium, following Cieslak & Pang (2021), this study tries to explain the shifts in the yield curve using the premium dynamics embedded in the government bond markets. Also, this study is the first to unveil the empirical asymmetry that while the bear flattener shift in the yield curve reduces the transmission and the bull steepener move magnifies the volatility transmission to the stock markets. Moreover, the variation of latent yield curve factors helps to improve the forecasting performance of equity market volatility.

Chapter 2

Volatility Forecasting in European Government Bond Markets

A version of the study was published in International Journal of Forecasting in 2021.

2.1 Introduction

Financial market participants, banks, firms and policymakers pay close attention to interest rate volatility since it plays a key role in a variety of settings, ranging from risk management (Faulkender (2005); Markellos & Psychoyios (2018)) and asset pricing (Flannery et al. (1997)) to firms investment decisions (Bo & Sterken (2002)) and the transmission mechanism of monetary policy (Landier et al. (2013); Hoffmann et al. (2018)). The market for government bonds is essential for the analysis of interest rate volatility since sovereign yields provide the basis for the pricing of other securities, derivatives, and loans. Moreover, this market has been the object of significant interventions by central banks (CBs) during Quantitative Easing programs, whereby the CB purchases assets from banks and other financial companies, in both the US and Europe.

Hence, it is important to develop models that generate good forecasts of bond market volatility in order to enhance the information set of various economic agents. Surprisingly, despite the importance of this exercise, there are only a few previous studies that attempted to forecast bond market volatility, and existing studies are in the context of the US market for Treasuries (Remolona & Fleming (1999); Balduzzi et al. (2001); Andersen, Bollerslev, Diebold & Vega (2007*a*)). At the same time, the literature on the forecasting of stock and commodity market volatility is quite dense. (Bollerslev et al. (2018); Dueker (1997); Bollerslev et al. (2016); Bollerslev & Mikkelsen (1996); Luo et al. (2022)).

In this study, I attempt to fill this gap in the bond market volatility forecasting literature by analysing the predictive power of the Heterogeneous Autoregressive model of Realized Volatility (HAR-RV), developed by Corsi (2009), for the volatility term structure of European bond markets. HAR-type volatility forecasting models utilize the continuous and the discontinuous (jump) component of volatility and are popular in studies of stock and commodity markets (Degiannakis et al. (2022); Luo et al. (2022)) [1]. The primary motivation to focus on the European bond markets is the increased turbulence in European economies, especially in the post-2007 crisis period. During the 2007-2008 global financial crisis and the subsequent European sovereign debt crisis,

[1]The relevant literature on HAR modeling and volatility forecasting in bond markets has been extensively focused on US government bond market. Andersen, Bollerslev & Diebold (2007) and Corsi et al. (2010) depend on US T-bond future data for fixed income market. Also, Andersen & Benzoni (2010) employ the HAR-type model to show the unspanned stochastic volatility phenomenon using US bond data.

the volatility of government bond markets soared to unprecedented levels and therefore became a major concern for fixed income investors, banks, firms, and European policymakers. In order to have a more comprehensive picture, I use government bond data for two major euro-area markets (France and Germany) and two important non-euro-area members (Switzerland and the UK) between 2005 and 2019.

I collect intraday bond market data for these four economies over the period January 2005 to October 2019. Specifically, I use data between 10:00 am and 16:00 pm in 10-minute intervals to estimate the realized volatility of bond returns. In order to compute the zero-coupon prices for 1-year, 2-year, 5-year, 10-year, 20-year, and 30-year maturity securities, I employ the Nelson & Siegel (1987) (NS) model in the intraday frequency. I then estimate HAR-type volatility forecasting models for daily, weekly, and monthly forecasting horizons.

The results reveal that the HAR components of realized volatility are robust and statistically significant predictors of European bond return volatility across different maturities at 1-day, 5-day, and 22-day horizons. The in-sample R^2 values range from 40% up to 80%. Furthermore, out-of-sample forecasts show that HAR models can be used for real-time forecasting since the respective out-of-sample R^2s remain high, ranging from 20% to 70%, especially for bonds with short-term maturities. These results provide evidence of the long-memory property of government bond volatility since regardless of forecasting horizon 1-day to 22-day components of HAR models are found to be effective on future volatility. Moreover, including price jumps as an additional predictor in the HAR model, the jump tail risk component is found to be a significant predictor of bond return volatility.

I proceed by examining the role of monetary policy announcements within HAR models of bond return volatility. I show that large jumps in realized bond market volatility tend to coincide with monetary policy announcements. More specifically, 80% of all policy announcement dates for the case of Switzerland, 40% in Germany and the UK, and 34% in France overlap with at least one statistically significant bond price jump in the respective bond market. In addition, using the HAR model framework, I identify the impact of monetary policy announcements on volatility forecasts. My findings indicate that there is a positive and significant monetary policy pre-announcement impact on future bond market volatility. This analysis is motivated by Lucca & Moench (2015), which document large excess returns on US stock markets one day ahead of the FOMC meetings. Although Lucca & Moench (2015) find the presence of pre-FOMC drift in the equity market, the drift is not found to be present for fixed income securities. On the contrary, findings in this paper verify the monetary policy pre-announcement drift on the European bond market volatility. In addition, I report that the pre-announcement drift is effective through the continuous part of the volatility, integrated variation, not the jump variation.

My work is related, and contributes, to several strands of the literature. This is the first study to demonstrate the in-sample and out-of-sample forecasting power of HAR-type models on the term structure of European bond volatility. Thus, it extends the literature that developed following the seminal work by Corsi (2009) and provides additional evidence to the successful forecasting performance of HAR-type for the stock and commodity market volatility (Bollerslev et al. (2018); Dueker (1997); Bollerslev et al. (2016); Bollerslev & Mikkelsen (1996); Degiannakis et al. (2022); Gong & Lin (2018); Luo et al. (2022); Franses & Van Dijk (1996); Tian et al. (2017); Wen et al. (2016)). Furthermore, the findings on the importance of jumps for bond market volatility forecasting reveal differences between European markets and the US. While the bond volatility literature (see for example Andersen, Bollerslev & Diebold (2007)) identifies a negative and insignificant jump effect on future US bond volatility, I show that bond price jumps have a positive impact on European bond return volatility. The results are in line with those of Corsi et al. (2010) who find that US bond price jumps have a positive and significant impact on US bond return volatility. I also show that the monetary policy announcements are an important determinant of bond market volatility, and the pre-announcement drift is present in the European bond market using the HAR model structure.

This analysis is also related to the extant literature that considers the effect of macroeconomic and monetary policy announcements on stock and commodity market volatility forecasting and shows that such announcements, and the associated jumps, are key drivers of volatility releases (Bomfim (2003); Engle & Siriwardane (2018); Evans (2011); Lahaye et al. (2011); Miao et al. (2014); Papadamou & Sogiakas (2018); Rangel (2011); Andersen, Bollerslev, Diebold & Vega (2003); Andersen, Bollerslev & Diebold (2007); Andersen, Bollerslev, Diebold & Vega (2007*a*); Corsi et al. (2010), Huang (2018); Lee (2012); Prokopczuk et al. (2016); Schmitz et al. (2014))[2]. It is also linked to previous work on the impact of such announcements for US treasuries (Remolona & Fleming (1999); Balduzzi et al. (2001); Andersen, Bollerslev, Diebold & Vega (2007*a*); Corsi et al. (2010); Andersen & Benzoni (2010); Arnold & Vrugt (2010); de Goeij & Marquering (2006); Ederington & Lee (1993); Jones et al. (1998); Perignon & Smith (2007)) and FX markets (Andersen, Bollerslev, Diebold & Vega (2003); Andersen, Bollerslev, Diebold & Vega (2007*a*)). The empirical studies on the determinants of European bond return volatility tend to focus on the effects of the ECBs QE programme (Zhang & Dufour (2019); Ghysels et al. (2016)) and the link between volatility and liquidity (Beber et al. (2009); O'Sullivan & Papavassiliou (2020)). Finally, this chapter contributes to the pre-announcement drift literature by providing evidence of the significant pre-announcement effect on the bond market volatility prior to the monetary policy meetings.

The rest of the chapter is structured as follows. Section 2.2 reviews the literature in

[2]For example, Huang (2018) finds that large stock-price jump variations are more frequently observed during macroeconomic announcement days. Lahaye et al. (2011) show that the US stock market co-jumping behavior is positively affected by macroeconomic news and monetary policy announcements, while Miao et al. (2014) show that macroeconomic news announcements coincide with approximately three-fourths of the intra-day US stock-market index price jumps.

volatility models and forecasting. In Section 2.3, I provide the information regarding data and methodology. In Section 2.4 I present the results of the empirical findings. In Section 2.5 I report the robustness checks and in Section 2.6 I provide a brief conclusion along with some policy recommendations and suggestions for further research.

2.2 Literature Review

Volatility constitutes one of the most active research subject areas in the contemporary finance literature due to its importance in risk management, asset pricing, and asset allocation. Intrinsically, volatility is a latent stochastic process that evolves through time, and therefore uncertainty generated by volatility constitutes one of the main pillars in the financial decision-making process. Since the introduction of time-varying volatility models after the seminal auto-regressive conditional heteroscedasticity (ARCH) study of Engle (1982), research on the behavior of volatility became popular. With the conditional volatility models, there is strand literature accumulated in the empirical volatility modeling with various extensions. Depending on the availability of data, both parametric and non-parametric methods are utilized to measure volatility, and the development of high-frequency-based estimators led to estimating financial market volatility using non-parametric estimators.

Since Merton (1980) asserts that using sufficiently high-frequency returns volatility may arbitrarily be estimated, there is a pile of volatility modeling literature accumulated with the help of increased data availability. Intuitively, high-frequency volatility modeling exploits the stochastic diffusive setting in asset pricing by assuming that since the long-term trend component of the prices barely changes in the shorter-term intervals, it is straightforward to use price changes in volatility estimation when the time intervals are sufficiently small enough. The realized volatility provides an efficient estimator using intraday data (see Andersen & Bollerslev (1998); Bollerslev et al. (2000); and Barndorff-Nielsen & Shephard (2002)). In addition, Andersen, Bollerslev, Diebold & Labys (2003) find that simple non-parametric realized volatility outperforms parametric models, such as GARCH and stochastic volatility models, in out-of-sample forecasting. Thus, non-parametric volatility modeling has become more popular as being practical and computationally efficient to estimate.

The empirical literature using high-frequency, or intraday, financial time series argued that the autocorrelations of squared and absolute returns tend to decay at a slow rate and have a long memory (see eg. Andersen & Bollerslev (1998); and Andersen, Bollerslev & Diebold (2007)). Also, the volatility structure of asset returns seems to be highly dependent on its longer window trends which constitutes one of the most puzzling issues of volatility modeling. Andersen (1996) indicates the mixture of distributions hypothesis (MDH) could be employed in understanding the slow decay of volatility through the time spectrum by aggregation of numerous components and processes that apply to financial market instruments. The MDH relates volatility with the diverse arrival of heterogeneous information on its pattern. The empirical evidence suggests that volatility clusters in terms of intra-daily and inter-daily frequencies and it is best described as following a long persistent pattern. To handle the persistent behavior of return volatility is therefore attempted to be incorporated in models.

The persistence of shocks and their implications in terms of modeling financial time series is underscored to avoid the restrictive knife-edge restrictions on stochastic trends. Therefore, long-memory fractionally integrated (FI) processes were introduced in associating the slow hyperbolic decay rate of persistent shocks (Adenstedt (1974); Granger (1980); and Baillie et al. (1996)). To capture both short and long memory dynamics of time series, Granger & Joyeux (1980) developed an autoregressive fractionally integrated moving average (ARFIMA) model, where autocorrelation exhibits a very slow rate of hyperbolic decay. Moreover, similar to the long-memory dependencies in the conditional mean models, there exists an extensive literature on the persistence of shocks to conditional variance models (Bollerslev (1986)). Therefore, modeling conditional variance accounting for decay rate becomes relevant. To incorporate the long memory feature Baillie et al. (1996) apply the ARFIMA notion using the fractionally differencing operator on autoregressive lag polynomial GARCH models and develop FIGARCH. Consequently, the volatility forecasts using FIGARCH do not exhibit an exponentially mean-reverting behavior as the models that follow standard short memory ones. In addition to conditional volatility models, researchers employ the stochastic volatility (SV) model in the estimation of latent instantaneous volatility. Although the preliminary SV models also suffer from having exponentially fast decaying, the attempts to constitute long-memory SV (LMSV) by Breidt et al. (1998) and Harvey (2007) were successful in including long memory properties, while providing an appropriate framework in discrete-time data.

In addition to, parametric methods in estimating the volatility structure of asset returns, observed data is used to measure latent volatility. In theory, as the intraday sampling frequency increases sufficiently, the cumulative sum of intraday returns converges to genuine unobserved volatility, which is so-called realized volatility (RV) (Andersen & Bollerslev (1998); and Andersen, Bollerslev, Diebold & Labys (2003)). Since the introduction of realized volatility as a natural measure of volatility and the increased availability of high-frequency data, both ex-post volatility estimation and ex-ante forecast models started to employ observation-based non-parametric methods to a great extent. Since RV-type models inherently reflect main features of volatility such as long memory, those models have become ubiquitous in the empirical practices using high-frequency data.

Besides the success of volatility estimation methods in representing the stylized facts of its nature, the forecast performance of volatility is crucial for its being an input for risk management, derivative pricing, and an overall financial market soundness indicator. The use of non-parametric volatility measures is preferred in the literature due to being successful in representing information of data and forecasting ex-ante volatility. There has been almost a consensus in using RV type models in volatility forecasting over parametric models as GARCH and stochastic volatility models (for a review see Andersen, Bollerslev, Diebold & Labys (2003); Andersen et al. (2005); Andersen, Bollerslev, Diebold & Vega (2007*b*)). Due to developments in computational capacity and the increased availability of high-frequency data, ex-post non-parametric volatility indicators gained popularity among academics and practitioners. RV-type models are a natural estimation method that incorporates the long-memory behavior of volatility while being resilient to microstructure noise (Andersen, Bollerslev, Diebold & Labys (2003)).

Although fractionally integrated (FI) parametric methods are found to be effective in capturing crucial stylized facts of volatility, their main drawback is that as sample size increases the estimation of parametric methods becomes challenging. In addition to estimation complexity, fractionally differencing operators in those models are criticized due to not having an economic interpretation whereas providing a framework for mathematical interpretation (Corsi (2009)). While the ARFIMA model of realized volatility and FIGARCH model of returns provide solid results in terms of stylized facts of quadratic variation (QV), those FI models pose some difficulties in resolving short-term and long-term characteristics and in extending models to multivariate cases (Comte & Renault (1998); and Corsi (2009)). Due to difficulties in estimating latent volatility with representing its stylized facts, Corsi (2009) proposes a cascade-type model called as Heterogeneous Autoregressive model (HAR) for realized volatility. The intuition of HAR is supported by the heterogeneous market hypothesis (HMH) of Müller et al. (1997). The MDH advocates differences among market participants have implications for the sensitivity of different time horizons, which is also effective in explaining the long memory of volatility indicators (Müller et al. (1997)). In addition, market agents' risk perceptions and therefore investment horizons differ, which creates an asymmetric transmission of volatility through the time span. The asymmetric propagation mechanism of volatility in short and long-time horizons contributed to the development of auto-regressive type cascade models in modeling and forecasting volatility. Ever since the introduction of HAR models, these additive volatility cascade structures became popular due to their simplicity and being able to reflect persistent memory facts in volatility.

In the HAR-type models, Corsi (2009) assumes that the general pattern of volatility structure is generated from three different frequencies; the high-frequency component for short-term traders is reflected by daily volatility, for medium-term traders weekly and for investors focusing on long term trends by monthly component with an additive cascade model. Corsi (2009) uses daily lagged volatility, weekly and monthly averages of RV as a restricted form of autoregression (AR) model for USD/CHF currency pair, SP500 Index, and US 10 year T-Bond futures and finds that HAR coefficients are significant in contributing to future volatility in except for daily coefficient for T-Bond. In addition to the significance of HAR parameters for volatility forecasts, the HAR model outperforms short memory models or unconstrained AR models, and its results are analogous to the ARFIMA model, which requires more complex estimation.

The simplicity to implement HAR models leads to extensions of volatility forecasting models. In the asset pricing literature, the price processes are generally represented using a jump diffusive setting, which considers a continuous path of volatility and the jumps or discontinuities (Merton (1976); and Chernov et al. (2003)). Barndorff-Nielsen & Shephard (2002, 2004) introduce realized power variation measures and show that using bipower variation, a sum-product of scaled consecutive intraday returns could be employed in extracting jumps on a high-frequency basis. Analogous to stochastic volatility models, bipower variation (BV) is introduced as a robust estimate of quadratic variation, the continuous part, where the difference between realized volatility and BV corresponds to model-free jumps, the discontinuous part. Therefore, in addition to forecasting volatility, intraday data could be employed to detect discrete jumps (Barndorff-Nielsen & Shephard (2004); Andersen, Bollerslev & Diebold (2007); Wright & Zhou (2009); and Tauchen & Zhou (2011)). Using this methodology, Andersen, Bollerslev & Diebold (2007) implement the idea of jump variation in the RV framework using the results of Barndorff-Nielsen & Shephard (2004) in extending the HAR model. Andersen, Bollerslev & Diebold (2007) find that the jump variations in the HAR framework are mostly ineffective in contributing to model forecasts for the S&P500 index futures, 30-year US T-Bond Futures, and spot foreign exchange markets. In comparison to other markets, they find the volatility in the fixed income is the least predictable. The jumps based on intraday data are found to be effective in explaining bond risk premia and credit spreads of corporate bonds (Wright & Zhou (2009); and Tauchen & Zhou (2011)).

In addition to RV models, Barndorff-Nielsen, Kinnebrock & Shephard (2008) introduced a new measure, realized semivariances (RSV), which considers the contribution of downward and upward market movements to the volatility separately. Using the logic of separation, Patton & Sheppard (2015) extend the HAR model into RSV estimates and use positive and negative RV and negative and positive jumps in the volatility forecasts. The findings indicate that negative RV has a larger impact on future volatility than positive RV. Also, disentangling the effects of jumps in up and down markets reveals the asymmetric relationship between positive and negative jumps in their impact on future volatility. Patton (2011) state that while negative jumps increase the volatility forecast, positive jumps decrease the volatility. Thus, the findings of the previous literature that assert that jumps have only a limited impact on volatility forecasts (see Andersen, Bollerslev & Diebold (2007) and Busch et al. (2011)) may be justified with the asymmetric effect of signed jumps.

2.3 Data and Methodology

2.3.1 Data

In this analysis, I include the European sovereign bond markets (UK, Germany, France, and Switzerland) using intraday data in the January 2005 October 2019 period from Thomson Reuters Tick History (TRTH) database. I use 1-, 2-, 5-, 10-, 20- and 30-year maturity bonds. The dataset relies on quotes for "on-the-run", generic, instruments which are more liquid in terms off-the-run securities.

There is a strand of the literature on optimal intraday sampling frequency using high-frequency data in the computation of RV (for example Barndorff-Nielsen & Shephard (2004) and Aït-Sahalia et al. (2005)). Zhang et al. (2005) provide a comprehensive review of the causes and effects of sampling bias in the high-frequency data-dependent volatility estimators. Although it is inevitable to remove all the microstructure noise from the high-frequency data, the problems resulting from sampling frequency are limited when the sampling frequency is 5 minute to 10 minute periods (Zhang et al. (2005)). Andersen et al. (2011) give a detailed framework on robust volatility estimation and how to cope with possible ramifications resulting from microstructure noise. In this study, I prefer to take into account not only the sampling effect of microstructure noise but also the liquidity component of noise. While a large part of the RV literature on equity market volatility utilizes 5-minute intervals in estimating realized volatility, in the case of European bond markets, I choose to use 10-minute time intervals due to liquidity considerations. The ten-minute sampling frequency for European government bond markets is consistent with the bias-variance tradeoff, and a large part of the bias is assumed to vanish at this frequency (Hansen & Lunde (2006)). I additionally control for remaining microstructure noise by employing realized kernel estimators for volatility and provide results using alternative volatility estimators that are more jump robust (see Section 2.5).

The bonds used in the analysis bear coupon payments, and they are subject to changes in terms of underlying notes. Thus, I convert the instruments to zero-coupon securities using the underlying bonds. In zero-coupon estimation, I take into consideration the changes in the underlying instruments on the daily basis. When there is a change in the underlying bond of the generic security, I assume the change takes place at the beginning of the trading day. Then, I aggregate the tick data bond returns using 10-minute intraday time intervals between 10:00 am and 4:00 pm to compute daily variations, since the liquidity in the fixed income markets may not be representative during the market opening and closing hours. Also, when defining the volatility indicators as a sum of squared intraday daily logarithmic bond returns, I include the price change between 10:00 am of the next day (t+1) and 4:00 pm of today (t) for the estimation of daily (t) realized volatility.

2.3.2 The Nelson-Siegel Model

In this analysis, I use the Nelson & Siegel (1987) model to obtain zero-coupon government bond returns. This model estimates the relationship between interest rates with various maturities by fitting a discount function to bond price data. It assumes the following functional form for the instantaneous forward rates (BIS (2005)).

$$f_{t,m} = \beta_{t,0} + \beta_{t,1} \exp(\frac{-m}{\tau_{t,1}}) + \beta_{t,2} \frac{m}{\tau_{t,1}} \exp(\frac{-m}{\tau_{t,1}}) \tag{2.1}$$

where, the forward rates $f_{t,m}$ are defined as the instantaneous rates and m is maturity. The parameters, $\beta_{t,0}, \beta_{t,1}, \beta_{t,2}$ and $\tau_{t,1}$ are estimated by minimizing the squared deviations of theoretical rates of equation Eq. (2.1) and observed rates.

The zero-coupon spot interest rates $s_{t,m}$, are then related to the NS procedure by defining forward rates as instantaneous rates and continuously compounding the forward rate up to given time to maturity as shown below:

$$s_{t,m} = -\frac{1}{m} \int_0^m f(u) du. \tag{2.2}$$

Thus, the NS function for zero coupon interest rates could easily be obtained by combining equations Eq. (2.1) and Eq. (2.2):

$$s_{t,m} = \beta_{t,0} + (\beta_{t,1} + \beta_{t,2}) \frac{\tau_{t,1}}{m} \left(1 - \exp(\frac{-m}{\tau_{t,1}})\right) - \beta_{t,2} \exp(\frac{-m}{\tau_{t,1}}). \tag{2.3}$$

For each 10-minute time interval, the zero-coupon curves of European government bonds are fitted using equation Eq. (2.2). The zero-coupon rates and bond prices of corresponding maturities which are obtained using the NS model are then used for the estimation of the realized volatility. In this study, I use bond prices (not yields) to estimate bond return volatility.

Since $P(t,T) = \exp(-\tau s_{t,m})$, the return series using prices are scaled to τ,

$$r(t+h,h,\tau) = p(t+h,\tau) - p(t,\tau) \tag{2.4}$$

where $p(t,\tau) = log(P(t,\tau))$. Then, the intraday return of zero-coupon bond is computed according to equation 2.5 below:

$$r_\tau\left(t+\frac{ih}{n},\frac{h}{n}\right) = -\tau\left(s_\tau\left(t+\frac{ih}{n}\right) - s_\tau\left(t+\frac{(i-1)h}{n}\right)\right). \tag{2.5}$$

2.3.3 Realized Volatility Measurement and Jump Detection

I follow the methodology of Andersen & Bollerslev (1998) for the estimation of realized volatility and jumps in the European sovereign bond markets. As the intraday sampling frequency increases sufficiently, the cumulative sum of intraday returns converges to genuine unobserved volatility, which is the so-called realized volatility (RV) (Andersen & Bollerslev (1998); Andersen, Bollerslev, Diebold & Labys (2003); Barndorff-Nielsen & Shephard (2002, 2004)). Since the returns are scaled to τ, the volatility also becomes proportional to τ^2 as follows:

$$vol^2_{r_\tau}(t+h,h) = \frac{1}{h}\sum_{i=1}^{n} \tau^2\left(s_\tau\left(t+\frac{ih}{n}\right) - s_\tau\left(t+\frac{(i-1)h}{n}\right)\right)^2. \tag{2.6}$$

Therefore, intraday bond volatility increases by the square of time to maturity. I then re-scale the volatility series, $vol^2_{r_\tau}(t+h,h)$, by τ^2 to obtain comparable realized volatility.

$$RV_\tau(t+h,h) = \frac{1}{\tau^2}\left(vol^2_{r_\tau}(t+h,h)\right). \tag{2.7}$$

The scaled estimator of volatility as shown in equation Eq. (2.7), ensures that realized bond return volatility satisfies the asymptotic properties of quadratic variation.

In addition to intraday volatility, I also focus on the importance of jumps on an intraday basis. To decompose realized volatility into its continuous and discontinuous components, I follow the procedure suggested by Barndorff-Nielsen & Shephard (2004). This provides a partial generalization of latent volatility, namely bipower variation (BV), which approaches the diffusive part of volatility in continuous sample paths and equally spaced discrete data. In estimating realized BV, I also need to re-scale the return series by the factor of τ. Therefore, the modified BV process is measured as:

$$BV_\tau(t+h,h) = \left(\frac{1}{\tau^2}\right)\mu_1^{-2}\left(\frac{n}{n-1}\right)\sum_{i=2}^{n} |\Delta_{i-1}p\big(t+\frac{(i-1)h}{n}\big)||\Delta_i p\big(t+\frac{(i)h}{n}\big)| \tag{2.8}$$

where $\mu_1 = \sqrt{2}/\sqrt{\pi}$.

The first term in equation Eq. (2.8), $1/\tau^2$, modifies the BV parameter proposed by Barndorff-Nielsen & Shephard (2004) as an extension for bond returns which have different time to maturity. In this article, I follow the jump separation process of Barndorff-Nielsen & Shephard (2004), where the realized volatility is assumed to have a continuous, quadratic variation, and a discontinuous, jump, component. The logarithmic price of a government bond is assumed to follow a semimartingale process, which can be formalized as a drift term plus a local martingale. Thus, a general class of arbitrage-free return process is given below:

$$dp(t) = \mu(t)dt + \sigma(t)dw(t) + \kappa(t)dq(t), 0 \leqslant t \leqslant T. \tag{2.9}$$

where $\mu(t)$ is a drift term having a locally finite variation process and the rest constitutes local martingale. $\sigma(t)$ is a strictly positive continuous volatility process with discrete jumps $\kappa(t)$. Barndorff-Nielsen & Shephard (2004) show that the quadratic variation equals the integrated variance of instantaneous returns as given in Equation 2.10 below:

$$RV \rightarrow QV \equiv \int_{t-1}^{t} \sigma^2(s)ds + \sum_{t-1<s\leqslant t} \kappa^2(s). \tag{2.10}$$

Therefore, equation Eq. (2.10) ensures that the realized volatility estimator does not converge to integrated volatility due to the presence of the discrete jump process even under observing no noise in the prices. Barndorff-Nielsen & Shephard (2004) extend the analysis on volatility and indicate that BV is an unbiased estimator of integrated variance (IV), asymptotically. Then BV is approximated as shown below:

$$BV \to IV \equiv \int_{t-1}^{t} \sigma^2(s)ds, for\ n \to \infty. \tag{2.11}$$

Thus, using equations Eq. (2.10) and Eq. (2.11), it is trivial to obtain an approximation of jump variation[3].

$$RV - BV \to \sum_{t-1<s\leqslant t} \kappa^2(s), for\ n \to \infty. \tag{2.12}$$

Under the assumption of absence of jumps:

$$\sqrt{n}\big(RV - BV\big) \longrightarrow MN\big(0,\ 2IQ\big), \tag{2.13}$$

where IQ is integrated quarticity.

In addition, integrated variation (IQ) could be represented by a generalized realized power quarticity measure, namely tripower quarticity (TQ), which is a robust and consistent estimator of IV even in the presence of jumps (Barndorff-Nielsen & Shephard (2002) and Andersen, Bollerslev & Diebold (2007)). I compute TQ as follows[4]:

[3]Barndorff-Nielsen & Shephard (2004) give the definitions of realized volatility (RV) and bipower variation (BV) for a general asset class, which does not have any time to maturity. Since the estimations are based on bond data, in order to have a comparable estimate, I scaled the return series by $1/\tau$ and thus RV and BV series by $1/\tau^2$.

[4]Similar to RV and BV estimations, TQ measure also requires scaling concerning time to maturity.

$$TQ \equiv n\mu_{4/3}^{-3} \sum_{i=3}^{n} |\Delta_{i-2} p\big(t + \frac{(i-2)h}{n}\big)|^{4/3} |\Delta_{i-1} p\big(t + \frac{(i-1)h}{n}\big)|^{4/3}$$
$$|\Delta_i p\big(t + \frac{(i)h}{n}\big)|^{4/3}, \qquad (2.14)$$
$$where\ TQ \rightarrow \int_{t-1}^{t} \sigma^4(s)ds\ for\ n \rightarrow \infty.$$

Since I assume that there exists a discrete jump variation process in the asset returns, I follow the jump detection methodology, according to which a jump occurs when the ratio statistic is significant. In the literature, there are plenty of jump detection techniques, which are compared in Huang & Tauchen (2005). They find that the usage of ratio-statistics gives more powerful results than the test statistics provided by Barndorff-Nielsen & Shephard (2004). I use the following ratio statistic to identify statistically significant bond price jumps following Huang & Tauchen (2005):

$$z = n^{-1/2} \frac{\big[RV - BV\big] RV^{-1}}{\sqrt{\big(\mu_1^{-4} + 2\mu_1^{-2} - 5\big) \max\left\{1, \frac{TQ}{BV^2}\right\}}} \sim N(0,1). \qquad (2.15)$$

I use z-test statistics to identify the statistically significant bond price jumps in the sample. This test has powerful properties and is quite accurate at detecting asset price jumps (Huang & Tauchen (2005); Andersen, Bollerslev & Diebold (2007); Wright & Zhou (2009); and Tauchen & Zhou (2011)).

Hence $TQ' = TQ/\tau^4$.

2.3.4 Realized Semivariance

The dynamic dependencies between volatility and underlying returns are also the research focus on the empirical volatility literature. In this study, I look for the relevance of the feedback effect, which is defined as the relationship between contemporaneous returns and volatility by Bollerslev & Zhou (2006), in the government bond markets [5].

To observe the feedback effect, I follow the seminal procedure of Barndorff-Nielsen et al. (2010) by estimating realized semivariance, which is then extended by Patton & Sheppard (2015) to incorporate the impact of signed jumps.

Realized semivariances (RSV) for positive and negative intraday returns are computed as follows:

$$RSV_\tau^+ = \frac{1}{\tau^2}\sum_{i=1}^{n} |\Delta_i p\big(t + \frac{(i)h}{n}\big)|^2 I\Big(\Delta_i p\big(t + \frac{(i)h}{n}\big) > 0\Big), \tag{2.16}$$

$$RSV_\tau^- = \frac{1}{\tau^2}\sum_{i=1}^{n} |\Delta_i p\big(t + \frac{(i)h}{n}\big)|^2 I\Big(\Delta_i p\big(t + \frac{(i)h}{n}\big) < 0\Big), \tag{2.17}$$

where $RV_\tau = RSV_\tau^+ + RSV_\tau^-$.

In the equation Eq. (2.16) and Eq. (2.17), $I(.)$ corresponds to indicator function. RSV series are calculated in the intraday basis in line with RV.

[5]The asymmetric response of current volatility to the lagged returns with respect to the sign of returns was firstly introduced by Black (1976). Although the empirical findings of the literature indicate that such an asymmetry exists, its power is found to be weak and insignificant (Nelson (1991) and Bekaert & Wu (2000)). In addition, Bollerslev & Zhou (2006) provide empirical evidence that there is no significant relationship between contemporaneous returns and volatility, therefore they reject the presence of feedback effect.

2.3.5 Heterogeneous Auto-Regression Model

In the HAR model of Corsi (2009), it is assumed that the heterogeneous markets hypothesis (HMH), which depends on market participants' non-homogeneity in terms of expectations and behaviors, is valid. Therefore, the general pattern of volatility structure can be generated from three different frequencies. The high-frequency component for short-term traders is reflected by daily volatility, for medium-term traders by weekly volatility, and for investors focusing on long-term trends by monthly volatility. Although the HAR structure does not externally impose long memory in the volatility process, the cascade type model generates slow decaying memory for the forecast horizons.

To represent weekly and monthly trends, I use simple averages as below.

$$RV_{t_1:t_2} = \frac{1}{t_2 - t_1 + 1} \sum_{t=t_1}^{t_2} RV_t, \; where \; t_1 \leqslant t_2. \tag{2.18}$$

Then, weekly and monthly averages[6] are given in the Eq. (2.19) below:

$$RV_{t-5:t-2} = \frac{1}{4} \sum_{t=t-5}^{t-2} RV_t. \tag{2.19}$$

$$RV_{t-22:t-6} = \frac{1}{17} \sum_{t=t-22}^{t-6} RV_t. \tag{2.20}$$

[6] I prefer to use non-coinciding periods in the HAR variables to avoid double counting lagged observations.

Then, HAR-RV model [7] is given in Eq. (2.21):

$$RV_{t+h-1:t} = \beta_0 + \beta_d RV_{t-1} + \beta_w RV_{t-5:t-2} + \beta_m RV_{t-22:t-6} + \epsilon_t, \tag{2.21}$$

h corresponds to forecast horizon.

I decompose the continuous and discontinuous part of RV by following Barndorff-Nielsen & Shephard (2004). Using the discontinuous jump variations, I can employ extended HAR models such as the HAR-RVJ model and HAR-CJ model of Andersen, Bollerslev & Diebold (2007). The inclusion of jump parameters in the volatility forecasting regressions enables us to measure the possible magnitude of daily jumps on the future volatility and its significant life span in the investment horizon.

I identify the significant jump series following jump ratio test of Huang & Tauchen (2005):

$$\hat{J}_t = I_{z_t > \psi_\alpha}(RV_t - BV_t)^+, \tag{2.22}$$

where ψ_α is the cumulative distribution function at α confidence level. In this paper I choose $\alpha = 0.999$, which corresponds to a critical value of 3.0902. In addition $(RV_t - BV_t)^+$ stands for $\max(0, RV_t - BV_t)$ and $I_{z_t > \psi_\alpha}$ is the indicator function that takes values of unity when there is a significant jump.

[7]For simplicity, I report the general form of HAR model, while the estimations are conducted using realized volatility, $RV^{1/2}$, in exchange for realized variance, RV.

Then, the continuous part quadratic variation accounts for the significant jumps given in Eq. (2.23).

$$\hat{C}_t = RV_t - \hat{J}_t. \tag{2.23}$$

I also compute weekly, $\hat{C}_{t-5:t-2}$, and monthly, $\hat{C}_{t-22:t-6}$, continuous variation series, $\hat{C}_t$ similar to Eq. (2.19) and Eq. (2.20).

$$\hat{C}_{t-5:t-2} = \frac{1}{4}\sum_{t=t-5}^{t-2}\hat{C}_t. \tag{2.24}$$

$$\hat{C}_{t-22:t-6} = \frac{1}{17}\sum_{t=t-22}^{t-6}\hat{C}_t. \tag{2.25}$$

Therefore, it becomes natural to extend the HAR-RV model to include the effect of continuous and jump variation separately.

HAR-RVJ model:

$$RV_{t+h-1:t} = \beta_0 + \beta_d RV_{t-1} + \beta_w RV_{t-5:t-2} + \beta_m RV_{t-22:t-6} + \beta_j \hat{J}_{t-1} + \epsilon_t. \tag{2.26}$$

HAR-CJ model:

$$RV_{t+h-1:t} = \beta_0 + \beta_d \hat{C}_{t-1} + \beta_w \hat{C}_{t-5:t-2} + \beta_m \hat{C}_{t-22:t-6} + \beta_j \hat{J}_{t-1} + \epsilon_t. \tag{2.27}$$

2.4 Empirical Findings

2.4.1 Descriptive Statistics

In this section I present the summary statistics in Table 2.1 and 2.4.

I report summary statistics of realized volatility, $\sqrt{RV}$, and significant realized jumps, $\sqrt{\hat{J}}$, for European government bond markets. The descriptive statistics reveal that the volatility term structure of European government bond markets indicates a U-shaped pattern on an intraday basis since the mean of RVs for short and long-term maturities is higher than the mean of medium-term maturities. The same pattern is followed for the volatility-of-volatility term structure (standard deviation of RVs) of European government bonds. On the other hand, there is no clear evidence of similar behavior for the realized jump series in Table 2.4.

Figure 2.1 shows the boxplots of intraday volatility across European T-bond markets across the maturity span.

In all of the markets except France, the volatility shows a U-shaped path for all the maturities. Moreover, the 1-year and 30-year maturities are more volatile compared to the other maturities. Also, the volatility of the volatility can be inferred from the spread between 1st and 3rd quartile of the plots. It is obvious that volatility of volatility is higher for short-term maturities, while some upward outliers are observed for the longer-term maturities.

Figure 2.2 and 2.3 show the boxplots of the realized semivariances (RSV).

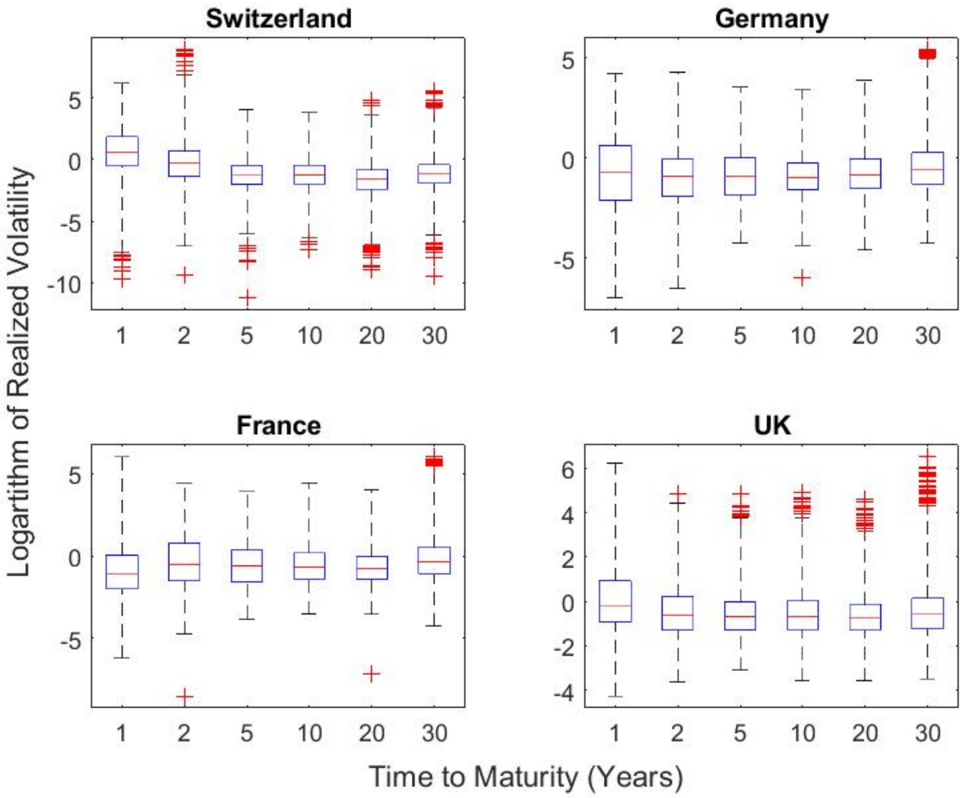

Figure 2.1: Box Plot of RV

Similar to the realized volatility in Figure 2.1, RSV series indicate a *U*-shaped pattern in the volatility yield curve with respect to 2^{nd} and 3^{rd} quartiles. In addition, the interquartile range for 1-year and 30-year securities is higher than the other maturities. In any quartile of the boxplot figures, I do not observe any fraction between negative and positive semivariances so any feedback effect. Therefore, in line with the literature (Nelson (1991); Bekaert & Wu (2000); and Bollerslev & Zhou (2006)) I reject asymmetry hypothesis between contemporaneous bond returns and volatility.

The most straightforward comparison is likely to be made between France's and

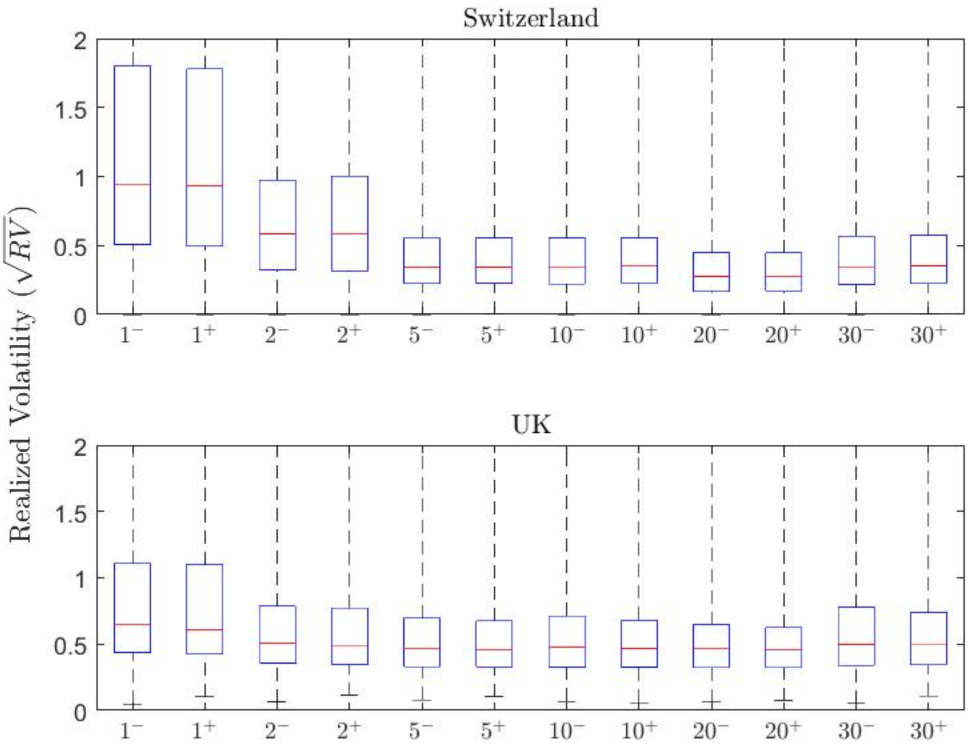

Figure 2.2: Feedback Effect: Box Plots of Negative, RSV$^-$, and Positive, RSV$^+$, Semi-variances across Maturity Span

Germany's sovereign bond markets due to both being euro denominated. Except for the 1-year T-bill, French markets are found to be reflecting a higher level of volatility in the median and other quartiles.

Figures 2.4 to 2.7 give the realized volatility series for the major European bond markets between January 2005 to October 2019.

These figures reveal a high degree of volatility co-movement across the maturity and market spectrum. I observe that government bond volatility peaks in the GFC period and the sovereign debt markets are faced with another common high volatility period

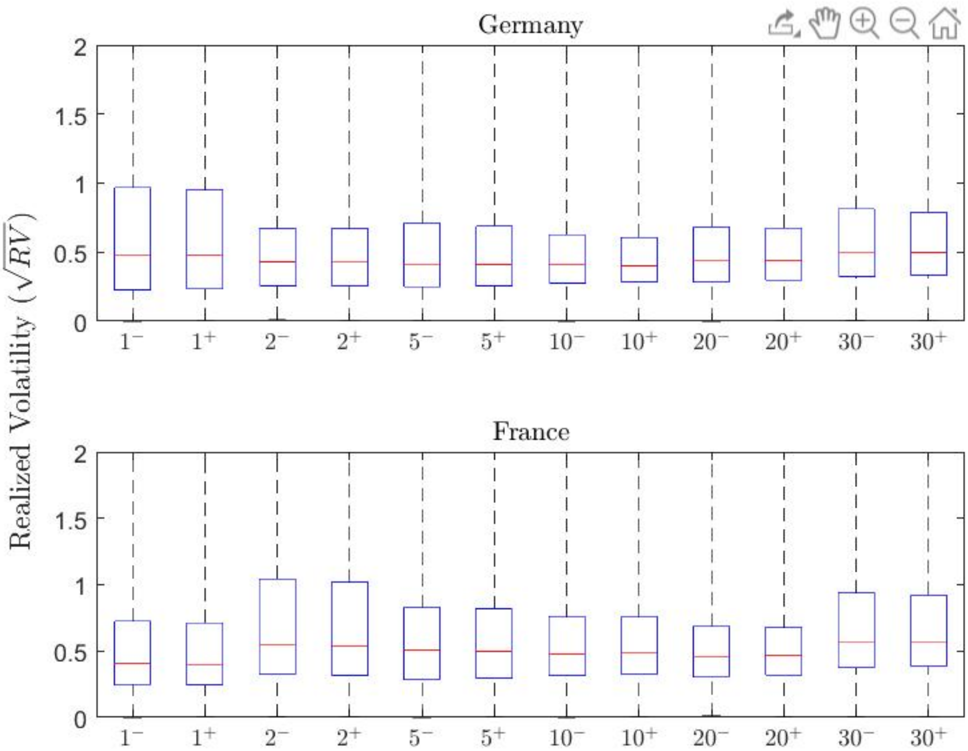

Figure 2.3: Feedback Effect: Box Plots of Negative, RSV$^-$, and Positive, RSV$^+$, Semivariances Maturity Span

during the European debt crisis of 2010. These periods correspond to the most important disruption of bond markets in the sample period.

In addition to the crisis impact on the bond yields and volatility, another key driver of heightened European bond volatility is the 2016 United States presidential elections. In addition to the surprising result of the election, the promises of expansionary fiscal policies in tax cuts and infrastructure expenditures resulted in a euphoria mood in the stock markets and at the same time triggered a sell-off in the bond markets in November 2016 due to heightened risk in the US budget balance. Andersson et al. (2009) study the

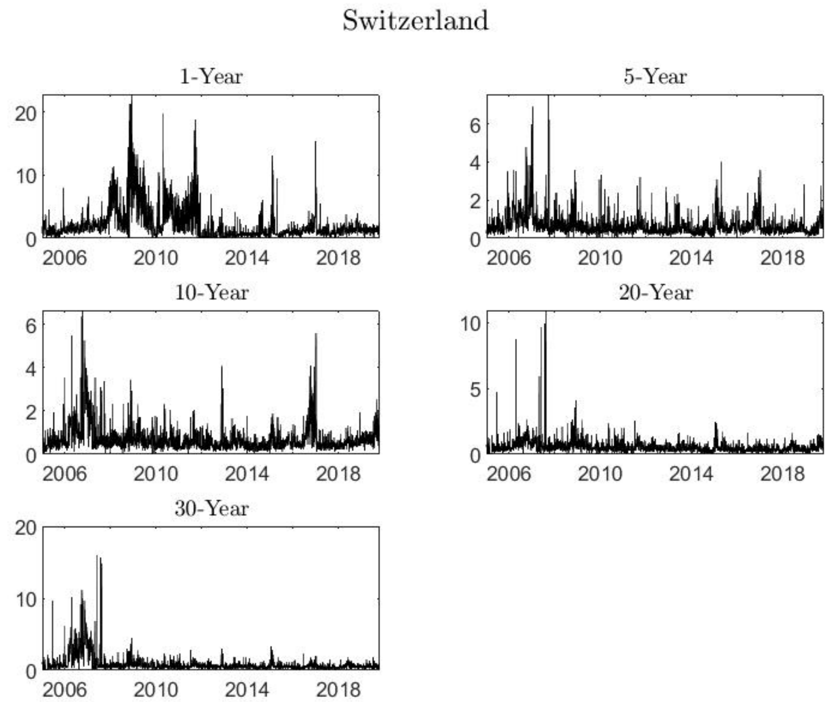

Figure 2.4: Realized Volatility: The squared root of realized volatility, $RV^{1/2}$, is given in percentages.

causes that move bond markets in the Euro area and shows that bond markets are more sensitive to the US-related news due to investor perceptions of the US as a main global factor. In this perspective, findings validate Andersson et al. (2009) since I show that the uncertainty generated by the elections at the end of 2016 is transmitted to the major European bond markets.

Moreover, from Figures 2.4 to 2.7 I can easily see that the Brexit referendum in June 2016 has a positive impact on the volatility term structure of the UK government bond market. On the contrary, the low reaction of 1-year UK T-bond volatility shows that the effect of UKs decision to leave the EU had an effect on medium to long-run UK bond

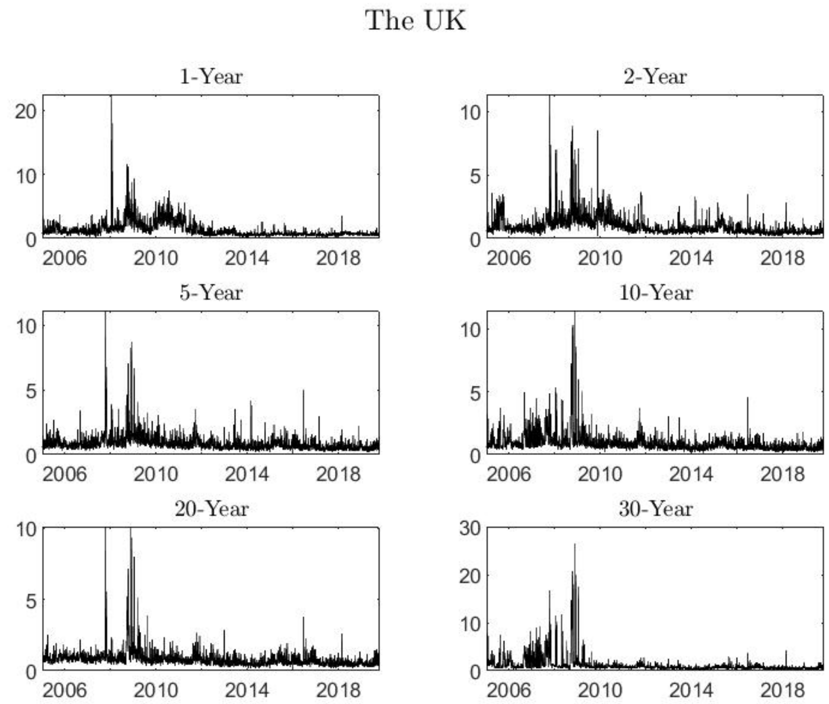

Figure 2.5: Realized Volatility: The squared root of realized volatility, $RV^{1/2}$, is given in percentages.

market expectations. Also, before and after the Brexit vote, financial market participants tried to hedge their positions by increasing their allocations of safe-haven securities, specifically Japanese yen, and Swiss franc denominated assets. This created a gradual rise in the volatility of the Swiss bond market.

In terms of idiosyncratic volatility periods, the analysis shows that the most significant country-specific event was the removal of the Swiss franc peg to the euro, which resulted in an immense volatility clustering in Swiss financial markets. On 15th January 2015, the Swiss National Bank unexpectedly removed the peg of the franc to the euro, which was effective since 2011. This decision led to a massive impact on Swiss FX and bond

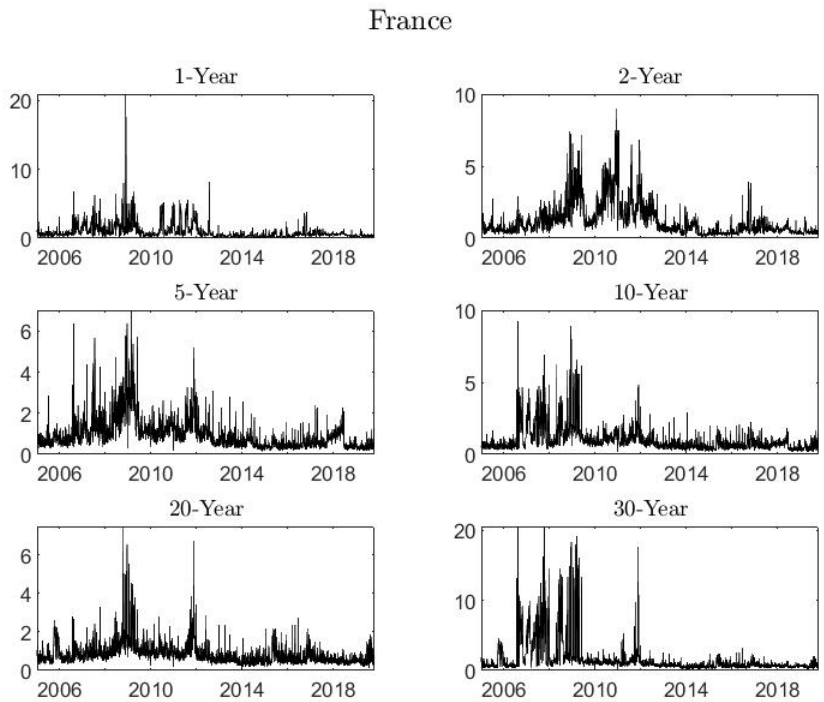

Figure 2.6: Realized Volatility: The squared root of realized volatility, $RV^{1/2}$, is given in percentages.

markets and resulted in to increase in Swiss bond return volatility during this period. In addition, the analysis shows that German bond volatility increased during May-June 2015, which is known as a "bund tantrum". The tantrum in the bond markets is mainly attributed to the ECBs Public Sector Purchase Program (PSPP) that is introduced in early 2015. While, low-interest rate and quantitative easing policies tame the market volatility in the bond markets, their impact on liquidity make the government bond markets more fragile and open to sudden volatility spikes Riordan & Schrimpf (2015)[8]. During this

[8] In Riordan & Schrimpf (2015), it is stated that the ECB purchased 46.3 billion of German bonds by June 30, 2015, since the start of PSPP.

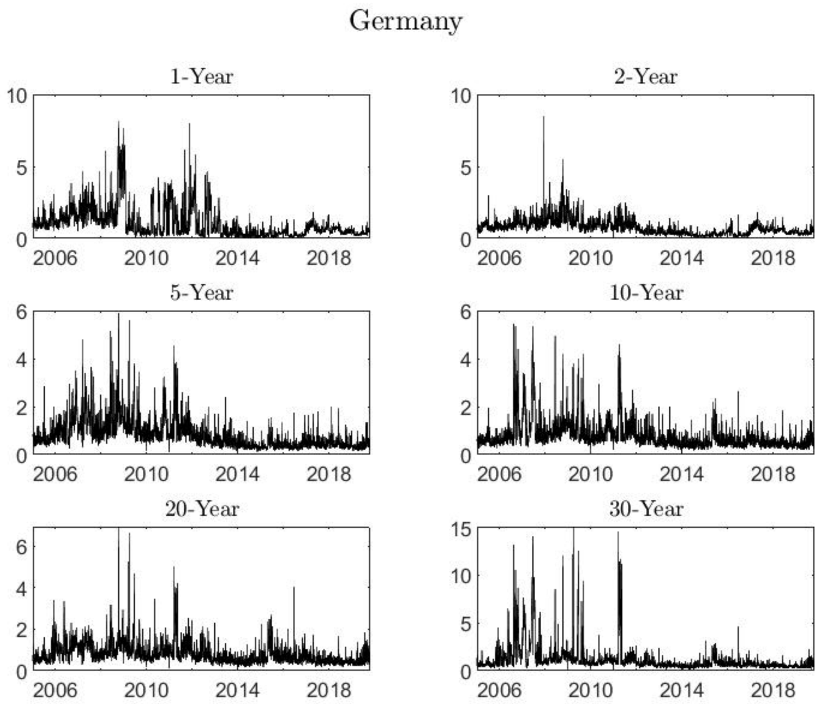

Figure 2.7: Realized Volatility: The squared root of realized volatility, $RV^{1/2}$, is given in percentages.

period the large price swings on the intraday basis lead to volatile bond markets due to deterioration of liquidity especially in the medium to long run securities (see Figure 2.7). These initial descriptive results are some preliminary evidence showing the significant effect of major macroeconomic events (e.g Brexit) on the volatility term structure of European bond markets.

2.4.2 HAR Results

In this section, I present the volatility forecasting results of HAR-type models. The econometric results for the Swiss, German, French, and UK realized bond return volatility term structure are given in Tables 4.3 to 4.10 [9].

In order to compare the results of the volatility forecasting models, I follow the procedure proposed by Patton (2011) according to which the $QLIKE$ loss function gives the most robust estimator in assessing volatility forecasts using imperfect volatility proxies. Additionally, I use Mincer-Zarnowitz (MZ) R^2 of forecasting regressions' for evaluating performance.

$$QLIKE = \frac{1}{T}\sum_{t=1}^{T}\left(\frac{RV_t}{\hat{RV_t}} - log(\frac{RV_t}{\hat{RV_t}}) - 1\right), \tag{2.28}$$

where RV_t is estimated using equation 2.21, 2.26 and 2.27.

I also report the $QLIKE$ and MZ R^2 when there is a jump at the time "t-1", which is denoted with J, and when the path is continuous for RV_{t-1}, denoted with C. These HAR-type models are similar to those of Corsi et al. (2010) for US financial markets.

The results are presented in Tables 4.3 to 4.10, indicating that daily, weekly and monthly trends of volatility are robust determinants of future bond market volatility, regardless of forecasting horizon and time to maturity of the securities. More specifically, the estimated coefficients of daily, weekly, and monthly realized variance are positive and statistically significant when forecasting the European government bond volatility term structure in the short (1-day) and medium-term (weekly and monthly) horizons. Following the HAR-type models of Corsi (2009), I aggregate realized volatility over

[9] I exclude the Swiss government bond with 2-year maturity from analysis due to some non-convergences in the estimations.

a diverse set of horizons, which is assumed to reflect the MDH and therefore relative contributions (weights) of non-homogeneous investors to the market volatility. As a result, short-term traders are found to have the largest impact on the volatility for one day forecasting horizon, while the impact of longer-term traders is found to increase as the forecasting horizon extends.

When the realized volatility is decomposed into its continuous and jump components, the jump variations have a high and positive effect on future volatility. The jump tail risk measure has a significantly positive effect on the volatility forecasts and its impact on volatility is found to be persistent for 1-day to 22-day horizons. Although the contribution of jump variation is present, its magnitude and effectiveness are relatively reduced as the forecasting horizon increases. The contribution of this study lies in demonstrating the volatility literature that jump tail risk is a significant determinant of volatility in European government bond markets for the first time. While the relevant literature so far has shown that the jump coefficient in the HAR-CJ model on equity (Forsberg & Ghysels (2006); Giot & Laurent (2007); Busch et al. (2011)) and bond market volatility (Corsi et al. (2010);Andersen, Bollerslev & Diebold (2007)) is negative and/or insignificant, this study shows that jumps play a significant role when forecasting European bond market volatility.

Moreover, my analysis is the first to show the superior forecasting power of HAR-type when used for European bond volatility forecasting, when compared to those of the literature focusing on US bond volatility forecasting. For example, I report in sample R^2 values ranging from 40% to 80%, while Andersen & Benzoni (2010), when testing the HAR regression model for the US treasury bond market their R^2 values ranging from 15% to 20%. Hence, the analysis is the first to show that HAR-type volatility models explain a much larger part of time-varying volatility in European bond markets as opposed to US bond markets.

I additionally examine the out-of-sample forecasting performance of the HAR-type volatility models using a rolling window. Tables 2.15 and 2.18 below report the out-of-sample forecasting results.

The results are in-line with those of the literature (see Andersen, Bollerslev & Diebold (2007); Corsi et al. (2010); Bollerslev et al. (2016); and Bollerslev et al. (2018)), as I find that the inclusion of jump variation as an explanatory variable helps to reduce forecast errors. According to Diebold & Mariano (1995) forecast comparison test results, extending the HAR model as HAR-RVJ and HAR-CJ improves the QLIKE loss functions significantly for most government bonds.

In addition, I report average out-of-sample forecast regression R^2s. Out-of-sample forecasting exercises show that the HAR-type models produce significant out-of-sample forecasts with out-of-sample R^2s ranging from 20% to 70%. As expected, the out-of-sample forecasting power is higher when forecasting the volatility of government bonds with short-term maturity.

2.4.3 Monetary Policy and Bond Market Volatility

Through risk-taking and uncertainty channels monetary policy is a major determinant of market volatility. In the literature, US stock and bond market volatility is largely attributed to monetary policy shocks and to the news regarding monetary policy(see Bekaert et al. (2013); David & Veronesi (2014); Bruno & Shin (2015); Triantafyllou & Dotsis (2017); and Mallick et al. (2017)). Motivated by these findings, I examine the impact of monetary policy meetings on realized volatility of European government bonds on an intraday basis. Figure 2.8 shows the response of financial markets to the monetary policy announcements among major European central banks. Firstly, the announcement calendar of the Swiss National Bank (SNB) is irregular in the estimation period. SNB announces the policy decision at 8:30 (GMT), 12:00 (GMT) and 13:00 (GMT), while the most frequent time is 8:30 (GMT). As I observe, on the top left of Figure 2.8, the volatility of Swiss bonds during these announcement dates is higher at the focused interval and its impact persists for one day long. Secondly, European Central Bank (ECB) always announces the decision at 12:45 (GMT). It is obvious that for France (bottom left of Figure 2.8), and Germany (top right of Figure 2.8), bond markets exhibit a gradual rise in volatility especially after the ECB announcement and during the governor's press conference. Lastly, the Bank of England (BoE) monetary policy meeting announcements are released at 12:00 (GMT), that is when UK gilt volatility (bottom right of Figure 2.8), shows a sudden spike[10].

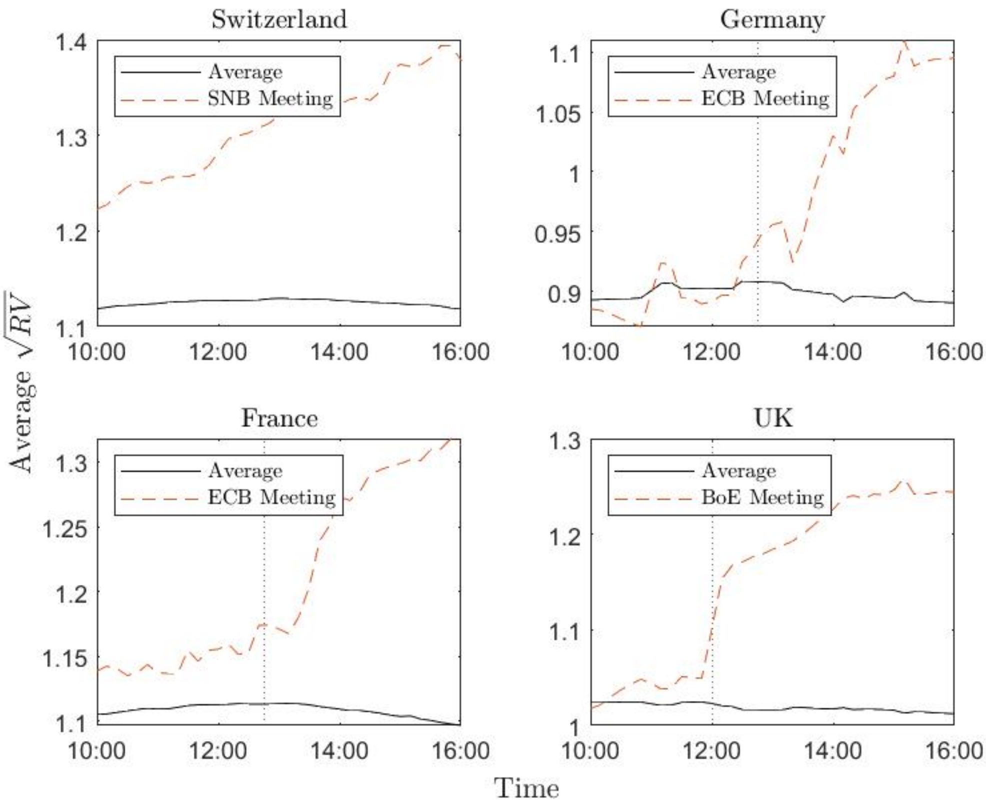

Figure 2.8: Realized Volatility Averages by Time of Day: The squared root of realized volatility, $RV^{1/2}$, is given in percentages. Averages correspond to the average volatility in the whole sample period of January 2005-October 2019. Lines represent the average volatility on the yield curves.

The jump variations for bond markets signal at least one jump in 80% of all central bank monetary policy announcement days for the Swiss market, at least one jump in 42% for the German market, at least one jump in 34% for the French market, and at least one jump in 40% for UK market. Therefore, results show that monetary policy (MP) announcements are key drivers and early warning signals of increasing turbulence

[10]The absolute returns for the time of the day basis given in Figure 2.9.

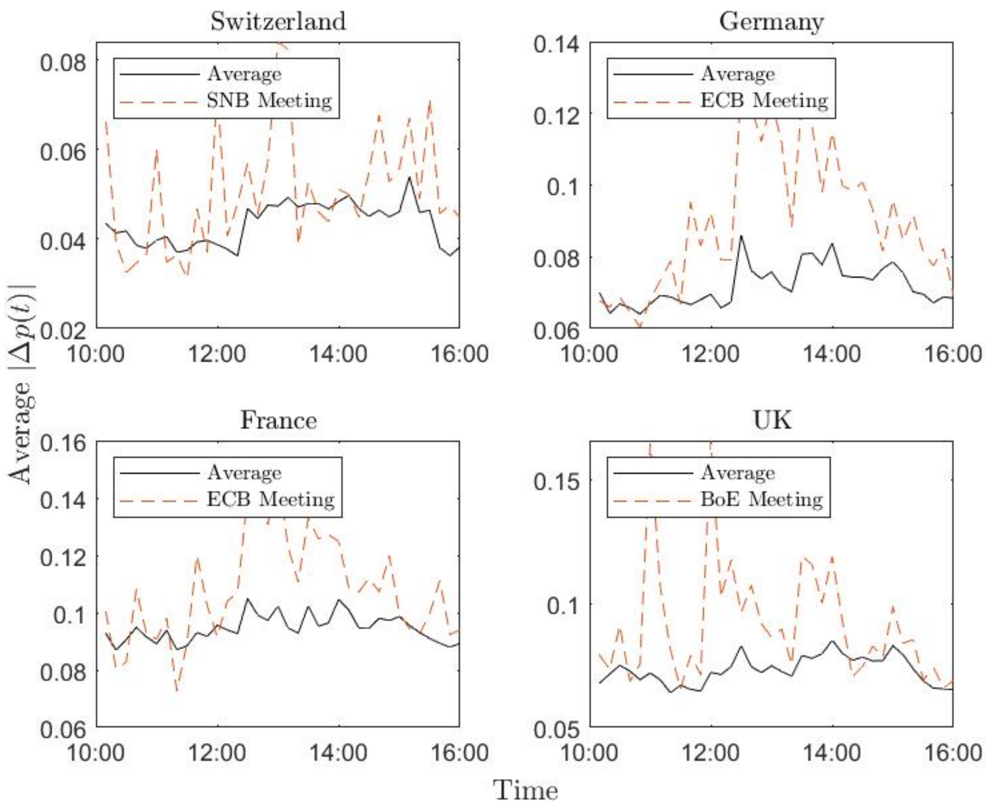

Figure 2.9: Absolute Returns by Time of Day: Averages correspond to the average absolute return in whole sample period of January 2005-October 2019.

in European government bond markets. Figure 2.10 reports the average jumps and volatility of the yield curve on the announcement dates[11].

The volatility spikes and the presence of jumps on the MP announcement days pave the way for studying the timing and the dynamics of the bond market volatility. In this framework, I investigate whether there exists any impact of the meeting days on the volatility forecasting dynamics in the HAR framework. Lucca & Moench (2015) document that there is a presence of excess return in the US equity market before the

[11]The distribution of jumps are available upon request.

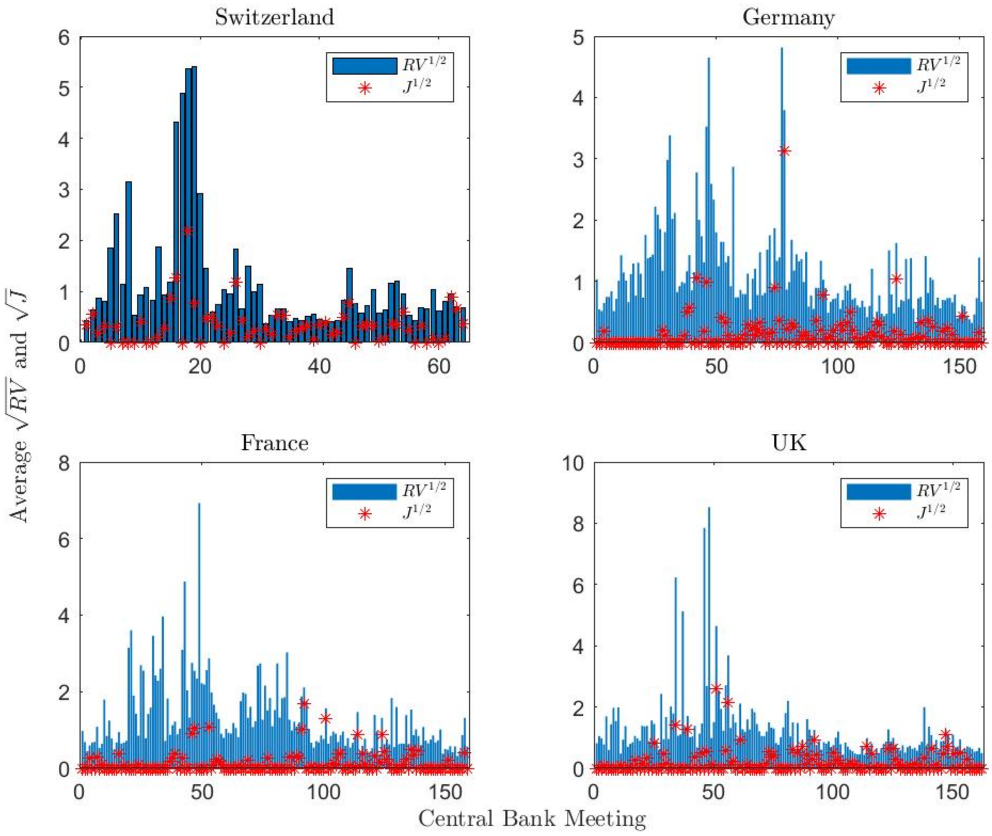

Figure 2.10: Average Volatility and Jump Variation: Averages correspond to the average variation in the date of monetary policy committee meetings of SNB, ECB and BoE respectively. Numbers represents number of meetings in the January 2005 and October 2019 period.

FOMC meetings, which is then called pre-FOMC drift. The excess return is justified by bearing non-diversifiable risk and systemic risk around the meeting (see Lucca & Moench (2015) for more detail). In addition, Guo et al. (2020) show that pre-FOMC drift is dependent on underlying economic sentiment and uncertainty. In this paper, I focus on the impact of pre-announcement and announcement day drifts on bond market volatility forecasts.

In this paper, I focus on the pre-MP announcement, called pre-announcement, impact on European bond market volatility. To my knowledge, it is the first paper trying to explain the pre-meeting impact in the volatility forecasting framework.

To test the impact of MP announcement, I simply extend HAR-RV models by incorporating a pre-announcement date and announcement date dummy variables, separately. Therefore, HAR-RV model[12] becomes:

$$RV_{t+h-1:t} = \beta_0 + \beta_d^1 RV_{t-1} 1(pre - announcement) + \beta_d RV_{t-1} + \beta_w RV_{t-5:t-2} + \beta_m RV_{t-22:t-6} + \epsilon_t, \tag{2.29}$$

and

$$RV_{t+h-1:t} = \beta_0 + \beta_d^1 RV_{t-1} 1(announcement) + \beta_d RV_{t-1} + \beta_w RV_{t-5:t-2} + \beta_m RV_{t-22:t-6} + \epsilon_t. \tag{2.30}$$

Table 2.21 gives the results for extended HAR-RV model using pre-announcement day dummy variable. Firstly, the contribution of daily lagged volatility onto future volatility in the non-announcement day forecasts is only material apart from the results in the previous section, which validates the robustness of estimations. In this study, I call the relationship between forecast period and daily lag as volatility transmission. The results indicate that the volatility transmission sensitivity of forecasts increases by

[12] Similar to the previous subsection, I conduct the analysis using realized volatility, $\sqrt{RV}$. For simplicity, I continue to give a general HAR model representation.

almost 40% on pre-announcement days. Increased sensitivity to the daily volatility in terms of 1-day forward volatility corresponds to faster movement of the markets before the monetary policy announcements. This outcome can be interpreted as a piece of evidence of the presence of pre-announcement drift in the bond market. Therefore, the inclusion of the day dummy variable highlights the importance of pre-announcement drift in the European bond market.

In addition, I analyse the announcement drift after the European central banks' meetings using equation 2.30. Table 2.22 shows that there is no change in the underlying dynamics of the HAR forecasting relationship after the MP announcement. This result provides the idea that after the announcement short-term tension is tamed by the central banks in the European government bond markets, which can be interpreted as evidence of the "buy the speculation, sell the fact" behavior of financial market agents. After the monetary policy announcements generally the opportunity to speculate in the markets evaporates and markets tend to turn back their fundamentals.

Moreover, I test the source of pre-announcement drift in the integrated variation and jump variation framework. Therefore, I estimate the extended model of HAR-CJ as follows:

$$RV_{t+h-1:t} = \beta_0 + \beta_d^1 C_{t-1} 1(pre - meeting) + \beta_j^1 J_{t-1} 1(pre - meeting) + \beta_d \hat{C}_{t-1} + \beta_w \hat{C}_{t-5:t-2} + \beta_m \hat{C}_{t-22:t-6} + \beta_j \hat{J}_{t-1} + \epsilon_t. \tag{2.31}$$

Table 2.23 shows that the transmission effect is still significantly higher on the days before policy announcements, even though its magnitude is weaker. Results indicate that the pre-announcement drift mostly results from the continuous component of the daily lagged volatility, not the jump variation.

2.5 Robustness

2.5.1 Market Microstructure Noise

In the realized volatility (RV) literature, the estimates are assumed to provide perfect estimators of quadratic variation (QV) under continuous-time and without measurement error. Therefore, using the highest possible homogeneous discrete time-frequency sum of squared returns is assumed to approximate true QV as the sampling frequency increases up to tick-by-tick observation.

On the other hand, in practice, it is emphasized that the presence of microstructure noise causes the bias in the estimates that significantly increases the error in the high frequency-based estimators (see Zhou (1996) and Hansen & Lunde (2006)). The market microstructure noise is generally documented by providing the intraday sampling frequency impact on estimates[13]. Even though, using high-frequency data poses the microstructure-related noise, volatility signature plots indicate that there is a trade-off between frequency and RV estimation (Hansen & Lunde (2006)). Therefore, the estimations are constructed by using moderate frequency, 5 minutes to 20 minutes, to handle the bias (see Zhang et al. (2005)). In addition to using optimal sampling frequency, there are some filtering (Andersen, Bollerslev, Diebold & Labys (2003)), two-scales estimator (Zhang et al. (2005)) and kernel-based techniques (Barndorff-Nielsen, Hansen, Lunde & Shephard (2008), Barndorff-Nielsen et al. (2009)) used in the literature in providing remedies to the market microstructure noise.

Since the seminal work by Zhou (1996), realized kernels in the volatility estimation became popular. In this paper, I follow Barndorff-Nielsen, Hansen, Lunde & Shephard (2008), Barndorff-Nielsen et al. (2009) to construct realized kernels, RK, which help in controlling the noise generated by microstructure noise. The RV_{Kernel} is formed as follows:

$$RV_{Kernel} = \sum_{h=-H}^{H} k\left(\frac{h}{H+1}\right)\gamma_h, \tag{2.32}$$

where $\gamma_h = \sum_{i=1}^{n} \Delta p_{i,n} \Delta p_{i-h,n}$[14] and $k(x)$ is non-stochastic weight function.

Following 2.32, Hansen & Lunde (2006) propose RV_{AC_1} to correct bias in the realized

[13]Zhang et al. (2005) document a review on the impact of sampling bias using volatility signature plots.
[14]$\Delta p_{i,n}$ corresponds to logarithmic change in prices.

volatility measure, where $k(x)$ is equal to unity, which is a restricted version of kernel-type estimators.

RV_{AC_1} is given as follows:

$$RV_{AC_1} = \sum_{i=1}^{n} \Delta p_{i,n}^2 + \sum_{i=1}^{n} \Delta p_{i,n} \Delta p_{i-1,n} + \sum_{i=1}^{n} \Delta p_{i,n} \Delta p_{i+1,n}, \tag{2.33}$$

This estimator provides a more efficient measure and reduces the noise compared to RV estimators (Hansen & Lunde (2006)).

In this paper, I estimate RV_{AC_1} and RV_{Kernel} as alternative realized variance estimators. Unfortunately, the intraday-based volatility estimator using the $AC - type$ model suffers from negative values. In order to overcome the negativity problem, I employ the Parzen kernel, which guarantees the non-negative estimates of volatility[15].

Hansen & Lunde (2006) assert that the asymptotic variance of RV_{AC_1} increases as the sampling frequency n increases. As a result of the trade-off between sampling frequency and estimation noise, intraday returns should not be sampled at the highest possible frequency. In addition to using a moderate sampling frequency, utilization of the realized kernel-based estimators helps more in reducing microstructure noise in the estimations.

The robustness results indicate that the main findings remain unaltered if I use RK instead of RV in the volatility modeling. Table 2.24 reports the out-of-sample regression

[15]In the Parzen kernel weighting function, I follow Zhou (1996), where H is equal to one (Barndorff-Nielsen, Hansen, Lunde & Shephard (2008)).

results of volatility forecasts. It verifies that the inclusion of jump variation into the HAR model improves volatility forecasts for most of the European bond markets.

2.5.2 Alternative Volatility Estimator

In addition to market microstructure noise, realized volatility models suffer from finite sample jump distortion that can result in upward bias in jump estimators. In order to achieve asymptotically more feasible results, I employ the estimators proposed by Andersen et al. (2012), which use nearest neighbor truncation. I estimate "MinRV" and "MedRV" as jump robust estimators in exchange for bipower variation (BV) and their relevant tripower variation measures, namely "MinRQ" and "MedRQ" in order to measure the significance of daily jumps.

Firstly, I compute "MinRV" as summing the square of the minimum of two sequential absolute returns as follows:

$$MinRV_\tau = (\frac{1}{\tau^2})\frac{\pi}{\pi-2}(\frac{n}{n-1})\sum_{i=1}^{n-1} min\Big(|\Delta_i p\big(t+\frac{(i)h}{n}\big)|, |\Delta_{i+1}p\big(t+\frac{(i+1)h}{n}\big)|\Big)^2 \quad (2.34)$$

where, $min(.,.)$ corresponds to the minimum of the returns.

MinRV benefits from one-sided truncation in estimating jump robust volatility estimator. On the other hand, MedRV depends on two-sided truncation as taking the median value of three consecutive absolute returns in volatility estimation as follows:

$$MedRV_\tau = \left(\frac{1}{\tau^2}\right)\frac{\pi}{6-4\sqrt{3}+\pi}\left(\frac{n}{n-2}\right)\sum_{i=2}^{n-1} med\Big(|\Delta_{i-1}p\big(t+\frac{(i-1)h}{n}\big)|, |\Delta_i p\big(t+\frac{(i)h}{n}\big)|, |\Delta_{i+1}p\big(t+\frac{(i+1)h}{n}\big)|\Big)^2 \tag{2.35}$$

where, $med(.,.,.)$ corresponds to the median of the returns.

The jump robust estimators have their unique asymptotic distribution properties for constructing jump statistics given in Andersen et al. (2012).

$$\begin{aligned} \sqrt{n}\big(RV - MinRV\big) &\longrightarrow MN\big(0,\ 3.81IQ\big), \\ \sqrt{n}\big(RV - MedRV\big) &\longrightarrow MN\big(0,\ 2.96IQ\big). \end{aligned} \tag{2.36}$$

where IQ is integrated quarticity.

Also, alternative to tripower quarticity given in 2.14, I estimate "MinRQ" and "MedRQ".

$$MinRV_\tau = \left(\frac{1}{\tau^4}\right)\frac{\pi n}{3\pi-8}\left(\frac{n}{n-1}\right)\sum_{i=1}^{n-1} min\Big(|\Delta_i p\big(t+\frac{(i)h}{n}\big)|, |\Delta_{i+1}p\big(t+\frac{(i+1)h}{n}\big)|\Big)^4 \tag{2.37}$$

, and

$$MedRV_\tau = \left(\frac{1}{\tau^4}\right)\frac{3\pi n}{9\pi + 72 - 52\sqrt{3}}\left(\frac{n}{n-2}\right)\sum_{i=2}^{n-1} med\Bigg(|\Delta_{i-1}p\big(t+\frac{(i-1)h}{n}\big)|, |\Delta_i p\big(t+\frac{(i)h}{n}\big)|, |\Delta_{i+1}p\big(t+\frac{(i+1)h}{n}\big)|\Bigg)^4. \tag{2.38}$$

Then, I adjust the jump z-test with respect, 2.15 to the asymptotic distribution of truncation based estimators, given in 2.36.

The volatility forecasting results of European bond markets are in line with the results in Section 2.4. Out-of-sample regression results verify that inclusion of jump variation into the HAR model improves volatility forecasts for most of the bond markets (See Tables 2.27 - 2.30).

2.6 Conclusion

In this paper, I study the forecasting power of HAR-type models on the volatility term structure of European government bond markets using intraday data covering the period from January 2005 up until October 2019. Econometric analysis shows that the daily, weekly, and monthly realized variance is a robust predictor of volatility in European government bond markets. In addition inclusion of jump variation helps to improve volatility forecasts. Overall, HAR models exhibit extraordinary in-sample and out-of-sample forecasting power with in sample R^2s ranging from 50% to 80% and out-of-sample R^2s ranging from 20% to 75%. Moreover, the analysis shows that 83% of central bank rate decisions for the Swiss market, 42% for the German market, 34% for the French market, and 40% for the UK market coincide with at least one statistically significant bond price jump. In addition, HAR-type models identify the significant predictive power of jumps in government bond volatility. Hence my analysis implicitly reveals that monetary policy announcements are early warning signals of rising volatility in European bond markets. Results also indicate the presence of pre-monetary policy meeting drift in the bond markets.

To the best of my knowledge, this is the first study that forecasts European bond volatility on an intraday basis using the HAR-type cascade model. Secondly, the findings indicate that the discrete jumps which are associated with monetary policy announcements are effective in ex-post bond return volatility forecasting. Thirdly, this paper reveals the dynamics of the volatility dependency structure of major European bond markets, where findings indicate that the future volatility is significantly affected by its short and medium-term trend components. I also show that the monetary policy announcements are an important determinant of bond market volatility and the pre-announcement drift is present in the European bond market using the HAR-model structure.

The policy recommendation which comes out of my analysis is that since monetary policy announcements are key determinants (and significant early warning signals) of rising volatility in the respective government bond markets, then the central banks are able to indirectly reduce instability in the respective bond markets if needed. For example, according to the analysis, a reduction of monetary policy announcements during a given time period will result in less turbulence and instability in European government markets during this period.

Table 2.1: Summary Statistics for Bond Price Volatility Across the Maturity Spectrum

Table 2.2: Statistics for $\sqrt{RV}$

	Swiss						German					
	1-	2-	5-	10-	20-	30-	1-	2-	5-	10-	20-	30-
Mean	0.022	—	0.007	0.007	0.005	0.008	0.011	0.007	0.008	0.008	0.008	0.012
St. dev.	0.026	—	0.006	0.006	0.005	0.011	0.011	0.005	0.006	0.006	0.006	0.016
Skewness	-0.545	—	0.113	0.393	-0.574	0.459	-0.112	-0.237	0.358	0.811	0.514	1.278
Kurtosis	4.605	—	5.277	4.620	6.902	6.677	2.549	2.907	2.725	4.066	3.523	5.073
Min	0.000	—	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.001	0.001
Max	0.228	—	0.076	0.067	0.109	0.161	0.082	0.085	0.059	0.054	0.069	0.151
DF Test St.	-16.838	—	-19.695	-17.178	-27.217	-21.631	-11.826	-13.293	-14.162	-13.401	-14.874	-15.999

Table 2.3: Statistics for $\sqrt{RV}$

	French						UK					
	1-	2-	5-	10-	20-	30-	1-	2-	5-	10-	20-	30-
Mean	0.010	0.012	0.010	0.010	0.008	0.017	0.014	0.010	0.009	0.009	0.008	0.012
St. dev.	0.012	0.012	0.008	0.009	0.006	0.025	0.014	0.009	0.007	0.008	0.006	0.018
Skewness	0.488	0.314	0.361	0.860	0.551	1.363	0.753	0.825	0.880	0.949	0.849	1.459
Kurtosis	3.211	2.718	2.734	3.695	4.087	4.613	3.398	3.924	5.001	4.906	5.865	5.886
Min	0.000	0.000	0.001	0.002	0.000	0.001	0.001	0.002	0.002	0.002	0.002	0.002
Max	0.209	0.090	0.070	0.092	0.075	0.206	0.225	0.113	0.111	0.115	0.101	0.266
DF Test St.	-15.973	-11.564	-13.309	-14.931	-14.235	-17.717	-14.848	-15.615	-15.914	-16.429	-14.658	-18.410

This table gives summary statistics of realized volatility ($\sqrt{RV}$) for European government bond markets. Daily volatility series are computed using 10-minute returns in the period of January 2005 to October 2019. The series are annualized by multiplying $\sqrt{252}$. Rows of panels represent mean, standard deviation, skewness, kurtosis, minimum, maximum, and Dickey-Fuller test statistics, respectively. For skewness and kurtosis statistics, $\log(\sqrt{RV})$ results are reported.

Table 2.4: Summary Statistics for Bond Price Jumps Across the Maturity Spectrum

Table 2.5: Statistics for $\sqrt{\hat{J}}$

	Swiss 1-	Swiss 2-	Swiss 5-	Swiss 10-	Swiss 20-	Swiss 30-	German 1-	German 2-	German 5-	German 10-	German 20-	German 30-
Mean	0.014	—	0.005	0.006	0.005	0.006	0.006	0.007	0.007	0.007	0.007	0.009
St. dev.	0.017	—	0.005	0.004	0.004	0.005	0.006	0.006	0.005	0.004	0.005	0.008
Skewness	-0.457	—	-0.045	0.069	-0.489	-0.074	0.074	-0.134	0.177	0.206	0.339	0.765
Kurtosis	3.829	—	5.707	3.691	5.623	5.053	2.642	2.887	2.843	3.259	3.213	4.432
Min	0.000	—	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.001	0.001
Max	0.134	—	0.063	0.035	0.058	0.095	0.056	0.051	0.038	0.035	0.055	0.088
DF Test St.	-11.916	—	-16.392	-13.375	-18.906	-17.613	-8.821	-6.411	-8.520	-9.053	-9.655	-10.287

Table 2.6: Statistics for $\sqrt{\hat{J}}$

	French 1-	French 2-	French 5-	French 10-	French 20-	French 30-	UK 1-	UK 2-	UK 5-	UK 10-	UK 20-	UK 30-
Mean	0.007	0.009	0.007	0.008	0.008	0.010	0.010	0.009	0.008	0.008	0.007	0.008
St. dev.	0.009	0.008	0.005	0.005	0.005	0.010	0.010	0.009	0.006	0.005	0.004	0.009
Skewness	0.171	0.133	0.382	0.569	0.078	0.913	0.793	0.881	0.647	0.481	0.418	1.061
Kurtosis	3.283	2.751	2.669	3.529	4.504	4.640	3.313	4.007	3.856	3.830	3.582	5.847
Min	0.000	0.001	0.002	0.001	0.000	0.001	0.002	0.002	0.002	0.002	0.002	0.002
Max	0.123	0.046	0.034	0.053	0.069	0.118	0.093	0.081	0.060	0.068	0.044	0.127
DF Test St.	-8.980	-5.468	-7.893	-9.001	-8.682	-9.357	-7.380	-8.931	-11.221	-10.981	-9.489	-12.683

This table gives summary statistics of significant daily jumps ($\sqrt{\hat{J}}$) for European government bond markets. Daily jump series are computed using 10-minute returns in the period of January 2005 to October 2019. The series are annualized by multiplying $\sqrt{252}$. Rows of panels represent mean, standard deviation, skewness, kurtosis, minimum, maximum, and Dickey-Fuller test statistics, respectively. For skewness and kurtosis statistics, $\log(\sqrt{\hat{J}})$ results are reported.

Table 2.7: Regression Results of Swiss Market on 1-day Forecast Horizon (h=1)

	1-Year			2-Year			5-Year		
	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ
β_0	0.001	0.001	0.002	—	—	—	0.001	0.001	0.002
	(3.01)***	(3.05)***	(5.37)***	—	—	—	(3.07)***	(3.03)***	(4.5)***
β_d	0.386	0.391	0.397	—	—	—	0.323	0.358	0.341
	(7.68)***	(7.59)***	(7.3)***	—	—	—	(9.08)***	(8.26)***	(7.76)***
β_w	0.306	0.306	0.276	—	—	—	0.344	0.338	0.341
	(5.72)***	(5.71)***	(4.76)***	—	—	—	(7.29)***	(6.94)***	(5.88)***
β_m	0.211	0.212	0.246	—	—	—	0.129	0.119	0.160
	(4.82)***	(4.81)***	(5.19)***	—	—	—	(2.61)***	(2.36)***	(2.51)***
β_j		-0.041	0.236	—	—	—		-0.080	0.206
		(-0.8)	(4.38)***	—	—	—		(-1.63)	(4.35)***
R^2	0.634	0.634	0.630	—	—	—	0.394	0.397	0.395
$QLIKE$	0.201	0.201	0.201	—	—	—	0.133	0.133	0.136
$J-R^2$	0.518	0.518	0.515	—	—	—	0.285	0.285	0.283
$J-QLIKE$	0.324	0.324	0.328	—	—	—	0.152	0.152	0.155
$C-R^2$	0.669	0.669	0.665	—	—	—	0.474	0.475	0.473
$C-QLIKE$	0.147	0.147	0.146	—	—	—	0.114	0.114	0.116

	10-Year			20-Year			30-Year		
	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ
β_0	0.001	0.001	0.001	0.002	0.002	0.003	0.001	0.001	0.002
	(2.74)***	(2.83)***	(6.31)***	(6.2)***	(6.46)***	(9.59)***	(2.38)***	(2.99)***	(5.92)***
β_d	0.349	0.358	0.364	0.148	0.159	0.159	0.341	0.350	0.331
	(8.91)***	(8.42)***	(8.31)***	(3.61)***	(3.23)***	(3.55)***	(6.08)***	(5.73)***	(5.87)***
β_w	0.358	0.355	0.331	0.137	0.137	0.167	0.293	0.289	0.326
	(6.56)***	(6.43)***	(6.05)***	(2.8)***	(2.86)***	(2.85)***	(4.88)***	(4.93)***	(5.27)***
β_m	0.159	0.156	0.168	0.258	0.256	0.219	0.214	0.210	0.186
	(3.77)***	(3.71)***	(3.9)***	(3.58)***	(3.51)***	(2.98)***	(3.8)***	(3.73)***	(3.18)***
β_j		-0.028	0.242		-0.030	0.111		-0.057	0.213
		(-0.8)	(6.93)***		(-0.67)	(2.71)***		(-1)	(3.24)***
R^2	0.520	0.520	0.510	0.119	0.120	0.116	0.511	0.512	0.517
$QLIKE$	0.117	0.117	0.119	0.166	0.165	0.168	0.162	0.161	0.161
$J-R^2$	0.431	0.432	0.412	0.128	0.127	0.126	0.259	0.257	0.273
$J-QLIKE$	0.129	0.128	0.131	0.161	0.161	0.163	0.162	0.162	0.162
$C-R^2$	0.565	0.565	0.559	0.103	0.102	0.099	0.574	0.573	0.576
$C-QLIKE$	0.108	0.108	0.110	0.170	0.170	0.174	0.159	0.159	0.158

(1) The results in the parenthesis indicates t-statistics. (2) ***, **, * show 1%, 5% and 10% statistically significant coefficients, respectively. (3) Newey-West standard errors are used to calculate the t statistics.

Table 2.8: Regression Results of German Market on 1-day Forecast Horizon (h=1)

	1-Year			2-Year			5-Year		
	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ
β_0	0.001	0.001	0.001	0.000	0.000	0.000	0.001	0.001	0.001
	(3.48)***	(3.69)***	(4.89)***	(2.93)***	(2.74)***	(3.16)***	(4.07)***	(4.85)***	(8.54)***
β_d	0.600	0.603	0.602	0.319	0.355	0.388	0.372	0.412	0.427
	(15.67)***	(15.82)***	(16.45)***	(8.15)***	(6.92)***	(6.65)***	(8.84)***	(7.67)***	(7.29)***
β_w	0.246	0.247	0.247	0.356	0.337	0.328	0.389	0.361	0.353
	(5.32)***	(5.37)***	(5.83)***	(6.61)***	(6.43)***	(6.07)***	(7.35)***	(6.12)***	(5.36)***
β_m	0.087	0.085	0.085	0.237	0.236	0.242	0.135	0.133	0.123
	(2.83)***	(2.73)***	(2.76)***	(4.23)***	(4.18)***	(3.98)***	(4.42)***	(4.44)***	(3.68)***
β_j		-0.055	0.279		-0.098	0.121		-0.116	0.130
		(-0.96)	(5.3)***		(-3.07)***	(4.66)***		(-2.91)***	(5.3)***
R^2	0.753	0.754	0.755	0.623	0.626	0.616	0.603	0.607	0.603
$QLIKE$	0.119	0.119	0.121	0.062	0.061	0.062	0.074	0.073	0.074
$J-R^2$	0.596	0.596	0.605	0.648	0.652	0.641	0.487	0.493	0.494
$J-QLIKE$	0.242	0.241	0.239	0.073	0.072	0.074	0.082	0.082	0.079
$C-R^2$	0.772	0.772	0.772	0.620	0.621	0.611	0.631	0.632	0.626
$C-QLIKE$	0.097	0.097	0.098	0.059	0.059	0.060	0.071	0.071	0.072
	10-Year			20-Year			30-Year		
	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ
β_0	0.001	0.001	0.001	0.001	0.001	0.002	0.001	0.001	0.002
	(4.03)***	(5.45)***	(8.37)***	(4.09)***	(4.49)***	(6.34)***	(4.28)***	(3.9)***	(4.97)***
β_d	0.454	0.528	0.531	0.396	0.429	0.442	0.538	0.551	0.541
	(11.79)***	(11.88)***	(11.68)***	(6.36)***	(5.32)***	(4.94)***	(9.32)***	(8.45)***	(8.11)***
β_w	0.372	0.317	0.319	0.359	0.339	0.345	0.320	0.313	0.326
	(8.3)***	(6.6)***	(6.02)***	(6.46)***	(4.99)***	(4.11)***	(5.68)***	(5.12)***	(5.05)***
β_m	0.058	0.051	0.038	0.075	0.069	0.050	0.017	0.013	0.009
	(1.82)*	(1.68)*	(1.14)	(2.58)***	(2.51)***	(1.77)*	(0.71)	(0.55)	(0.36)
β_j		-0.201	0.102		-0.073	0.190		-0.115	0.199
		(-5.17)***	(3.77)***		(-1.28)	(5.01)***		(-0.92)	(1.65)*
R^2	0.620	0.631	0.628	0.488	0.490	0.488	0.666	0.667	0.665
$QLIKE$	0.073	0.070	0.071	0.074	0.073	0.073	0.096	0.094	0.094
$J-R^2$	0.421	0.426	0.418	0.474	0.477	0.491	0.403	0.403	0.378
$J-QLIKE$	0.068	0.067	0.068	0.075	0.074	0.075	0.089	0.088	0.090
$C-R^2$	0.658	0.661	0.658	0.497	0.498	0.493	0.697	0.697	0.698
$C-QLIKE$	0.071	0.071	0.072	0.073	0.073	0.073	0.095	0.096	0.096

(1) The results in the parenthesis indicates t-statistics. (2) ***, **, * show 1%, 5% and 10% statistically significant coefficients, respectively. (3) Newey-West standard errors are used to calculate the t statistics.

Table 2.9: Regression Results of French Market on 1-day Forecast Horizon (h=1)

	1-Year			2-Year			5-Year		
	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ
β_0	0.001	0.001	0.001	0.000	0.000	0.000	0.001	0.001	0.001
	(4.32)***	(3.89)***	(2.97)***	(2.47)***	(2.63)***	(3.1)***	(2.73)***	(3.53)***	(5.38)***
β_d	0.610	0.585	0.586	0.412	0.417	0.439	0.390	0.421	0.450
	(16.65)***	(19.01)***	(19.66)***	(8.15)***	(8.15)***	(8.87)***	(9.54)***	(9.97)***	(10.32)***
β_w	0.197	0.188	0.215	0.377	0.375	0.483	0.325	0.308	0.413
	(2.77)***	(2.57)***	(3.98)***	(7.07)***	(7.02)***	(9.34)***	(7.9)***	(7.39)***	(9.85)***
β_m	0.058	0.067	0.043	0.159	0.158	0.053	0.204	0.194	0.058
	(1.65)*	(1.75)*	(2.29)**	(4.77)***	(4.71)***	(2.88)***	(6.23)***	(6.06)***	(2)**
β_j		0.348	0.618		-0.056	0.169		-0.131	0.118
		(2.18)**	(3.92)***		(-1.13)	(3.32)***		(-3.43)***	(3.4)***
R^2	0.626	0.637	0.637	0.782	0.782	0.779	0.659	0.662	0.658
$QLIKE$	0.107	0.107	0.108	0.062	0.062	0.063	0.068	0.067	0.069
$J-R^2$	0.542	0.548	0.541	0.733	0.740	0.729	0.576	0.592	0.609
$J-QLIKE$	0.186	0.191	0.187	0.097	0.096	0.090	0.078	0.076	0.075
$C-R^2$	0.663	0.664	0.665	0.786	0.786	0.784	0.668	0.669	0.662
$C-QLIKE$	0.099	0.099	0.099	0.060	0.060	0.061	0.066	0.066	0.068

	10-Year			20-Year			30-Year		
	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ
β_0	0.001	0.001	0.001	0.001	0.001	0.002	0.001	0.001	0.001
	(3.81)***	(3.64)***	(4.7)***	(2.91)***	(3.33)***	(6.15)***	(4.82)***	(2.34)***	(3.34)***
β_d	0.461	0.462	0.476	0.396	0.440	0.473	0.517	0.504	0.517
	(10.23)***	(9.65)***	(10.18)***	(9.33)***	(8.53)***	(9.22)***	(12.39)***	(12.21)***	(12.7)***
β_w	0.302	0.301	0.357	0.246	0.225	0.327	0.254	0.261	0.314
	(6.8)***	(6.61)***	(7.75)***	(4.85)***	(4.24)***	(5.51)***	(4.95)***	(5.24)***	(7.09)***
β_m	0.128	0.128	0.064	0.233	0.217	0.052	0.113	0.110	0.057
	(4.16)***	(4.11)***	(2.17)**	(5.5)***	(5.19)***	(1.67)*	(3.5)***	(3.54)***	(1.54)
β_j		-0.008	0.253		-0.101	0.175		0.415	0.697
		(-0.13)	(5.11)***		(-2.44)***	(6)***		(3.5)***	(5.99)***
R^2	0.621	0.621	0.623	0.523	0.526	0.522	0.638	0.646	0.645
$QLIKE$	0.077	0.077	0.077	0.066	0.065	0.066	0.103	0.112	0.113
$J-R^2$	0.594	0.595	0.613	0.374	0.382	0.413	0.610	0.587	0.587
$J-QLIKE$	0.105	0.105	0.097	0.086	0.085	0.087	0.162	0.225	0.193
$C-R^2$	0.630	0.630	0.629	0.569	0.570	0.559	0.665	0.665	0.664
$C-QLIKE$	0.073	0.073	0.073	0.060	0.060	0.062	0.096	0.096	0.099

(1) The results in the parenthesis indicates t-statistics. (2) ***, **, * show 1%, 5% and 10% statistically significant coefficients, respectively. (3) Newey-West standard errors are used to calculate the t statistics.

Table 2.10: Regression Results of the UK Market on 1-day Forecast Horizon (h=1)

	1-Year			2-Year			5-Year		
	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ
β_0	0.001	0.001	0.002	0.001	0.001	0.001	0.001	0.002	0.002
	(2.68)***	(2.65)***	(3.79)***	(4.24)***	(4.46)***	(6.19)***	(3.93)***	(4.84)***	(6.45)***
β_d	0.522	0.520	0.553	0.472	0.529	0.582	0.500	0.591	0.608
	(12.25)***	(12.1)***	(13.13)***	(6.49)***	(9.57)***	(10.66)***	(6.55)***	(8.19)***	(8.19)***
β_w	0.247	0.247	0.293	0.259	0.227	0.257	0.201	0.152	0.135
	(2.53)***	(2.53)***	(3.77)***	(3.05)***	(2.97)***	(3.79)***	(2.51)***	(1.91)*	(1.74)*
β_m	0.121	0.121	0.046	0.128	0.124	0.030	0.114	0.106	0.097
	(1.86)*	(1.87)*	(1.84)*	(2.86)***	(2.82)***	(2.82)***	(2.46)***	(2.4)***	(3.83)***
β_j		0.015	0.317		-0.173	0.180		-0.232	0.133
		(0.2)	(4.08)***		(-2.96)***	(2.71)***		(-4.68)***	(3.56)***
R^2	0.639	0.639	0.632	0.550	0.558	0.552	0.469	0.488	0.487
$QLIKE$	0.069	0.069	0.071	0.071	0.070	0.074	0.084	0.081	0.082
$J-R^2$	0.647	0.646	0.641	0.378	0.395	0.437	0.347	0.362	0.358
$J-QLIKE$	0.096	0.096	0.098	0.093	0.089	0.090	0.089	0.088	0.090
$C-R^2$	0.639	0.639	0.632	0.590	0.591	0.577	0.512	0.519	0.519
$C-QLIKE$	0.067	0.067	0.069	0.066	0.067	0.071	0.078	0.079	0.080

	10-Year			20-Year			30-Year		
	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ
β_0	0.001	0.002	0.002	0.001	0.002	0.001	0.002	0.002	0.002
	(3.15)***	(4.41)***	(7.35)***	(4.12)***	(4.98)***	(4.44)***	(3.68)***	(3.78)***	(4.88)***
β_d	0.483	0.525	0.502	0.583	0.630	0.620	0.576	0.574	0.552
	(9.83)***	(9.79)***	(8.58)***	(8.46)***	(10.55)***	(9.61)***	(11.12)***	(10.54)***	(9.69)***
β_w	0.286	0.260	0.283	0.146	0.118	0.112	0.233	0.234	0.248
	(6.91)***	(6.65)***	(6.57)***	(1.65)*	(1.41)	(1.41)	(4.78)***	(4.83)***	(5.13)***
β_m	0.050	0.047	0.059	0.088	0.090	0.142	0.030	0.030	0.045
	(1.46)	(1.45)	(2.78)***	(2.1)**	(2.23)**	(3.89)***	(1.03)	(1.01)	(2.32)**
β_j		-0.163	0.137		-0.159	0.187		0.037	0.339
		(-2.89)***	(3.4)***		(-2.78)***	(2.9)***		(0.29)	(2.99)***
R^2	0.510	0.517	0.527	0.513	0.521	0.529	0.594	0.594	0.601
$QLIKE$	0.087	0.083	0.082	0.070	0.067	0.067	0.106	0.107	0.105
$J-R^2$	0.466	0.477	0.505	0.462	0.470	0.493	0.693	0.692	0.701
$J-QLIKE$	0.085	0.083	0.081	0.075	0.074	0.076	0.103	0.104	0.100
$C-R^2$	0.521	0.522	0.529	0.538	0.540	0.545	0.583	0.583	0.589
$C-QLIKE$	0.084	0.084	0.082	0.066	0.066	0.066	0.111	0.111	0.107

(1) The results in the parenthesis indicates t-statistics. (2) ***, **, * show 1%, 5% and 10% statistically significant coefficients, respectively. (3) Newey-West standard errors are used to calculate the t statistics.

Table 2.11: Regression Results of Swiss Market on 22-day Forecast Horizon (h=22)

	1-Year			2-Year			5-Year		
	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ
β_0	0.005	0.005	0.006	—	—	—	0.003	0.003	0.003
	(7.1)***	(7.04)***	(8.86)***	—	—	—	(4.48)***	(5.12)***	(7.55)***
β_d	0.212	0.207	0.216	—	—	—	0.212	0.275	0.224
	(10.35)***	(10.22)***	(9.69)***	—	—	—	(6.22)***	(6.05)***	(6.3)***
β_w	0.393	0.393	0.348	—	—	—	0.257	0.245	0.298
	(6.43)***	(6.43)***	(6.49)***	—	—	—	(4.75)***	(4.67)***	(5.71)***
β_m	0.243	0.242	0.294	—	—	—	0.208	0.190	0.249
	(4)***	(3.98)***	(5.17)***	—	—	—	(2.65)***	(2.47)***	(3.15)***
β_j		0.037	0.214	—	—	—		-0.145	0.071
		(0.81)	(4.23)***	—	—	—		(-3.82)***	(3.06)***
R^2	0.695	0.696	0.685	—	—	—	0.425	0.439	0.482
$QLIKE$	0.096	0.096	0.100	—	—	—	0.058	0.057	0.055
$J-R^2$	0.619	0.620	0.610	—	—	—	0.365	0.375	0.410
$J-QLIKE$	0.135	0.134	0.139	—	—	—	0.052	0.052	0.051
$C-R^2$	0.723	0.723	0.713	—	—	—	0.444	0.446	0.494
$C-QLIKE$	0.079	0.079	0.083	—	—	—	0.062	0.063	0.059

	10-Year			20-Year			30-Year		
	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ
β_0	0.002	0.002	0.003	0.003	0.003	0.004	0.002	0.002	0.003
	(5.17)***	(5.34)***	(9.28)***	(5.78)***	(5.92)***	(10.47)***	(4.18)***	(4.65)***	(8.93)***
β_d	0.192	0.204	0.194	0.103	0.121	0.124	0.194	0.208	0.198
	(7.07)***	(6.12)***	(6.65)***	(3.42)***	(2.86)***	(3.18)***	(4.63)***	(4.43)***	(4.39)***
β_w	0.246	0.243	0.240	0.174	0.173	0.177	0.244	0.238	0.241
	(3.84)***	(3.83)***	(3.35)***	(2.84)***	(2.88)***	(2.71)***	(3.92)***	(3.88)***	(3.68)***
β_m	0.376	0.372	0.395	0.315	0.311	0.280	0.416	0.410	0.409
	(4.42)***	(4.33)***	(4.37)***	(3.77)***	(3.69)***	(3.3)***	(4.9)***	(4.79)***	(4.53)***
β_j		-0.039	0.132		-0.049	0.070		-0.094	0.081
		(-1.14)	(4.88)***		(-1.41)	(3.98)***		(-2.23)**	(3.43)***
R^2	0.608	0.608	0.618	0.259	0.261	0.238	0.631	0.633	0.641
$QLIKE$	0.050	0.049	0.049	0.065	0.065	0.070	0.080	0.079	0.079
$J-R^2$	0.567	0.567	0.581	0.261	0.259	0.239	0.429	0.426	0.470
$J-QLIKE$	0.046	0.046	0.045	0.059	0.059	0.063	0.079	0.078	0.074
$C-R^2$	0.616	0.615	0.624	0.243	0.241	0.217	0.672	0.671	0.670
$C-QLIKE$	0.052	0.052	0.052	0.073	0.074	0.079	0.081	0.081	0.085

(1) The results in the parenthesis indicates t-statistics. (2) ***, **, * show 1%, 5% and 10% statistically significant coefficients, respectively. (3) Newey-West standard errors are used to calculate the t statistics.

Table 2.12: Regression Results of German Market on 22-day Forecast Horizon (h=22)

	1-Year			2-Year			5-Year		
	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ
β_0	0.003	0.003	0.003	0.001	0.001	0.001	0.002	0.002	0.003
	(6.07)***	(6.13)***	(6.75)***	(4.93)***	(5.04)***	(5.97)***	(6.96)***	(7.04)***	(10.08)***
β_d	0.325	0.323	0.330	0.208	0.198	0.243	0.230	0.243	0.263
	(9.65)***	(9.39)***	(9.63)***	(8.43)***	(7.56)***	(7.44)***	(10.6)***	(9.3)***	(9.51)***
β_w	0.283	0.283	0.276	0.313	0.318	0.282	0.298	0.289	0.271
	(7.47)***	(7.46)***	(7.09)***	(6.46)***	(6.1)***	(6.92)***	(5.93)***	(5.55)***	(5.18)***
β_m	0.187	0.188	0.186	0.341	0.341	0.366	0.280	0.279	0.276
	(2.91)***	(2.91)***	(2.85)***	(6.38)***	(6.4)***	(7.12)***	(6.1)***	(6.1)***	(5.72)***
β_j		0.017	0.214		0.028	0.168		-0.038	0.118
		(0.33)	(4.22)***		(0.66)	(3.62)***		(-1.11)	(3.61)***
R^2	0.634	0.634	0.629	0.714	0.714	0.695	0.626	0.626	0.618
$QLIKE$	0.123	0.123	0.127	0.036	0.036	0.038	0.044	0.043	0.045
$J-R^2$	0.421	0.421	0.412	0.713	0.713	0.677	0.560	0.560	0.547
$J-QLIKE$	0.212	0.212	0.216	0.042	0.042	0.046	0.046	0.046	0.044
$C-R^2$	0.666	0.666	0.663	0.715	0.715	0.700	0.643	0.643	0.637
$C-QLIKE$	0.105	0.105	0.109	0.035	0.035	0.037	0.042	0.042	0.044

	10-Year			20-Year			30-Year		
	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ
β_0	0.003	0.003	0.004	0.003	0.003	0.004	0.006	0.006	0.006
	(8.15)***	(8.52)***	(10.45)***	(8.11)***	(8.59)***	(10.91)***	(8.5)***	(8.73)***	(9.62)***
β_d	0.288	0.317	0.327	0.236	0.272	0.267	0.360	0.378	0.363
	(8.83)***	(7.81)***	(8.6)***	(10.36)***	(9.46)***	(9.04)***	(9.15)***	(8.79)***	(8.71)***
β_w	0.313	0.292	0.278	0.213	0.191	0.196	0.242	0.233	0.245
	(6.4)***	(5.63)***	(5.04)***	(3.7)***	(3.48)***	(2.97)***	(4.28)***	(4.05)***	(4.22)***
β_m	0.066	0.063	0.066	0.210	0.203	0.217	0.057	0.052	0.059
	(1.09)	(1.05)	(1.08)	(5.05)***	(4.81)***	(4.48)***	(1.14)	(1.05)	(1.17)
β_j		-0.078	0.109		-0.078	0.093		-0.149	0.070
		(-2.1)**	(4.16)***		(-2.85)***	(4.56)***		(-1.61)	(0.76)
R^2	0.472	0.474	0.473	0.407	0.411	0.422	0.429	0.432	0.434
$QLIKE$	0.055	0.055	0.055	0.048	0.048	0.046	0.145	0.144	0.142
$J-R^2$	0.377	0.382	0.390	0.442	0.447	0.478	0.296	0.298	0.290
$J-QLIKE$	0.057	0.056	0.054	0.042	0.041	0.038	0.099	0.098	0.098
$C-R^2$	0.497	0.499	0.496	0.398	0.399	0.406	0.442	0.442	0.446
$C-QLIKE$	0.054	0.054	0.055	0.049	0.050	0.048	0.154	0.154	0.152

(1) The results in the parenthesis indicates t-statistics. (2) ***, **, * show 1%, 5% and 10% statistically significant coefficients, respectively. (3) Newey-West standard errors are used to calculate the t statistics.

Table 2.13: Regression Results of French Market on 22-day Forecast Horizon (h=22)

	1-Year			2-Year			5-Year		
	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ
β_0	0.004	0.004	0.002	0.001	0.001	0.001	0.001	0.002	0.002
	(7.4)***	(7.19)***	(2.92)***	(4.49)***	(4.58)***	(2.4)***	(4.87)***	(5.25)***	(4.54)***
β_d	0.285	0.273	0.249	0.253	0.255	0.287	0.203	0.221	0.260
	(8.38)***	(7.91)***	(7.4)***	(7.27)***	(7.16)***	(9.39)***	(8.45)***	(7.85)***	(10.21)***
β_w	0.156	0.151	0.224	0.373	0.372	0.550	0.289	0.279	0.473
	(1.82)*	(1.76)*	(3.16)***	(6.51)***	(6.48)***	(13.21)***	(5.6)***	(5.44)***	(10.95)***
β_m	0.254	0.258	0.283	0.283	0.283	0.178	0.386	0.381	0.186
	(3.02)***	(3)***	(3.19)***	(4.44)***	(4.44)***	(3.3)***	(6.49)***	(6.38)***	(2.56)***
β_j		0.170	0.151		-0.023	0.106		-0.075	0.063
		(1.34)	(1.33)		(-0.64)	(2.47)***		(-2.35)***	(2.46)***
R^2	0.408	0.411	0.463	0.809	0.809	0.804	0.740	0.741	0.721
$QLIKE$	0.139	0.138	0.122	0.046	0.046	0.052	0.038	0.038	0.040
$J-R^2$	0.327	0.322	0.369	0.842	0.843	0.810	0.641	0.648	0.647
$J-QLIKE$	0.174	0.179	0.148	0.052	0.052	0.053	0.046	0.046	0.045
$C-R^2$	0.431	0.431	0.484	0.807	0.807	0.803	0.749	0.749	0.728
$C-QLIKE$	0.134	0.134	0.118	0.046	0.046	0.052	0.036	0.036	0.039

	10-Year			20-Year			30-Year		
	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ
β_0	0.002	0.002	0.002	0.002	0.002	0.003	0.004	0.004	0.004
	(6.13)***	(6.34)***	(4.11)***	(4.26)***	(4.36)***	(7.08)***	(5.62)***	(5.2)***	(4.26)***
β_d	0.219	0.228	0.233	0.166	0.182	0.240	0.210	0.207	0.235
	(7.7)***	(7.45)***	(9)***	(7.41)***	(5.89)***	(8.93)***	(7.24)***	(7.14)***	(9.09)***
β_w	0.286	0.281	0.383	0.232	0.224	0.400	0.262	0.264	0.405
	(5.04)***	(4.98)***	(7)***	(5.55)***	(5.63)***	(7.62)***	(4.47)***	(4.49)***	(7.82)***
β_m	0.312	0.309	0.305	0.442	0.436	0.145	0.380	0.379	0.344
	(4.99)***	(4.94)***	(3.81)***	(7.63)***	(7.29)***	(2.3)**	(5.12)***	(5.11)***	(3.82)***
β_j		-0.060	0.065		-0.038	0.097		0.105	0.240
		(-1.65)*	(2.01)**		(-1.33)	(4.84)***		(1.33)	(3.17)***
R^2	0.614	0.615	0.632	0.652	0.653	0.595	0.635	0.636	0.620
$QLIKE$	0.055	0.055	0.053	0.031	0.031	0.033	0.108	0.109	0.117
$J-R^2$	0.606	0.610	0.610	0.584	0.586	0.581	0.715	0.712	0.701
$J-QLIKE$	0.057	0.056	0.056	0.038	0.038	0.036	0.071	0.075	0.072
$C-R^2$	0.612	0.612	0.631	0.664	0.664	0.597	0.625	0.625	0.609
$C-QLIKE$	0.055	0.055	0.053	0.030	0.030	0.033	0.117	0.117	0.126

(1) The results in the parenthesis indicates t-statistics. (2) ***, **, * show 1%, 5% and 10% statistically significant coefficients, respectively. (3) Newey-West standard errors are used to calculate the t statistics.

Table 2.14: Regression Results of the UK Market on 22-day Forecast Horizon (h=22)

	1-Year			2-Year			5-Year		
	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ
β_0	0.004	0.004	0.003	0.003	0.003	0.004	0.003	0.003	0.004
	(3.82)***	(3.86)***	(4.4)***	(5.66)***	(5.68)***	(8.56)***	(4.67)***	(4.82)***	(10.36)***
β_d	0.290	0.288	0.309	0.231	0.242	0.292	0.193	0.229	0.214
	(5.44)***	(5.17)***	(6.36)***	(7.27)***	(6.48)***	(8.75)***	(6.1)***	(6.28)***	(6.69)***
β_w	0.304	0.305	0.384	0.235	0.229	0.370	0.151	0.131	0.196
	(3.06)***	(3.07)***	(4.6)***	(4.66)***	(4.66)***	(7.22)***	(3.05)***	(2.71)***	(3.73)***
β_m	0.191	0.191	0.168	0.290	0.289	0.061	0.348	0.345	0.258
	(1.86)*	(1.86)*	(3.83)***	(4.57)***	(4.55)***	(3.27)***	(3.95)***	(3.89)***	(5.57)***
β_j		0.028	0.194		-0.033	0.151		-0.092	0.048
		(0.48)	(4.08)***		(-0.73)	(4.26)***		(-3.02)***	(2.09)**
R^2	0.561	0.561	0.562	0.508	0.508	0.469	0.401	0.405	0.403
$QLIKE$	0.059	0.059	0.060	0.053	0.053	0.061	0.046	0.045	0.046
$J-R^2$	0.544	0.546	0.560	0.465	0.466	0.487	0.405	0.412	0.391
$J-QLIKE$	0.063	0.063	0.060	0.059	0.059	0.060	0.040	0.039	0.041
$C-R^2$	0.562	0.562	0.562	0.515	0.515	0.468	0.401	0.401	0.403
$C-QLIKE$	0.058	0.058	0.060	0.051	0.051	0.061	0.047	0.047	0.047

	10-Year			20-Year			30-Year		
	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ
β_0	0.003	0.003	0.004	0.003	0.003	0.003	0.004	0.004	0.005
	(3.96)***	(4.51)***	(9.42)***	(4.33)***	(4.45)***	(5.01)***	(4.34)***	(4.81)***	(8.05)***
β_d	0.228	0.266	0.239	0.213	0.237	0.196	0.279	0.300	0.254
	(4.03)***	(4.41)***	(3.55)***	(5.14)***	(5.25)***	(4.16)***	(4.47)***	(4.83)***	(3.88)***
β_w	0.147	0.122	0.247	0.089	0.075	0.105	0.103	0.095	0.228
	(2.15)**	(1.93)*	(4.31)***	(1.75)*	(1.5)	(1.91)*	(1.56)	(1.48)	(4.26)***
β_m	0.361	0.359	0.199	0.406	0.407	0.482	0.387	0.389	0.207
	(4.13)***	(4.09)***	(4.31)***	(4.32)***	(4.32)***	(4.91)***	(4)***	(4.05)***	(4.23)***
β_j		-0.152	-0.004		-0.082	0.046		-0.283	-0.092
		(-3.73)***	(-0.1)		(-2.39)***	(1.5)		(-3.92)***	(-1.91)*
R^2	0.448	0.456	0.425	0.404	0.407	0.423	0.463	0.471	0.446
$QLIKE$	0.054	0.053	0.053	0.042	0.042	0.040	0.123	0.121	0.111
$J-R^2$	0.320	0.334	0.262	0.337	0.336	0.398	0.366	0.399	0.288
$J-QLIKE$	0.049	0.048	0.053	0.042	0.042	0.037	0.083	0.082	0.085
$C-R^2$	0.477	0.477	0.455	0.422	0.421	0.427	0.472	0.472	0.457
$C-QLIKE$	0.054	0.054	0.053	0.042	0.042	0.042	0.131	0.131	0.118

(1) The results in the parenthesis indicates t-statistics. (2) ***, **, * show 1%, 5% and 10% statistically significant coefficients, respectively. (3) Newey-West standard errors are used to calculate the t statistics.

Table 2.15: One-Day Ahead Out of Sample Forecast Results (h=1)

Table 2.16: QLIKE Estimates

	Swiss			German			French			UK		
	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ
1-Year	1.000	1.001	1.006	1.000	0.998[a]	1.003	1.000	1.008	1.013	1.000	1.003	1.043
2-Year	—	—	—	1.000	0.998[a]	1.017	1.000	1.004	1.037	1.000	0.994[a]	1.05
5-Year	1.000	0.996[a]	1.02	1.000	0.992[a]	1.013	1.000	0.979[a]	1.014	1.000	0.981[a]	0.999[a]
10-Year	1.000	0.999[a]	1.015	1.000	0.977[a]	0.993[a]	1.000	1.001[a]	1.009	1.000	0.99[a]	0.978[a]
20-Year	1.000	0.997[a]	1.006	1.000	1.003	1.015	1.000	1.000	1.033	1.000	0.996[a]	1.01
30-Year	1.000	0.996[a]	0.99	1.000	1.002[a]	1.014	1.000	1.016	1.047	1.000	1.016	0.999[a]

(1) QLIKE ratios are given in the table. (2) The ratios are scaled to QLIKE estimators of HAR-RV model. (3) Rolling window, 1000 observation, forecasts are estimated. (4) [a] corresponds to significant Diebold-Mariano Test at 5% level.

Table 2.17: Average R^2

	Swiss			German			French			UK		
	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ
1-Year	51.5%	51.5%	51.1%	66.2%	66.2%	66.3%	57.2%	58.5%	58.5%	39.8%	40.1%	38.8%
2-Year	—	—	—	48.3%	48.7%	47.9%	63.6%	63.8%	63.7%	38.2%	39.5%	38.6%
5-Year	27.3%	27.3%	26.0%	34.9%	35.4%	34.6%	47.8%	48.6%	48.6%	26.2%	27.2%	26.8%
10-Year	37.9%	37.9%	34.8%	39.4%	40.3%	39.5%	40.9%	41.5%	42.0%	28.7%	29.1%	29.0%
20-Year	10.6%	10.7%	9.7%	37.1%	37.6%	36.9%	35.3%	35.4%	35.2%	32.2%	32.5%	32.1%
30-Year	23.3%	23.4%	22.2%	46.5%	46.6%	46.1%	37.0%	38.2%	38.2%	35.5%	36.0%	35.4%

(1) Average R^2's are given in the table. (2) Rolling window, 1000 observation, forecasts are estimated.

Table 2.18: One-Month Ahead Out of Sample Forecast Results (h=22)

Table 2.19: QLIKE Estimates

	Swiss			German			French			UK		
	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ
1-Year	1.000	0.994[a]	1.041	1.000	0.997[a]	1.009	1.000	1.001	0.897	1.000	0.999[a]	1.049
2-Year	—	—	—	1.000	1.002	1.087	1.000	0.999	1.208	1.000	0.995[a]	1.129
5-Year	1.000	0.974[a]	0.932	1.000	0.999	1.028	1.000	0.978[a]	1.167	1.000	0.993[a]	0.981[a]
10-Year	1.000	0.99[a]	0.953[a]	1.000	0.998[a]	1.008	1.000	0.994[a]	1.016	1.000	0.99[a]	1.039
20-Year	1.000	0.996[a]	1.044	1.000	1.001	0.995	1.000	1.004	1.109	1.000	0.994[a]	0.999[a]
30-Year	1.000	0.994[a]	0.973	1.000	0.999[a]	0.999[a]	1.000	1.005	1.312	1.000	0.991[a]	1.032

(1) QLIKE ratios are given in the table. (2) The ratios are scaled to QLIKE estimators of HAR-RV model. (3) Rolling window, 1000 observation, forecasts are estimated. (4) [a] corresponds to significant Diebold-Mariano Test at 5% level.

Table 2.20: Average R^2

	Swiss			German			French			UK		
	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ
1-Year	49.7%	50.0%	49.1%	49.3%	49.5%	49.7%	27.7%	28.1%	30.7%	38.8%	39.1%	38.4%
2-Year	—	—	—	52.4%	52.7%	50.1%	63.4%	63.5%	61.9%	34.3%	35.0%	34.4%
5-Year	30.0%	30.7%	31.0%	34.0%	34.3%	33.7%	55.8%	57.1%	59.5%	24.0%	24.8%	26.1%
10-Year	40.0%	40.1%	38.7%	32.3%	32.5%	32.8%	38.4%	38.9%	44.2%	33.4%	34.0%	31.5%
20-Year	20.0%	20.2%	16.0%	33.3%	33.8%	35.6%	45.9%	45.9%	43.5%	35.4%	35.5%	32.4%
30-Year	28.9%	28.9%	26.2%	36.9%	37.0%	37.9%	37.7%	38.1%	40.9%	35.4%	35.8%	29.6%

(1) Average R^2's are given in the table. (2) Rolling window, 1000 observation, forecasts are estimated.

Table 2.21: HAR-RV Model with Pre-Announcement Dummy Variable, Equation Eq. (2.29)*(h=1)*

	Swiss						German					
	1-Year	2-Year	5-Year	10-Year	20-Year	30-Year	1-Year	2-Year	5-Year	10-Year	20-Year	30-Year
β_0	0.001	—	0.001	0.001	0.002	0.001	0.001	0.000	0.001	0.001	0.001	0.001
	(3.21)***	—	(3.07)***	(2.74)***	(6.27)***	(2.38)***	(3.48)***	(3.19)***	(4.26)***	(4.05)***	(4.18)***	(4.27)***
β_d^1	0.159	—	0.021	0.051	0.288	0.070	-0.001	0.195	0.223	0.180	0.187	0.157
	(1.13)	—	(0.18)	(0.37)	(1.72)*	(0.35)	(-0.03)	(4.6)***	(5.22)***	(3.88)***	(4.46)***	(2.37)***
β_d	0.377	—	0.323	0.348	0.145	0.340	0.600	0.304	0.356	0.444	0.380	0.527
	(7.27)***	—	(8.95)***	(8.86)***	(3.59)***	(6.02)***	(15.72)***	(8.28)***	(8.77)***	(11.51)***	(6.56)***	(8.97)***
β_w	0.309	—	0.344	0.358	0.135	0.292	0.246	0.362	0.396	0.379	0.368	0.328
	(5.71)***	—	(7.28)***	(6.55)***	(2.76)***	(4.84)***	(5.37)***	(6.56)***	(7.61)***	(8.51)***	(6.61)***	(5.76)***
β_m	0.210	—	0.129	0.160	0.258	0.214	0.087	0.235	0.130	0.053	0.071	0.013
	(4.79)***	—	(2.6)***	(3.76)***	(3.59)***	(3.8)***	(2.88)***	(4.22)***	(4.26)***	(1.67)*	(2.46)***	(0.54)
R^2	0.635	—	0.393	0.520	0.121	0.511	0.753	0.628	0.609	0.623	0.493	0.667
$QLIKE$	0.201	—	0.133	0.117	0.166	0.162	0.119	0.060	0.073	0.072	0.073	0.095

	French						UK					
	1-Year	2-Year	5-Year	10-Year	20-Year	30-Year	1-Year	2-Year	5-Year	10-Year	20-Year	30-Year
β_0	0.001	0.000	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.002
	(4.32)***	(2.57)***	(2.75)***	(3.88)***	(2.94)***	(4.83)***	(2.7)***	(4.36)***	(3.98)***	(3.11)***	(4.08)***	(3.6)***
β_d^1	-0.014	0.123	0.075	0.144	0.091	0.101	0.141	0.155	0.212	0.262	0.264	0.346
	(-0.21)	(2.08)**	(2)**	(1.67)*	(1.34)	(1.22)	(1.68)*	(2.08)**	(2.63)***	(3.01)***	(3.18)***	(3.36)***
β_d	0.611	0.404	0.388	0.452	0.387	0.513	0.514	0.461	0.490	0.477	0.577	0.567
	(16.65)***	(7.88)***	(9.37)***	(10.58)***	(8.99)***	(12.24)***	(11.79)***	(6.22)***	(6.4)***	(9.7)***	(8.25)***	(11.05)***
β_w	0.198	0.379	0.327	0.307	0.251	0.255	0.251	0.266	0.203	0.285	0.142	0.229
	(2.77)***	(7.1)***	(7.86)***	(6.91)***	(4.85)***	(4.98)***	(2.56)***	(3.08)***	(2.55)***	(6.82)***	(1.63)	(4.67)***
β_m	0.058	0.158	0.202	0.125	0.232	0.112	0.118	0.124	0.111	0.049	0.087	0.029
	(1.65)*	(4.68)***	(6.13)***	(4.04)***	(5.39)***	(3.46)***	(1.82)*	(2.76)***	(2.42)***	(1.43)	(2.1)**	(1.01)
R^2	0.626	0.784	0.659	0.623	0.523	0.638	0.641	0.552	0.473	0.515	0.519	0.600
$QLIKE$	0.107	0.062	0.068	0.076	0.065	0.102	0.068	0.070	0.083	0.086	0.069	0.106

(1) The results in the parenthesis indicates t-statistics. (2) ***, **, * show 1%, 5% and 10% statistically significant coefficients, respectively. (3) Newey-West standard errors are used to calculate the t statistics.

Table 2.22: HAR-RV Model with Announcement Dummy Variable, Equation Eq. (2.30) *(h=1)*

	Swiss						German					
	1-Year	2-Year	5-Year	10-Year	20-Year	30-Year	1-Year	2-Year	5-Year	10-Year	20-Year	30-Year
β_0	0.001	—	0.001	0.001	0.002	0.001	0.001	0.000	0.001	0.001	0.001	0.001
	(2.71)***	—	(3.06)***	(2.74)***	(6.2)***	(2.37)***	(3.49)***	(3.02)***	(4.12)***	(4.03)***	(4.2)***	(4.28)***
β_d^1	-0.134	—	0.127	0.027	0.037	0.186	-0.036	0.039	0.022	0.045	0.128	0.014
	(-2.88)***	—	(1.39)	(0.37)	(0.47)	(2.06)**	(-1.26)	(0.6)	(0.44)	(0.84)	(1.48)	(0.12)
β_d	0.394	—	0.320	0.348	0.147	0.338	0.602	0.314	0.369	0.449	0.382	0.537
	(7.71)***	—	(8.9)***	(8.76)***	(3.56)***	(5.99)***	(15.59)***	(8.24)***	(8.68)***	(11.62)***	(6.53)***	(9.29)***
β_w	0.304	—	0.345	0.358	0.137	0.293	0.247	0.358	0.389	0.374	0.365	0.320
	(5.68)***	—	(7.29)***	(6.56)***	(2.8)***	(4.86)***	(5.34)***	(6.56)***	(7.29)***	(8.35)***	(6.54)***	(5.67)***
β_m	0.211	—	0.129	0.159	0.258	0.214	0.086	0.238	0.135	0.057	0.073	0.016
	(4.84)***	—	(2.62)***	(3.77)***	(3.58)***	(3.8)***	(2.76)***	(4.25)***	(4.43)***	(1.8)*	(2.5)***	(0.68)
R^2	0.635	—	0.394	0.519	0.119	0.512	0.753	0.623	0.603	0.620	0.491	0.666
$QLIKE$	0.201	—	0.133	0.117	0.166	0.162	0.119	0.062	0.074	0.072	0.073	0.095

	French						UK					
	1-Year	2-Year	5-Year	10-Year	20-Year	30-Year	1-Year	2-Year	5-Year	10-Year	20-Year	30-Year
β_0	0.001	0.000	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.002
	(4.36)***	(2.46)***	(2.72)***	(3.83)***	(2.93)***	(4.84)***	(2.68)***	(4.28)***	(3.98)***	(3.23)***	(4.22)***	(3.92)***
β_d^1	-0.094	-0.018	0.006	0.056	0.130	0.023	0.127	0.215	0.185	0.003	0.036	0.067
	(-1.27)	(-0.52)	(0.12)	(0.83)	(1.89)*	(0.2)	(1.07)	(1.73)*	(1.14)	(0.02)	(0.22)	(0.29)
β_d	0.613	0.415	0.390	0.456	0.384	0.516	0.512	0.452	0.476	0.483	0.577	0.569
	(16.9)***	(7.93)***	(9.37)***	(10.43)***	(9.08)***	(12.54)***	(11.74)***	(6.72)***	(7.41)***	(10)***	(10.15)***	(11.37)***
β_w	0.198	0.376	0.325	0.304	0.252	0.254	0.250	0.269	0.211	0.286	0.149	0.236
	(2.77)***	(6.98)***	(7.81)***	(6.87)***	(4.87)***	(4.98)***	(2.54)***	(3.27)***	(2.87)***	(6.73)***	(1.77)*	(4.81)***
β_m	0.059	0.159	0.204	0.128	0.233	0.113	0.121	0.126	0.113	0.050	0.088	0.029
	(1.67)*	(4.77)***	(6.24)***	(4.15)***	(5.42)***	(3.5)***	(1.86)*	(2.8)***	(2.42)***	(1.49)	(2.1)**	(1.03)
R^2	0.627	0.782	0.659	0.621	0.525	0.637	0.641	0.556	0.474	0.510	0.512	0.594
$QLIKE$	0.107	0.062	0.068	0.077	0.066	0.102	0.069	0.071	0.083	0.087	0.070	0.106

(1) The results in the parenthesis indicates t-statistics. (2) ***, **, * show 1%, 5% and 10% statistically significant coefficients, respectively. (3) Newey-West standard errors are used to calculate the t statistics.

Table 2.23: HAR-CJ Model with Pre-Announcemet Dummy Variable, Equation Eq. (2.31) *(h=1)*

	Swiss						German					
	1-Year	2-Year	5-Year	10-Year	20-Year	30-Year	1-Year	2-Year	5-Year	10-Year	20-Year	30-Year
β_0	0.002	—	0.002	0.001	0.003	0.002	0.001	0.000	0.001	0.001	0.002	0.002
	(5.51)***	—	(4.47)***	(6.43)***	(9.73)***	(6)***	(4.8)***	(3.34)***	(8.79)***	(8.43)***	(6.63)***	(4.98)***
β_d^1	-0.003	—	0.005	-0.010	0.007	-0.019	0.002	0.015	0.017	0.014	0.015	0.010
	(-0.59)	—	(0.29)	(-1.21)	(0.54)	(-3.14)***	(0.46)	(4.9)***	(5.91)***	(3.56)***	(3.61)***	(2.23)**
β_j^1	0.976	—	-0.013	0.355	0.330	0.656	-0.182	0.070	-0.011	0.037	-0.009	0.054
	(4.79)***	—	(-0.09)	(1.79)*	(1.09)	(4.91)***	(-1.42)	(1.02)	(-0.16)	(0.46)	(-0.14)	(0.36)
β_d	0.393	—	0.340	0.366	0.158	0.333	0.599	0.379	0.411	0.522	0.430	0.529
	(7.04)***	—	(7.68)***	(8.4)***	(3.53)***	(5.86)***	(16.73)***	(6.66)***	(7.11)***	(11.57)***	(4.95)***	(7.77)***
β_w	0.287	—	0.341	0.331	0.165	0.327	0.251	0.326	0.362	0.325	0.352	0.334
	(4.9)***	—	(5.85)***	(6.04)***	(2.85)***	(5.26)***	(6.01)***	(6.1)***	(5.62)***	(6.22)***	(4.23)***	(5.13)***
β_m	0.241	—	0.161	0.166	0.219	0.182	0.083	0.240	0.115	0.030	0.043	0.005
	(5.12)***	—	(2.51)***	(3.88)***	(2.99)***	(3.11)***	(2.75)***	(4.02)***	(3.52)***	(0.94)	(1.48)	(0.2)
β_j	0.195	—	0.206	0.232	0.102	0.194	0.300	0.109	0.130	0.095	0.182	0.200
	(3.55)***	—	(4.2)***	(6.41)***	(2.54)***	(2.78)***	(5.28)***	(3.88)***	(5.19)***	(3.73)***	(5.28)***	(1.63)
R^2	0.637	—	0.394	0.511	0.118	0.519	0.755	0.623	0.609	0.631	0.493	0.666
$QLIKE$	0.202	—	0.136	0.119	0.168	0.161	0.120	0.060	0.072	0.070	0.072	0.094

	French						UK					
	1-Year	2-Year	5-Year	10-Year	20-Year	30-Year	1-Year	2-Year	5-Year	10-Year	20-Year	30-Year
β_0	0.001	0.000	0.001	0.001	0.002	0.001	0.002	0.001	0.002	0.002	0.001	0.002
	(2.84)***	(3.19)***	(5.43)***	(4.65)***	(6.03)***	(3.03)***	(3.79)***	(6.26)***	(6.91)***	(7.02)***	(4.42)***	(4.47)***
β_d^1	0.005	0.009	0.007	0.015	0.016	0.004	0.011	0.013	0.014	0.017	0.020	0.021
	(1.51)	(2.14)**	(3.04)***	(2.69)***	(5.12)***	(0.82)	(1.81)*	(2.71)***	(2.18)**	(2.29)**	(2.53)***	(2.09)**
β_j^1	-0.879	-0.155	0.038	-0.288	-0.148	-0.169	-0.015	0.046	0.227	0.176	0.062	0.167
	(-5.04)***	(-1.25)	(0.47)	(-3.39)***	(-2.73)***	(-0.79)	(-0.1)	(0.46)	(1.29)	(1.1)	(0.35)	(0.91)
β_d	0.582	0.432	0.448	0.467	0.468	0.517	0.547	0.574	0.605	0.499	0.619	0.548
	(19.48)***	(8.67)***	(10.19)***	(10.56)***	(9.24)***	(12.56)***	(12.79)***	(10.28)***	(8.14)***	(8.52)***	(9.62)***	(9.88)***
β_w	0.213	0.482	0.412	0.358	0.328	0.312	0.294	0.259	0.130	0.278	0.104	0.243
	(3.88)***	(9.37)***	(9.73)***	(7.9)***	(5.51)***	(7.02)***	(3.77)***	(3.76)***	(1.72)*	(6.29)***	(1.37)	(5)***
β_m	0.046	0.052	0.057	0.063	0.049	0.057	0.044	0.028	0.094	0.057	0.138	0.043
	(2.29)**	(2.82)***	(1.97)**	(2.15)**	(1.56)	(1.55)	(1.76)*	(2.7)***	(3.87)***	(2.64)***	(3.8)***	(2.22)**
β_j	0.671	0.178	0.113	0.275	0.186	0.727	0.307	0.171	0.106	0.123	0.176	0.293
	(4.43)***	(3.26)***	(3.06)***	(5.07)***	(5.22)***	(5.11)***	(3.29)***	(2.35)***	(3.51)***	(3.1)***	(2.63)***	(2.46)***
R^2	0.640	0.781	0.659	0.627	0.527	0.645	0.633	0.555	0.495	0.532	0.537	0.606
$QLIKE$	0.107	0.062	0.068	0.076	0.065	0.114	0.071	0.073	0.081	0.081	0.066	0.103

(1) The results in the parenthesis indicates t-statistics. (2) ***, **, * show 1%, 5% and 10% statistically significant coefficients, respectively. (3) Newey-West standard errors are used to calculate the t statistics.

Table 2.24: Microstructure Bias Corrected One-Month Ahead Out of Sample Forecast Results (h=22)

Table 2.25: QLIKE Estimates

	Swiss			German			French			UK		
	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ
1-Year	1.000	0.996[a]	1.042	1.000	1	1.016	1.000	1.003	0.903	1.000	0.999[a]	1.041
2-Year	—	—	—	1.000	1.002	1.083	1.000	0.998	1.205	1.000	0.994[a]	1.115
5-Year	1.000	0.968[a]	0.929[a]	1.000	1.001	1.032	1.000	0.973[a]	1.127	1.000	0.993[a]	0.977[a]
10-Year	1.000	0.985[a]	0.947[a]	1.000	0.996[a]	1.004	1.000	0.994[a]	1.003[a]	1.000	0.989[a]	1.02
20-Year	1.000	0.996[a]	1.05	1.000	0.999[a]	0.987[a]	1.000	1[a]	1.08	1.000	0.995[a]	1.004[a]
30-Year	1.000	0.99[a]	0.967	1.000	0.999[a]	0.999[a]	1.000	1.004	1.207	1.000	0.99[a]	1.017

(1) QLIKE ratios are given in the table. (2) The ratios are scaled to QLIKE estimators of HAR-RV model. (3) Rolling window, 1000 observation, forecasts are estimated. (4) [a] corresponds to significant Diebold-Mariano Test at 5% level.

Table 2.26: Average R^2

	Swiss			German			French			UK		
	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ
1-Year	50.5%	50.7%	49.7%	48.6%	48.8%	49.0%	27.4%	27.7%	30.4%	36.8%	37.1%	36.6%
2-Year	—	—	—	54.1%	54.3%	51.5%	62.8%	63.0%	61.5%	31.5%	32.2%	31.9%
5-Year	29.3%	30.2%	30.5%	34.0%	34.2%	33.5%	53.4%	55.1%	57.7%	23.4%	24.0%	25.7%
10-Year	39.6%	39.7%	38.6%	31.9%	32.1%	32.2%	37.2%	37.7%	43.2%	32.4%	33.0%	30.7%
20-Year	19.6%	19.7%	15.3%	33.0%	33.7%	35.6%	46.1%	46.1%	43.8%	36.2%	36.2%	33.4%
30-Year	28.1%	28.3%	25.5%	36.5%	36.7%	37.5%	38.9%	39.0%	41.5%	36.2%	36.6%	30.7%

(1) Average R^2's are given in the table. (2) Rolling window, 1000 observation, forecasts are estimated.

Table 2.27: One-Month Ahead Out of Sample Forecast Results using MinRV (h=22)

Table 2.28: QLIKE Estimates

	Swiss			German			French			UK		
	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ
1-Year	1.000	0.999[a]	1.021	1.000	1.001	1.005	1.000	0.997[a]	0.901	1.000	0.999	1.046
2-Year	—	—	—	1.000	0.999	1.025	1.000	0.999[a]	1.202	1.000	0.998[a]	1.123
5-Year	1.000	0.995[a]	0.976[a]	1.000	0.999[a]	1.005	1.000	0.987[a]	1.155	1.000	0.996[a]	0.985[a]
10-Year	1.000	0.995[a]	0.993	1.000	0.999[a]	0.994	1.000	0.995[a]	1.021	1.000	0.994[a]	1.059
20-Year	1.000	0.996[a]	1.015	1.000	0.999	0.999	1.000	0.998[a]	1.096	1.000	0.995[a]	1.001[a]
30-Year	1.000	1.025	1.047	1.000	0.999	0.998	1.000	1.003	1.348	1.000	0.999[a]	1.039

(1) QLIKE ratios are given in the table. (2) The ratios are scaled to QLIKE estimators of HAR-RV model. (3) Rolling window, 1000 observation, forecasts are estimated. (4) [a] corresponds to significant Diebold-Mariano Test at 5% level.

Table 2.29: Average R^2

	Swiss			German			French			UK		
	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ
1-Year	49.7%	49.9%	49.7%	49.3%	49.3%	49.6%	27.7%	28.0%	30.7%	38.8%	38.9%	37.8%
2-Year	—	—	—	52.4%	52.5%	51.5%	63.4%	63.6%	62.3%	34.3%	34.7%	33.7%
5-Year	30.0%	30.4%	31.3%	34.0%	34.1%	34.0%	55.8%	56.8%	58.8%	24.0%	24.4%	25.4%
10-Year	40.0%	40.2%	39.0%	32.3%	32.5%	33.8%	38.4%	38.6%	43.7%	33.4%	33.7%	29.5%
20-Year	20.0%	20.1%	19.3%	33.3%	33.5%	34.4%	45.9%	45.9%	44.1%	35.4%	35.4%	32.8%
30-Year	28.9%	29.1%	27.3%	36.9%	37.0%	38.3%	37.7%	37.8%	40.5%	35.4%	35.4%	29.2%

(1) QLIKE ratios are given in the table. (2) The ratios are scaled to QLIKE estimators of HAR-RV model. (3) Rolling window, 1000 observation, forecasts are estimated.

Table 2.30: One-Month Ahead Out of Sample Forecast Results using MedRV (h=22)

Table 2.31: QLIKE Estimates

	Swiss			German			French			UK		
	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ
1-Year	1.000	1.002	1.015	1.000	0.999	1.011	1.000	0.995[a]	0.896	1.000	0.998[a]	1.047
2-Year	—	—	—	1.000	1.001	1.091	1.000	1.001	1.21	1.000	0.993[a]	1.127
5-Year	1.000	0.985[a]	0.979	1.000	0.998[a]	1.041	1.000	0.984[a]	1.184	1.000	0.994[a]	0.976[a]
10-Year	1.000	0.992[a]	0.977[a]	1.000	0.999	1.011	1.000	0.992[a]	1.009	1.000	0.988[a]	1.039
20-Year	1.000	0.992[a]	1.018	1.000	1.003	1.003	1.000	1.004	1.113	1.000	0.996[a]	0.995[a]
30-Year	1.000	1.035	0.974	1.000	1.005	1.008	1.000	1.006	1.259	1.000	0.999	1.04

(1) QLIKE ratios are given in the table. (2) The ratios are scaled to QLIKE estimators of HAR-RV model. (3) Rolling window, 1000 observation, forecasts are estimated. (4) [a] corresponds to significant Diebold-Mariano Test at 5% level.

Table 2.32: Average R^2

	Swiss			German			French			UK		
	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ
1-Year	49.7%	49.8%	49.6%	49.3%	49.3%	49.4%	27.7%	28.5%	31.1%	38.8%	39.1%	38.6%
2-Year	—	—	—	52.4%	52.7%	49.7%	63.4%	63.5%	61.9%	34.3%	35.1%	34.6%
5-Year	30.0%	30.6%	30.7%	34.0%	34.2%	33.3%	55.8%	56.7%	59.3%	24.0%	24.8%	26.6%
10-Year	40.0%	40.2%	38.9%	32.3%	32.5%	32.8%	38.4%	39.1%	44.9%	33.4%	34.1%	31.8%
20-Year	20.0%	20.3%	15.0%	33.3%	33.8%	35.6%	45.9%	45.9%	43.0%	35.4%	35.5%	31.9%
30-Year	28.9%	29.2%	26.8%	36.9%	37.1%	38.0%	37.7%	38.0%	41.0%	35.4%	35.4%	28.6%

(1) QLIKE ratios are given in the table. (2) The ratios are scaled to QLIKE estimators of HAR-RV model. (3) Rolling window, 1000 observation, forecasts are estimated.

Chapter 3

Intraday Monetary Policy Shocks and Asset Prices in the Euro Area: A Latent Yield Curve Factor Approach

3.1 Introduction

Since the Global Financial Crisis the role of monetary policy, policy tools and scope diversified in order to convey the Fine Tuning in the economy. The use of unconventional monetary policy tools through forward guidance and quantitative easing policies required innovative tools besides the short term rates to gauge the policy effects. Therefore, measuring the impact of monetary policy on the economy via asset prices became a great challenge for not only policy makers but also investors and academics.

There exists a strand literature on identifying monetary policy shocks that primarily focus on Federal Reserves policies. In this paper, I aim to identify European Central Banks (ECB) policy framework and measure the shocks using market based indicators. This paper primarily links the behavior of shape factors of yield curve with ECB's monetary policy shocks on the announcement days by focusing on press release and press conference windows. In this scope, I introduce target rate, monetary policy stance (MPS) and quantitative easening (QE) shocks[1] using intraday government bond market data[2].

Changes in fixed income securities' prices/yields at monetary policy announcements windows reveal significant information about monetary policy surprises (Kuttner (2001); Gürkaynak et al. (2005); Gürkaynak et al. (2007)). While there is extensive literature linking US securities with the Feds policy announcements, there are only a few empirical studies relating European yield curve fluctuations to the ECB's policy actions (Altavilla et al. (2019); Andrade & Ferroni (2021); Leombroni et al. (2021)). Since the seminal study of Litterman & Scheinkman (1991) most of the variation in the yield curve is attributed to three latent factors, namely level, slope and curvature of the yield curve. In this paper, I start by analysing the link between time variation in the latent shape factors of the German yield curve and the ECBs actions. I adopt an event study approach, focusing on intraday windows that are constructed on announcement days, and are centred around the ECBs press releases and subsequent press conferences. In this scope, I introduce target rate, monetary policy stance (MPS henceforth), and Quantitative Easing (QE

[1]Kuttner (2001) finds that the interest rates' response to unanticipated shocks are more prominent than the anticipated shocks. Therefore, I use monetary policy shocks and surprises interchangeably, since I extract those factors directly from government bond yield curve.

[2]In order to represent Euro Area yield curve, I use German government bonds. Ehrmann et al. (2011) indicate that after the after the single currency implementation, there has been a substantial convergence between sovereign yields in the Euro zone. Also, I try to exclude peripheral divergences due to credit risk turmoils during the estimation period.

henceforth) shocks using intraday government bond latent factors.

Importantly, I demonstrate that the QE factor is not only effective during the conference window, but also during the press release window. This is another key difference between my work and previous studies, including Altavilla et al. (2019). Moreover, I show that the impact of the QE factor on asset prices and inflation expectations significantly increases in magnitude following the introduction of ECBs unconventional policies. The results are more clear-cut for the case of QE shocks, relative to the other two indicators, thereby highlighting the importance of QE as a monetary policy tool. They reveal that expansionary QE surprises lower sovereign bond yields and spreads. Additionally, they are associated with a weakening Euro against the US dollar, lower cost of euro-denominated corporate credit, and higher market-based inflation expectations.

This chapter relates, and contributes, to several strands of the extant literature. First, the literature on the high-frequency identification of monetary policy shocks (see Kuttner (2001); Gürkaynak et al. (2005); Gürkaynak et al. (2007)). This study relies on the identification of surprises using intraday variations of bond factors by assuming that the main driver of market movements in a short intraday window surrounding monetary policy announcements is solely the information content of the release itself. Second, I extend the relatively scarce existing literature on the impact of ECB policy surprises (see Brand et al. (2010); Altavilla et al. (2019); Leombroni et al. (2021)). Third, I contribute to the literature by using a yield curve-based identification methodology in the high-frequency setting. The high-frequency identification of monetary policy surprises typically depends on a factor rotation of changes in money market rates, such as using FFRs in Gürkaynak et al. (2005), and OIS in Altavilla et al. (2019), at the predetermined intraday windows around the policy release and communication with some restrictions. Our approach is similar to Inoue & Rossi (2018), Inoue & Rossi (2019), and Kortela & Nelimarkka (2020), who use daily yield curve shifts during the announcement days for the extraction of monetary policy surprises. Finally, the findings shed new light on the significant financial market effects of ECB policy surprises. Overall, the impact of QE surprises dominates that of target rate and stance shocks both in terms of magnitude and statistical significance (see Altavilla et al. (2019) and Rogers et al. (2014)).

The rest of the chapter is structured as follows. Section 3.2 reviews the literature on the extraction methods of monetary policy shocks. In Section 3.3, I provide the information regarding data and methodology by detailing on the identification strategy. In Section 3.4 I present the results of the empirical models. In Section 3.5 I provide a brief conclusion of this research.

3.2 Literature Review

Measuring the impact of monetary policy announcements constitutes the main focus of this study. The multidimensional nature of policy decisions especially in the unconventional monetary policy era is challenging to gauge the effect of policies. There are alternative approaches in attempting to extract monetary policy shocks. Some researchers measure the policy shocks by depending their analysis on the theoretical foundations of monetary policy and macroeconomic stance using the vector autoregression (VAR) structure. In those models, policy shocks are identified through restrictions on VARs that constitute the link between the theory and policy announcements (Bernanke & Blinder (1992); Christiano et al. (1996); Uhlig (2005)). Also, the presence of heteroscedasticity within financial time series is being exploited in order to identify monetary policy shocks within VAR models (Rigobon & Sack (2004); Gilchrist & Zakrajsek (2013)). In addition, with the high-frequency data being widely available the policy surprises are identified using the intraday variations of fixed income assets on the announcement days (Kuttner (2001); Gürkaynak et al. (2005); Altavilla et al. (2019)). Those approaches assume that the main driver of market movements in a short intraday window around monetary policy announcements is solely the information content of the release itself.

While employing high-frequency data approach measures the instantaneous impact of policy shocks, it has some limitations especially in identifying the persistence of shocks and the response of macroeconomic variables. Thus, some studies combine a hybrid approach that follows the VAR models with high-frequency data, which in turn led them to examine the dynamic responses of real and financial variables (Hanson & Stein (2015), Nakamura & Steinsson (2018), Gertler & Karadi (2015)).

In the identification of monetary policy shocks, I employ high-frequency data approach following Kuttner (2001), which enables us to extract indicators without suffering from severe endogeneity issues. In focusing on the windows around announcements, I avoid using exact release points in time since it takes time to digest new information from the financial market players, especially during the press conferences. Therefore, a convenient time interval is chosen by considering that a narrow window may not catch all the news, and a wide window would be contaminated by other shocks (Rogers et al. (2014)).

In the literature, various indicators are used to extract monetary policy shocks. Due to the availability of liquid monetary policy rate futures contract, the studies focusing on the US monetary policy depend their analysis on Fed Funds Futures (FFR) (Kuttner (2001); Gürkaynak et al. (2005); Gertler & Karadi (2015); Swanson (2021)). Further, Overnight Index Swaps (OIS) are used to identify monetary policy shocks, especially when the liquidity of monetary policy futures contracts is not prominent. Studies focusing on the ECB policies are generally use a factor analysis to extract the information within OIS rates (Altavilla et al. (2019); Andrade & Ferroni (2021); Leombroni et al. (2021)). Not only the money market rates but also government sovereign bonds and bills are exercised to identify monetary policy shocks in a high-frequency setting. To evaluate the monetary policy surprises of the Federal Reserve (Fed), ECB, Bank of England (BoE), and Bank of Japan (BoJ), Rogers et al. (2014) depend on the intraday movement of government bond yields. Also, Altavilla et al. (2019) use German short-term bills and bonds in exchange for OIS for the period that short-term OIS rates are not available and find that the change of results after using whether OIS or German bonds are indistinguishable.

Furthermore, the impact of monetary policy surprises can be decomposed around monetary policy releases, especially during the conference, or communication, window, into two distinct parts; the information channel on economic fundamentals and the risk premium channel using the co-movement between interest rates and stock returns (some contemporary studies are Cieslak & Schrimpf (2019); Jarociski & Karadi (2020); and Andrade & Ferroni (2021)).

Using high-frequency data, the monetary policy indicators are extracted by factor rotations but there is a challenge on how many factors are enough to represent the multidimensional impact of policy announcements. While, in the era of conventional monetary policy, a single factor is used to measure the monetary policy surprises (Kuttner (2001)), Gürkaynak et al. (2005) show that only a single policy rate surprise is not sufficient to represent the market reaction to the announcements. In order to incorporate the surprise component regarding the path of monetary policy, they introduce a second factor for the future horizons of the policy. In addition, the use of unconventional policies in the form of asset purchase programs led to the introduction of a third factor, namely the QE factor by Swanson (2021). Following these developments, Altavilla et al. (2019) posit that ECB policy surprises are multi-dimensional, in having a target, timing, path/forward guidance, and QE surprises. Also, scheduled policy announcements of the

ECB have a multi-step structure. At the time of press release they find that target surprise is significant, while during press release timing, forward guidance, and QE surprises are effective on asset prices. In addition to using rotated factors, Bomfim (2003) suggests that the variation due to monetary policy changes is captured by latent factors, where the level moves in line with the short-term rates and the slope is associated with the expected short rate in the future.

Following those developments, my approach is similar to Rogers et al. (2014) that use intraday change in the government bond yields around monetary policy announcement windows in order to capture the impact of policy shocks on asset prices. While trying to capture the pass through the policy release shocks from bond markets to asset prices, Rogers et al. (2014) use a single factor model without decomposing the separate effects policy tools. I follow the foundations that the first three latent factors explain most of the variation of the yield curve by Litterman & Scheinkman (1991), and use those factors to represent the multidimensional nature of monetary policy announcements similar to Swanson (2021), and Altavilla et al. (2019). I contribute to the literature by examining whether the government sovereign bonds carry the information value in representing all the dimensions of policy announcements.

There exists a large empirical literature on the monetary policy shocks and asset prices and economic indicators. I study the effects of ECB shocks on the government bond markets, exchange rates, corporate spreads, and inflation indicators. Using the two-step nature of ECB policy decision announcements, some investigate the impact of information flow in separate windows (Brand et al. (2010); Altavilla et al. (2019); Leombroni et al. (2021)), and some use a combined window (Rogers et al. (2014)). Also, some studies use a single target rate shock (Rogers et al. (2014)), while others employ both target rate and path surprises in measuring the effect of policy surprises (Brand et al. (2010); Leombroni et al. (2021)). To this extent, my approach is in line with Altavilla et al. (2019) and Andrade & Ferroni (2021) that use not only target rate and path surprises, but also QE surprises to measure the monetary policy impact in a separate window setting.

This study contributes to the literature by exploring the effects of monetary policy announcements on asset prices. I show that monetary policy is an effective tool in lowering euro area yield spreads (Altavilla et al. (2019)) and there presents a preserving euro effect of monetary policy (Brand et al. (2010)). One of the major findings of this paper is that QE policies are the most effective tool in reducing long-term bond yields, sovereign bond spreads, and credit costs even though the short-term interest rates are restricted by an effective lower bound. Conversely, in the standard macroeconomic models, QE operations are neutral, and therefore the QE should be ineffective as the future rate reaction function is held constant (Bhattarai et al. (2015)). Therefore, some frictions are incorporated in order to reduce the neutrality and accommodate the expansionary QE shocks to have an impact, especially at the long end of the yield curve. The significance of QE purchases on longer-term yields is explained using a reduction in risk premium (Chen et al. (2012)), existing limits to arbitrage (Gertler & Karadi (2013)), and signaling channel[3] (Bhattarai et al. (2015); Krishnamurthy & Vissing-Jorgensen (2011); and Bauer & Rudebusch (2014)).

3.3 Data and Methodology

3.3.1 Data

To identify euro-area monetary policy surprises, which constitute the key explanatory variable, I use high-frequency German government bond data spanning the period from 1st January 2005 to 31st October 2019. It consists of 10-minute discrete intervals between 10:00 am and 16:00 pm (GMT). I employ 1-, 2-, 5-, 10-, 20- and 30-year maturity bonds in my analysis. I estimate the Nelson & Siegel (1987) model using underlying bonds information to obtain zero-coupon bond yields (see Özbekler et al. (2021), and Chapter 2 for more details). The monetary policy shocks are mapped to a vast array of euro-area financial market variables. These include French-German government bond yield spreads and the euro-dollar exchange rate, using intraday data from the Thomson Reuters Tick History (TRTH) database; intraday Spanish and German government bond yields, sourced from the euro-area Monetary Policy event study database (EA-MPD) of Altavilla et al. (2019); and daily data on credit spreads and market-based inflation

[3]The signaling channel refers QE policies to contain information and driving expectations on future interest rates.

expectations, proxied, respectively, using Markits iBoxx EUR benchmark indices and inflation-linked swap data from Refinitiv Eikon.

3.3.2 Identification of monetary policy shocks

I identify the monetary policy surprises around ECB's target rate announcements and the press conference. The key feature of my identification strategy is using intraday data around the announcement and conference windows. Since the aim is to extract the true impact of the shocks, the inflow of information regarding external factors throughout the announcement days cannot be eliminated using a lower data frequency, such as daily. Another hardship in the estimation of shocks is the target rate changes to be anticipated at least in a partly manner (Gürkaynak et al. (2005); Rogers et al. (2014)). Therefore, in the identification process, I try to extract the surprise that is priced in the fixed-income securities in the announcement windows. I set an interval around the monetary policy windows that is narrow enough to capture the total impact of the surprises without being disturbed by any other external factors by assumption similar to Altavilla et al. (2019). The identification strategy is based on the German government bonds to represent the generic Euro Area sovereign bond market movements with the limited risk premium, compared to peripheral countries' markets, and the pass-through from bond markets captures the policy changes. Thus, I propose that the German sovereign bond yield curve changes move with the information on monetary policy decisions in the tight windows.

I suggest that the term structure of government bonds is capable of representing the monetary policy surprises, which is then be used to measure the pass-through of surprises on asset prices. A similar structure is also employed by Inoue & Rossi (2018), Inoue & Rossi (2019), and Kortela & Nelimarkka (2020). While, in the literature, there are attempts to extract the monetary policy shocks by the shifts in the term structure of interest rates, the novelty of this paper is estimating the term structure on an intraday basis to employ an event analysis of policy decisions. Since, the previous papers use daily data to estimate term structure shifts, the scope of their studies is only limited to showing the longer-term effect of policy surprises.

I have a two-stage identification structure. Firstly, Nelson & Siegel (1987) model is used to obtain zero-coupon government bond returns.

$$f_{t,m} = \beta_{t,0} + \beta_{t,1} e^{\left(\frac{-m}{\tau_{t,1}}\right)} + \beta_{t,2} \frac{m}{\tau_{t,1}} e^{\left(\frac{-m}{\tau_{t,1}}\right)}, \tag{3.1}$$

where, $f_{t,m}$ is the instantaneous forward rates and m is maturity[4].

In equation 3.1, $\beta_{t,i}$ represents level, slope and curvature factors, respectively. Similarly, Litterman & Scheinkman (1991) show that most of the variation of the yield curve can be explained by level, slope, and curvature factors. Therefore, using those foundations, I can infer that the intraday shifts of the term structure can be represented

[4]Coroneo et al. (2008) show that Nelso-Siegel model satisfies the no-arbitrage constraints both in-sample and out-of-sample exercises.

by the shifts of the shape factors of the yield curve.

$$f_{t,m} - f_{t-k,m} = \Delta f_{t,m} = \Delta\beta_{t,0} + \Delta\beta_{t,1} e^{(\frac{-m}{\tau_{t,1}})} + \Delta\beta_{t,2} \frac{m}{\tau_{t,1}} e^{(\frac{-m}{\tau_{t,1}})}. \tag{3.2}$$

I use German government bonds in a maturity spectrum of 1-, 2-, 5-. 10-, 20-, and 30-year, which has a 10-minute sampling frequency in January 2005 and October 2019 period to extract policy surprises from equation 3.2. I then standardize the policy shocks to have a consistent structure within each other.

In this paper, I attribute level, slope, and curvature factors to the principal components (PC). Although my approach mechanically seems quite different than the popular methods such as Gürkaynak et al. (2005)[5], the approaches are quite similar, intrinsically. In the identification setup of Gürkaynak et al. (2005), there are some restrictions such as the second component having no effect on the short end of the yield curve, a similar strategy is also used by Altavilla et al. (2019), Leombroni et al. (2018) do not rely on any restrictions in the factor estimation process. Furthermore, Leombroni et al. (2018) report that these approaches bring similar results. Therefore, since the data set's maturity spectrum starts with 1-year bonds in the short term and by the findings of Leombroni et al. (2018), I construct an identification strategy without putting extra restrictions on

[5]In the seminal study of Gürkaynak et al. (2005), the policy shocks are estimated using factor rotations using short term maturity money market rates. $\Delta Y = F\Omega^{'} + \epsilon$, where ΔY is the short-term rate change matrix for the announcements, F is unobservable policy shocks, and $|omega$ is the covariance matrix. Then, the latent factors can be obtained by the following rotation $F = \Delta Y \Omega$. While factor rotations give the policy surprises in the popular approaches, I rely on the Nelson-Siegel model to reflect the shifts in the term structure, not only the short end of the curve, to represent policy surprises.

equation 3.2. I give more details on the estimation process of monetary policy surprises in the next section.

3.3.3 Estimation of ECB monetary policy shocks

To identify monetary policy surprises, I follow a high-frequency data event study approach and assume that shocks are priced by market participants in government bond yields. In other words, I posit that intraday shape factors of the yield curve are sufficient to represent the shocks. The ECB employs a two-tier communication policy. The ECB first releases its monetary policy decision at 12:45 (GMT). Following the press release, the press conference starts at 13:30 (GMT), where the President of the ECB communicates the introductory statement, followed by a question and answer session. During the sample period, the ECB has been conducting one meeting per month up to December 2014. Since January 2015, the frequency of meetings decreased to 8 meetings per year spread over, approximately, 6-week intervals.

More specifically, I measure the magnitude of monetary policy shocks using the changes of the German yield curves principal components (PC henceforth), which are sufficient to represent market reaction at separate windows: press release (between 12:30 (GMT) and 13:00 (GMT)) and press conference (between 13:20 (GMT) and 14:40 (GMT)) windows. I use German sovereign bonds in representing ECB monetary policy since German bonds have the lowest risk premium within the euro area and are typically consisted to be a flight-to-safety asset during periods of financial turmoil (Arghyrou & Kontonikas (2012)). Altavilla et al. (2019) state that using German sovereign yields as a proxy for euro-area risk-free rates makes no significant difference compared to OIS. In addition, I obtain results using the French yield curve (available upon request) that have only material discrepancies compared to using the German curve. This is due to the PCs of those markets curves being almost identical, especially during the monetary policy windows.

Similar methods are followed by Gürkaynak et al. (2005), Swanson (2021) and Altavilla et al. (2019) using rotated factors of interest rate changes to extract policy indicators. Unlike Altavilla et al. (2019), who use the PC of overnight interest swap (OIS) rate changes to estimate the latent indicators for ECB policies, I employ PC analysis on German government bond yields. I assert that the changes in the PCs during announcement windows are significant market-based indicators of monetary policy, and therefore the first three PCs represent target rate, MPS, and QE monetary policy shocks. I attribute the time variation of the first PC, level, to the target rate. The second PC, the slope of the yield curve, reflects most of the information regarding the future path of the monetary policy, thus the intraday variation of the slope factor reflects the MPS shock. Additionally, I attribute the changes in the third latent factor to QE shocks since the third PC of the yield curve gives the convexity/curvature of the yield curve. Convexity measures the sensitivity of (modified) duration to interest rate changes. Eser et al. (2019) highlight that QE policies could be associated with lower overall duration, which helps policymakers to achieve control among long-term rates through the risk premium channel. Therefore, the changes in the convexity factor of the yield curve (PC3) quantify the QE shock resulting from the ECB announcements. In this paper, positive (negative) innovations in the monetary policy shock indicators represent contractionary (expansionary) shocks.

Table 3.1 gives the descriptive statistics for the monetary policy shocks in the estimation period. The Jacque-Bera test results indicate a normal distribution within the estimation period of shocks.

Table 3.1: Descriptive Statistics

	$PC1_{release}$	$PC2_{release}$	$PC3_{release}$	$PC1_{conference}$	$PC2_{conference}$	$PC3_{conference}$
Mean	0.000	0.000	0.000	0.000	0.000	0.000
Median	0.028	0.101	0.175	-0.124	-0.035	-0.121
Skewness	-0.029	-0.659	-2.385	0.518	1.152	0.341
Kurtosis	4.334	6.207	12.368	2.626	5.809	1.466
Min	-4.052	-4.508	-5.721	-3.436	-2.742	-3.354
Max	4.457	3.899	2.516	3.987	5.516	2.816
JB-Stat	124.475	266.738	1164.241	52.811	258.779	17.314
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Negative Surprises	79	59	62	86	85	90
Positive Surprises	80	100	97	73	74	69
No. of Obs.	159	159	159	159	159	159

(1) The monetary policy surprises are given in the normalized terms January 2005 to October 2019 period. (2) p-value corresponds to Jacque-Bera test results p-value with respect to chi-square distribution.

Figure 3.1 plots the average response of policy shocks indicators at the ECB announcement dates vs. non-announcement dates over the trading window 10:00 am - 4:00 pm. The evidence in Figure 3.1 highlights that there is substantially higher variation in the policy shocks during announcement dates, in line with the identifying assumption that policy information is released on the announcement dates. Moreover, Figure 3.2 depicts that the QE shock becomes apparent around the MP announcements for the post-2013 period, which coincides with the use of unconventional monetary policies and a similar outcome is highlighted by Altavilla et al. (2019).

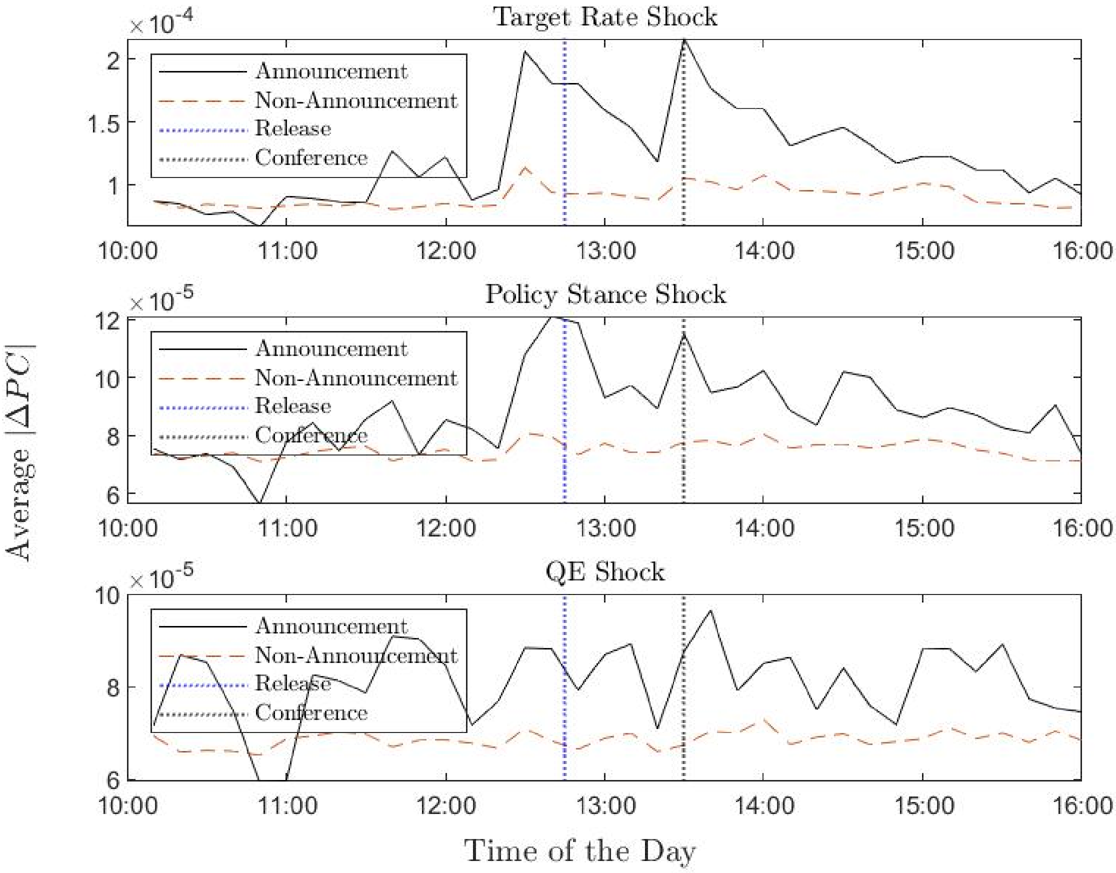

Figure 3.1: Policy shocks on the announcement and non-announcement days of ECB. The absolute value of average policy shocks, principal components, are given on the announcement (solid line) and non-announcement (dashed line). The vertical dotted lines correspond to the release of the statement (blue) and the start of the conference (black). The figure represents the period between January 2005 to October 2019.

Figure 3.3 and 3.4 report the developments in the MP surprise indicators on selected

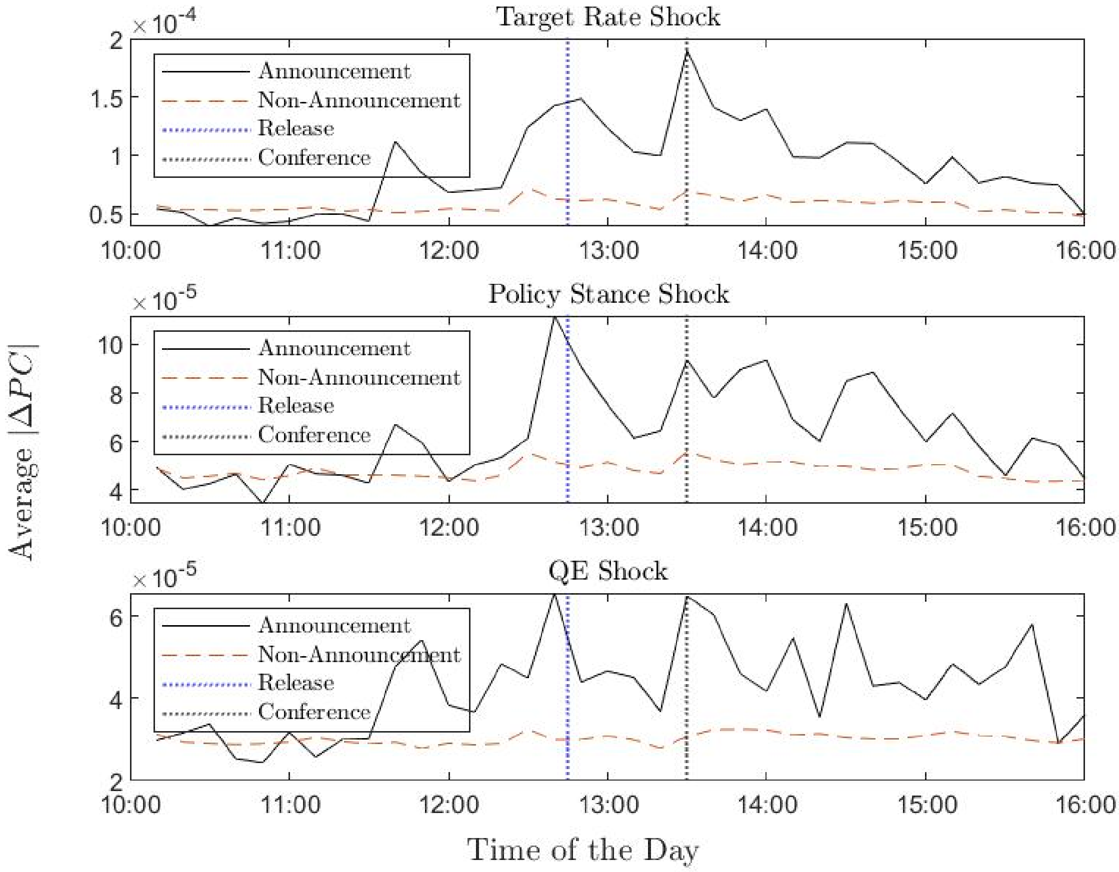

Figure 3.2: Policy shocks on the announcement and non-announcement days of ECB. The absolute value of average policy shocks, principal components, are given on the announcement (solid line) and non-announcement (dashed line). The vertical dotted lines correspond to the release of the statement (blue) and the start of the conference (black). The figure represents the period between January 2014 to October 2019.

dates. Firstly, in July 2013 during the press conference, ECB communicated in form of forward guidance by stating the rates to remain at present or lower for an extended period of time (see Figure 3.3). This was a substantial change in the ECB's communication policy and providing forward guidance directly affected the MPS shock by lowering expected future rates. Figure 3.4 shows the announcement in December 2015 that shows the market's disappointment with the ECB policy decision. While, ECB announced to decrease of the deposit rate by 10 basis points, which was in line with the expectations, the QE program was not increased. This results in a sell-off in the markets including bond markets and a negative, substantial increase in the factor, QE shock.

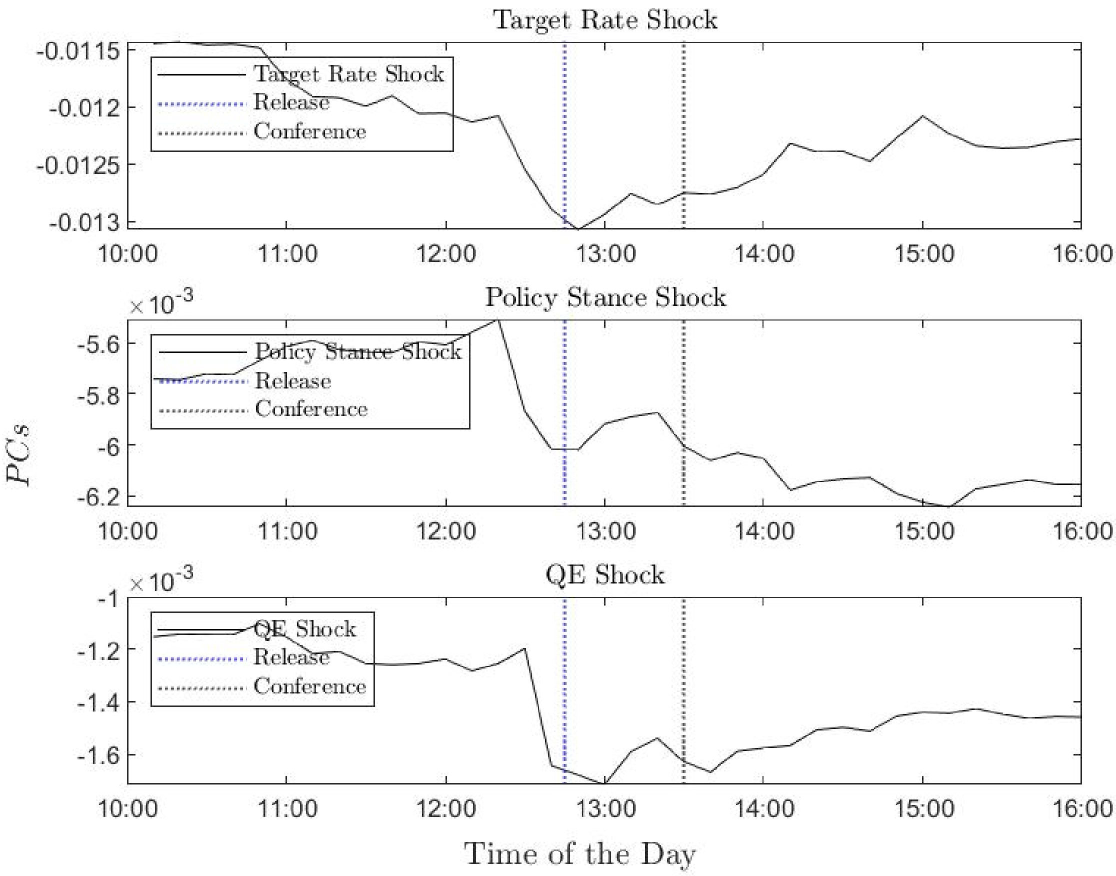

Figure 3.3: Monetary Policy Shock on July 4th, 2013

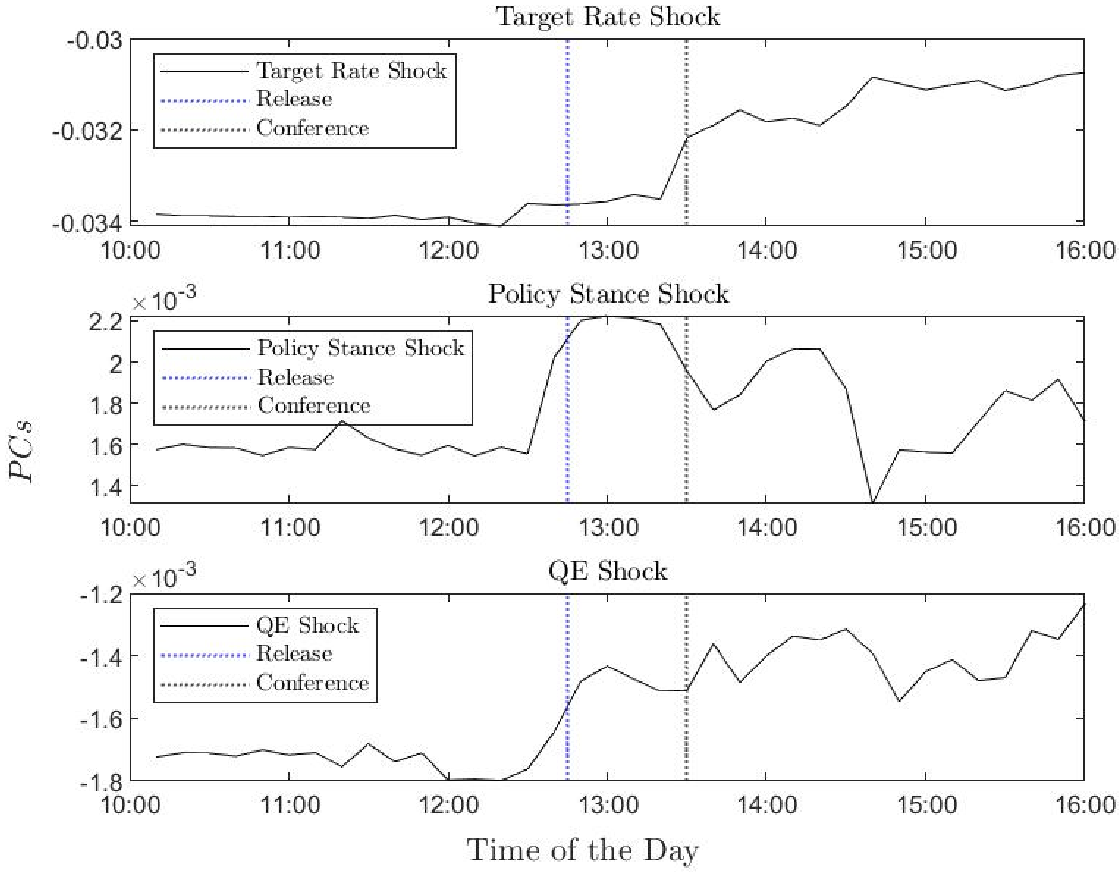

Figure 3.4: Monetary Policy Shock on December 3rd, 2015

3.3.4 Empirical models

In this section, I present the models that are used to analyse the impact of ECB monetary policy shocks on French-German spreads and other variables of interest. Using equation 3.2, I proxy for the effect of policy shocks, by using the changes in PC(1), PC(2), and PC(3) which correspond to the target rate, MPS and QE shocks respectively[6]. The dependent variable in Equation 3.3 is the maturity spectrum of French and German

[6]The monetary policy shocks are standardized (Z-scores).

government bond spreads, $Spread$[7]. I control for the relative macroeconomic fundamentals between French and German economies using the ratio of Economic Sentiment Indicators (esi) and the impact of the Global Financial Crisis using a dummy variable, D^{GFC}. I focus on the impact of monetary policy shocks on intraday intervals of release window and conference window[8].

$$\begin{aligned}\Delta Spread^{j}_{t,i} = \beta^{j}_{0} + \beta^{j}_{1} D^{GFC} \Delta PC(1)^{j}_{t} + \beta^{j}_{2} D^{GFC} \Delta PC(2)^{j}_{t} + \beta^{j}_{3} D^{GFC} \Delta PC(3)^{j}_{t} + \\ \beta^{j}_{4} \Delta PC(1)^{j}_{t} + \beta^{j}_{5} \Delta PC(2)^{j}_{t} + \beta^{j}_{6} \Delta PC(3)^{j}_{t} + \beta_{7} \Delta esi^{j}_{t} + \epsilon^{j}_{t,i},\end{aligned} \tag{3.3}$$

where $j = \{Release\ Window,\ Conference\ Window\}$ and i corresponds to maturity spectrum of 5-year to 30-year bonds.

Furthermore, using the EA-MPD database, I test for the impact of monetary policy shocks on Spain government bond returns versus Germany bonds for 10-year maturity using equation 3.4.

$$\begin{aligned}return^{j}_{t,i} = \gamma^{j}_{0} + \gamma^{j}_{1} D^{GFC} \Delta PC(1)^{j}_{t} + \gamma^{j}_{2} D^{GFC} \Delta PC(2)^{j}_{t} + \gamma^{j}_{3} D^{GFC} \Delta PC(3)^{j}_{t} + \\ \gamma^{j}_{4} \Delta PC(1)^{j}_{t} + \gamma^{j}_{5} \Delta PC(2)^{j}_{t} + \gamma^{j}_{6} \Delta PC(3)^{j}_{t} + \epsilon^{j}_{t,i},\end{aligned} \tag{3.4}$$

[7]Sovereign bond spreads are measured in basis points. The French-German bond spreads are, on average, at a 30 basis points level.

[8]I take the period from late 2007 to June 2009, the last date of NBER's trough month of recession, as GFC in my estimations. This period also coincides with extreme observations of the constructed monetary policy surprises. During the European debt crisis, such extremity is not observed.

where $j = \{Release\ Window,\ Conference\ Window\}$ and i corresponds to Spain and Germany government bonds.

The policy shock sensitivity of Euro-US dollar parity[9] is examined using equation 3.5.

$$\begin{aligned}\Delta eur_t^j = \delta_0^j + \delta_1^j D^{GFC} \Delta PC(1)_t^j + \delta_2^j D^{GFC} \Delta PC(2)_t^j + \delta_3^j D^{GFC} \Delta PC(3)_t^j + \\ \delta_4^j \Delta PC(1)_t^j + \delta_5^j \Delta PC(2)_t^j + \delta_6^j \Delta PC(3)_t^j + \epsilon_t^j,\end{aligned} \tag{3.5}$$

where $j = \{Release\ Window,\ Conference\ Window\}$.

Since intraday time series are unavailable for corporate bond yields and market-based inflation expectations, I study the effect of intraday shocks on the daily changes of those indicators using equation 3.6. I measure the impact of monetary policy shocks on corporate yields[10]. In addition, I examine the impact of intraday monetary policy shocks on daily changes in inflation-linked swap (ILS) rates[11], as a market-based inflation measure.

[9]The changes in the parity are measured in pip points. The increases (decreases) in the parity correspond to appreciation (depreciation) of Euro against US dollar.

[10]Corporate bond yields are measured in basis points. I use Markit's iBoxx EUR BBB index yields that have 3-year to 5-year and 5-year to 7-year maturities

[11]I use 5-year 5-year forward (5Y5Y) ILS rates that are measured in basis points.

$$\Delta Y_{t,i}^{j} = \alpha_0^j + \alpha_1^j D^{GFC} \Delta PC(1)_t^j + \alpha_2^j D^{GFC} \Delta PC(2)_t^j + \alpha_3^j D^{GFC} \Delta PC(3)_t^j + \\ \alpha_4^j \Delta PC(1)_t^j + \alpha_5^j \Delta PC(2)_t^j + \alpha_6^j \Delta PC(3)_t^j + \epsilon_{t,i}^j, \tag{3.6}$$

where $j = \{Release\ Window,\ Conference\ Window\}$.

$Y_i = \left[CorporateYield_{3Y-5Y},\ CorporateYield_{5Y-7Y},\ ILS_{5Y5Y} \right]$

Apart from the full sample analysis, to examine the impact of Forward Guidance (FG) and Quantitative Easing (QE) on asset prices and indicators, I perform a subsample analysis for the FG period and for the QE-period[12].

3.4 Empirical analysis

In this section, I present the regression results of the time series regression models analytically presented in Subsection 3.3.4. Tables 3.2 to 3.9 report the regression results. The market-based monetary policy shocks are sufficient to capture up to 35% of the variation in French-German government bond spreads (Table 3.2). In most of the maturities, I find the expansionary monetary policy to help narrow core Eurozone sovereign bond spreads which is in line with Altavilla et al. (2019). Although the target rate and QE shocks are more coherent with this finding, the results for the MPS shock

[12]I define FG-period starting from July 2013, with respect to ECB's first forward guidance communication, and onward. I define the QE period starting from January 2015, the introduction of ECB's Public Sector Purchase Program. Since both FG-period and QE-period are in the post-GFC era, GFC-dummy interaction terms are excluded.

are more ambiguous, especially during the GFC period. This outcome is suspected to be a result of the information content of the monetary policy communications regarding the policy stance. Andrade & Ferroni (2021) highlight the importance of forward guidance by focusing on Delphic and Odyssean shocks and assert that even though both shocks move the yield curve in the same way, their impact on financial conditions and macroeconomic expectations may have opposite signs. Since this is out of the scope of this paper, I leave this discussion as a further study. Additionally, the results indicate that the magnitude of the QE shock on spreads becomes stronger as maturity increases. Finally, while the MPS shock has a more, usual signed and, powerful effect on spreads during the conference, the QE information is more apparent during the release window.

Moreover, I test for the impact of monetary policy shocks on 10-year government bond yields during release and conference windows (see Table 3.5). This analysis reveals that expansionary target rate and QE shocks reduce 10-year government bond yields. The sensitivity of Spain's sovereign yields to the QE shock, γ_6, is higher than the German yields. Therefore, expansionary QE shocks help the spreads between Spain and Germany get narrower.

Moving on to the monetary policy effects on the Euro-dollar exchange rate in Table 3.8, the findings reveal that policy shocks can explain more than 60% of its variation. The exchange rate reaction to monetary policy shocks can be summarized as follows: expansionary surprises are associated with the depreciation of the euro, which is in line with the findings of Rogers et al. (2014) for the US monetary policy. Although the impact of monetary policy on the exchange rate is more limited during the GFC period, the results still support a link between expansionary monetary policy and the depreciation of the euro. Furthermore, the target rate shock is found to have a stronger effect on exchange rates that is magnified by the new information released during the conference window. The relative impact of QE on the euro-dollar exchange rate is higher in the release window, while the MPS becomes prominent in the conference window.

Table 3.9 presents daily changes in corporate borrowing costs and market-based inflation expectations to the intraday monetary policy shocks. I associate the expansionary monetary policy shocks with lowering corporate bond yields and so forth borrowing costs. The findings reveal that the target rate and QE shocks are more effective on corporate bond yields during the release window, while QE shocks are more apparent during the conference window. Also, similar to the French-German spread, as the maturity increases the impact of QE on yields also magnifies. Furthermore, the impact of monetary policy shocks on inflation expectations, 5Y5Y, unveils that the expansionary target rate and MPS shock result in a downward shift in market-based inflation expectations. Similar to my findings following an expansionary shock, Nakamura & Steinsson (2018) report a negative and insignificant reaction to inflation, and Kontonikas et al. (2019) associate the expansionary policy with downward revisions in inflation indicators. Conversely, the findings indicate that expansionary QE shocks stimulate inflation expectations in the post-QE period.

3.5 Conclusion

In this chapter, I identify euro area monetary policy shocks using German intraday government bond yields. We show that the intraday latent factors of the German government bond yield curve can act as indicators of euro-area monetary policy, namely target rate, MPS, and QE shocks. I find that intraday monetary policy shocks have a significant impact on a broad range of euro-area financial market variables, including a sample of core and periphery countries sovereign bond yields and spreads, the euro-dollar exchange rate, corporate bond yields, and market-based inflation expectations. Finally, the results are more univocal for the QE shocks by emphasizing the importance of QE policies. Expansionary QE shocks are found to lower sovereign bond yields and spreads, and are associated with a weakening Euro against the US dollar, lower cost of euro-denominated corporate credit, and higher inflation expectations.

To the best of my knowledge, contribution in the relevant literature is that I show for the first time that bond-based Target Rate, MPS, and QE factors have a significant impact on a broad range of euro-area financial market variables, including a sample of core and periphery countries sovereign bond yields and spreads, the Euro-dollar exchange rate, European corporate bond yields, and European market-based inflation expectations.

My analysis highlights that the ECB policy announcements are priced by the markets both in the press release and conference windows. The findings are in line with Rosa (2011), who finds that the communication tone of policy decisions matters more for asset prices than the policy decisions themselves. The findings of this paper have important policy implications by emphasizing the significance of the policy surprises and the associated information flows, especially those related to QE.

Table 3.2: Monetary Policy Shocks and French-German Government Bond Yield Spreads

Table 3.3: Monetary Policy Release Window

	5-Year			10-Year			20-Year			30-Year		
	All	FG	QE	All	FG	QE	All	FG	QE	All	FG	QE
β_0	-0.03	-0.15	-0.04	-0.23	-0.38	-0.22	-0.15	-0.47	-0.37	0.13	-0.50	-0.43
	(-0.23)	(-1.36)	(-0.34)	(-1.52)	(-2.79)***	(-1.64)	(-1.19)	(-3.17)***	(-2.22)**	(0.46)	(-3.05)***	(-2.22)**
β_1	0.30	—	—	-0.76	—	—	0.33	—	—	3.10	—	—
	(1.04)	—	—	(-2.07)**	—	—	(1.09)	—	—	(4.69)***	—	—
β_2	-1.08	—	—	0.84	—	—	-0.28	—	—	-4.19	—	—
	(-3.53)***	—	—	(2.2)**	—	—	(-0.87)	—	—	(-6.08)***	—	—
β_3	-0.42	—	—	0.63	—	—	0.33	—	—	-1.39	—	—
	(-1.45)	—	—	(1.75)*	—	—	(1.1)	—	—	(-2.16)**	—	—
β_4	0.30	0.20	0.40	-0.25	0.34	0.55	-0.56	0.06	0.31	-0.30	-0.06	0.23
	(1.66)*	(1.05)	(1.94)*	(-1.14)	(1.47)	(2.39)***	(-2.98)***	(0.23)	(1.13)	(-0.74)	(-0.2)	(0.71)
β_5	0.82	0.19	-0.30	0.27	0.02	-0.61	0.23	-0.08	-0.64	1.40	-0.04	-0.55
	(4.6)***	(0.79)	(-1.31)	(1.23)	(0.08)	(-2.35)***	(1.25)	(-0.25)	(-2.03)**	(3.51)***	(-0.12)	(-1.5)
β_6	-0.54	-0.12	0.17	-0.67	0.41	0.65	0.07	0.89	1.15	1.91	1.05	1.31
	(-3.3)***	(-0.48)	(0.68)	(-3.29)***	(1.42)	(2.38)***	(0.44)	(2.84)***	(3.46)***	(5.21)***	(3.06)***	(3.39)***
β_7	-19.63	26.64	8.41	26.38	29.42	0.70	22.82	12.11	-16.25	-35.78	2.94	-23.57
	(-1.39)	(1.89)*	(0.62)	(1.49)	(1.76)*	(0.05)	(1.55)	(0.66)	(-0.89)	(-1.13)	(0.15)	(-1.1)
R^2	23.6%	1.6%	18.4%	15.9%	12.4%	33.4%	6.3%	14.4%	24.9%	35.0%	16.4%	22.2

Table 3.4: Monetary Policy Conference Window

	5-Year			10-Year			20-Year			30-Year		
	All	FG	QE	All	FG	QE	All	FG	QE	All	FG	QE
β_0	0.03	-0.09	0.14	-0.15	0.03	0.23	-0.06	0.02	0.25	0.03	0.00	0.24
	(0.18)	(-0.75)	(1.21)	(-1.04)	(0.2)	(1.81)*	(-0.62)	(0.16)	(1.81)*	(0.13)	(0.01)	(1.5)
β_1	0.46	—	—	0.29	—	—	-0.33	—	—	-0.61	—	—
	(1.24)	—	—	(0.81)	—	—	(-1.29)	—	—	(-0.96)	—	—
β_2	0.27	—	—	0.34	—	—	0.08	—	—	-0.62	—	—
	(0.78)	—	—	(1)	—	—	(0.35)	—	—	(-1.04)	—	—
β_3	0.12	—	—	-0.28	—	—	-0.05	—	—	1.40	—	—
	(0.32)	—	—	(-0.77)	—	—	(-0.21)	—	—	(2.2)**	—	—
β_4	-0.36	0.10	0.23	-0.17	0.42	0.54	-0.15	0.11	0.23	-0.32	-0.03	0.08
	(-1.94)*	(0.52)	(1.44)	(-0.91)	(2.2)**	(3.17)***	(-1.13)	(0.52)	(1.23)	(-0.99)	(-0.11)	(0.36)
β_5	0.08	0.03	0.27	0.18	0.38	0.67	0.07	0.15	0.38	-0.05	0.03	0.23
	(0.46)	(0.15)	(1.58)	(1.04)	(2.14)**	(3.64)***	(0.56)	(0.74)	(1.93)*	(-0.15)	(0.11)	(0.98)
β_6	-0.50	-0.23	-0.21	-0.15	-0.02	0.13	0.26	0.22	0.43	0.40	0.28	0.50
	(-2.75)***	(-1.51)	(-1.42)	(-0.83)	(-0.12)	(0.79)	(2.05)**	(1.2)	(2.47)***	(1.29)	(1.29)	(2.41)***
β_7	-1.74	1.81	-9.76	12.45	-0.91	-8.55	3.54	-16.96	-17.57	-18.76	-24.76	-22.02
	(-0.1)	(0.12)	(-0.71)	(0.75)	(-0.06)	(-0.58)	(0.3)	(-0.9)	(-1.11)	(-0.65)	(-1.15)	(-1.17)
R^2	9.5%	-1.7%	-0.6%	1.7%	5.8%	34.0%	2.6%	3.8%	30.3%	5.4%	1.9%	20.6%

(1) The results in the parenthesis indicates p-values. (2) ***, **, * show 1%, 5% and 10% statistically significant coefficients, respectively. (3) All indicates the period between January 2005 and October 2019. (4) FG corresponds to the period between July 2013 and October 2019. QE corresponds to the period between January 2015 and October 2019.

Table 3.5: Monetary Policy Shocks and Government Bond Yields

Table 3.6: Monetary Policy Release Window

	Germany 10-Year			Spain 10-Year		
	All	FG	QE	All	FG	QE
γ_0	-0.03	-0.47	-0.42	-0.26	-0.99	-0.75
	(-0.23)	(-1.99)**	(-1.39)	(-1.5)	(-2.52)***	(-1.74)*
γ_1	0.06	—	—	0.35	—	—
	(0.23)	—	—	(0.87)	—	—
γ_2	-0.66	—	—	-0.53	—	—
	(-2.1)**	—	—	(-1.11)	—	—
γ_3	0.12	—	—	-0.07	—	—
	(0.37)	—	—	(-0.15)	—	—
γ_4	0.17	0.47	0.51	0.04	0.20	0.27
	(1.09)	(1.16)	(0.98)	(0.16)	(0.3)	(0.37)
γ_5	-0.02	-0.36	-0.93	-0.29	-0.64	-1.91
	(-0.15)	(-0.75)	(-1.64)	(-1.2)	(-0.79)	(-2.34)***
γ_6	0.19	0.82	1.05	0.39	1.63	2.13
	(1.33)	(1.64)	(1.68)*	(1.87)*	(1.95)*	(2.38)***
R^2	2.7%	7.5%	9.7%	1.7%	4.2%	14.5%

Table 3.7: Monetary Policy Conference Window

	Germany 10-Year			Spain 10-Year		
	All	FG	QE	All	FG	QE
γ_0	-0.08	0.27	0.16	0.14	0.31	0.26
	(-0.46)	(0.89)	(0.46)	(0.38)	(0.73)	(0.5)
γ_1	-0.16	—	—	0.69	—	—
	(-0.29)	—	—	(0.62)	—	—
γ_2	0.23	—	—	0.24	—	—
	(0.52)	—	—	(0.27)	—	—
γ_3	0.05	—	—	-0.12	—	—
	(0.1)	—	—	(-0.12)	—	—
γ_4	2.21	2.87	2.51	1.24	1.81	1.73
	(9.68)***	(6.35)***	(5.24)***	(2.68)***	(2.78)***	(2.36)***
γ_5	-0.17	-0.05	-0.16	-0.28	-1.27	-1.16
	(-0.78)	(-0.12)	(-0.31)	(-0.63)	(-2.08)**	(-1.47)
γ_6	0.26	0.16	0.80	0.43	1.44	1.38
	(1.19)	(0.44)	(1.8)*	(0.96)	(2.66)***	(2.03)**
R^2	49.9%	65.7%	67.0%	7.8%	52.0%	46.8%

(1) The results in the parenthesis indicates p-values. (2) ***, **, * show 1%, 5% and 10% statistically significant coefficients, respectively. (3) All indicates the period between January 2005 and October 2019. (4) FG corresponds to the period between July 2013 and October 2019. QE corresponds to the period between January 2015 and October 2019.

Table 3.8: Monetary Policy Shocks and Euro-US Dollar Parity

	Release Window			Conference Window		
	All	FG	QE	All	FG	QE
δ_0	-4.92	-10.46	-6.25	-0.18	-10.03	-8.28
	(-2.12)**	(-2.47)***	(-1.12)	(-0.06)	(-1.8)*	(-1.46)
δ_1	-8.48	—	—	-16.20	—	—
	(-1.56)	—	—	(-2.12)**	—	—
δ_2	-3.65	—	—	-3.10	—	—
	(-0.64)	—	—	(-0.43)	—	—
δ_3	-4.22	—	—	-14.04	—	—
	(-0.78)	—	—	(-1.82)*	—	—
δ_4	19.39	32.67	25.41	32.33	51.60	39.72
	(5.78)***	(4.46)***	(2.63)***	(8.37)***	(6.17)***	(5.06)***
δ_5	-5.04	7.25	-1.21	10.45	22.32	20.90
	(-1.51)	(0.84)	(-0.12)	(2.82)***	(2.84)***	(2.48)***
δ_6	9.15	19.44	23.82	7.65	8.90	21.78
	(2.99)***	(2.15)**	(2.07)**	(2.02)**	(1.27)	(3)***
R^2	25.4%	40.7%	23.0%	42.1%	54.5%	64.0%

(1) The results in the parenthesis indicates p-values. (2) ***, **, * show 1%, 5% and 10% statistically significant coefficients, respectively. (3) All indicates the period between January 2005 and October 2019. (4) FG corresponds to the period between July 2013 and October 2019. QE corresponds to the period between January 2015 and October 2019.

Table 3.9: Monetary Policy Shocks, Corporate Bond Returns and Inflation Expectations

Table 3.10: Monetary Policy Release Window

	Corporate 3Y-5Y			Corporate 5Y-7Y			5Y5Y Inflation		
	All	FG	QE	All	FG	QE	All	FG	QE
α_0	-0.41	-1.23	-1.40	-0.27	-1.17	-1.43	0.33	0.20	0.25
	(-1.19)	(-2.89)***	(-2.59)***	(-0.77)	(-2.29)**	(-2.26)**	(1.77)*	(0.65)	(0.67)
α_1	0.55	—	—	0.27	—	—	0.77	—	—
	(0.67)	—	—	(0.33)	—	—	(1.78)*	—	—
α_2	-2.61	—	—	-1.74	—	—	-0.19	—	—
	(-2.71)***	—	—	(-1.79)*	—	—	(-0.41)	—	—
α_3	2.29	—	—	1.33	—	—	-0.59	—	—
	(2.36)***	—	—	(1.37)	—	—	(-1.37)	—	—
α_4	1.20	2.19	2.76	1.38	2.32	2.95	0.10	0.15	-0.50
	(2.48)***	(2.97)***	(2.95)***	(2.82)***	(2.62)***	(2.7)***	(0.37)	(0.27)	(-0.78)
α_5	0.86	2.63	2.30	0.55	2.18	1.68	-0.13	-0.09	0.14
	(1.78)*	(3.01)***	(2.26)**	(1.14)	(2.09)**	(1.4)	(-0.5)	(-0.15)	(0.2)
α_6	0.27	0.83	1.10	0.30	1.05	1.25	-0.30	-0.04	-0.49
	(0.64)	(0.91)	(0.98)	(0.7)	(0.96)	(0.95)	(-1.23)	(-0.06)	(-0.63)
R^2	12.5%	28.9%	27.9%	9.4%	20.3%	18.7%	5.2%	-5.4%	-4.8%

Table 3.11: Monetary Policy Conference Window

	Corporate 3Y-5Y			Corporate 5Y-7Y			5Y5Y Inflation		
	All	FG	QE	All	FG	QE	All	FG	QE
α_0	-0.55	-0.70	-0.62	-0.38	-0.54	-0.60	0.32	-0.03	0.00
	(-1.94)*	(-1.87)*	(-1.4)	(-1.37)	(-1.25)	(-1.24)	(1.7)*	(-0.1)	(-0.01)
α_1	1.52	—	—	2.03	—	—	-0.14	—	—
	(1.99)**	—	—	(2.72)***	—	—	(-0.29)	—	—
α_2	2.22	—	—	1.99	—	—	-0.58	—	—
	(3.26)***	—	—	(3)***	—	—	(-1.3)	—	—
α_3	-1.17	—	—	-1.55	—	—	0.77	—	—
	(-1.54)	—	—	(-2.08)**	—	—	(1.58)	—	—
α_4	2.29	1.56	1.73	2.15	1.30	1.43	0.30	0.92	1.35
	(6.39)***	(2.76)***	(2.83)***	(6.16)***	(2.01)**	(2.15)**	(1.2)	(2.27)**	(3.22)***
α_5	0.27	-0.28	-0.38	-0.17	-0.75	-1.12	0.38	1.52	1.56
	(0.77)	(-0.53)	(-0.57)	(-0.51)	(-1.24)	(-1.56)	(1.61)	(3.99)***	(3.45)***
α_6	0.66	1.53	1.18	0.87	1.96	1.47	0.03	-0.44	-0.78
	(1.88)*	(3.25)***	(2.08)**	(2.54)***	(3.64)***	(2.38)***	(0.1)	(-1.29)	(-2)**
R^2	40.8%	44.1%	46.5%	42.3%	42.9%	47.5%	1.6%	21.5%	22.9%

(1) The results in the parenthesis indicates p-values. (2) ***, **, * show 1%, 5% and 10% statistically significant coefficients, respectively. (3) All indicates the period between January 2005 and October 2019. (4) FG corresponds to the period between July 2013 and October 2019. QE corresponds to the period between January 2015 and October 2019.

Chapter 4

Intraday Variation in the Latent Yield Curve Factors and Stock Markets

4.1 Introduction

I examine the impact of government bond market volatility on the stock market volatility conditional on the shape of the yield curve. The changes in the yield curve have the potential to reflect the macroeconomic stance. Therefore, the volatility of the yield curve during different phases of the curve shifts can reveal precious information for the market players. The changes in the interest rates affect the equity prices through both expected cash flows and discount rates channels under the discounted cash flow model. In this study, I try to identify the link between interest rate volatility and stock market volatility in the high-frequency setting, which helps us to focus only on the impact of the discount rate channel on stock prices. I show that the yield curve volatility is an important determinant of equity market volatility. This approach particularly focuses on the yield curve moves to unveil whether the equity market volatility is associated with the bear or bull bond markets and/or steepening or flattening of the yield curve. The findings indicate that the transmission of volatility from bond markets to stock markets can be represented using the shape factors of the yield curve, namely level, slope, and curvature. I assert that the bond market volatility is transmitted to the stock markets depending on the shape of the yield curve. Using the latent factors, I find that the positive transmission of volatility from bond markets to equity markets is more apparent following a bull steepener episode in the sovereign yield curves, whereas the transmission is generally less significant when the yield curve moves in a bear flattening shift[1].

In this study, I use German, French, Swiss, and the UK sovereign bond markets with a maturity span of 1-year to 30-year, and countries' generic stock market indices using high-frequency data from January 2005 to October 2019. To specify the shifts in the yield curve, I depend on the analysis of the seminal paper of Litterman & Scheinkman (1991), which states the level, slope, and curvature factors of the yield curve explain almost all the variation in the yield curve. Therefore, I classify the bull (bear) bond market when the change in the level factor is negative (positive) in the intraday close-to-open periods. Also, the slope factor is used to define flatten (steepen) when the intraday change in the slope factor is negative (positive).

[1]Although this result is quite striking since the positive transmission of volatility is higher when interest rates decrease (bull market) and lower when rates increase (bear market), the reaction of the stock market does not only depend on the direction move in rates but also the slope of the yield curve. Subramanian et al. (2018) also find a similar result using the monthly return series of aggregate stock market indices. The report indicates that the bull steepening yield curve is the worst environment for the equity markets, while the bear flattening is the best environment in terms of returns.

An old wall street proverb says that the central bank determines the level of short-term rates while the expectations drive the yield curve, which explains the determinants of interest rates (Ilmanen (1995)). The short end and long end of the yield curve have different underlying factors such as market expectations and risk premiums. The market participants generally relate the expectations regarding economic conditions, and monetary policy stance, with the short end of the yield curve. In a nutshell, as economic growth increases (decreases), it is expected that both the real interest rates and shorter-term inflation to increase (decrease). Also, bond markets price the expectations of monetary policy in the shorter term of the yield curve. Since monetary policy reacts to macroeconomic conditions to eliminate overheating of the economy, a countercyclical policy setting follows economic developments. Thus, increases (decreases) in the economic growth, analogously could be interpreted as clustering expectations on tightening (easing) of monetary policy. In addition, the long end of the yield curve is associated with the risk premium. In this paper, I separate risk premium into two parameters: (common) risk premium and hedging premium following Cieslak & Pang (2021). The (common) risk premium shows the risk-taking behavior of market players while the hedging premium indicates the hedging demand pressure on the long-term bond markets.

I generalize the discounted dividend model to develop the theoretical foundations of the proposed framework on the relationship between the yield curve and stock market volatility. This model indicates that the covariances between growth expectations and risk premiums, common risk premium, and hedging premium, determine the magnitude of the transmission of volatility from bond markets to stock markets. Then, I test the transmission of bond market volatility to stock market volatility using an extended Heterogeneous Auto-Regression (HARQ) model with yield curve factor volatility.

To my knowledge, this is the first paper to provide a theoretical background for the yield curve episodes and bond market to stock market volatility transmission in a testable framework. Using the foundations from the findings of Cieslak & Pang (2021), this chapter provides the first attempt to explain the moves of the yield curve such as bear, or bull, and flattener, or steepener, using the combination of the risk premium and hedging premium. Secondly, this study unveils the empirical asymmetry that during the bear flattener yield curve episodes the sensitivity of the equity market volatility to bond markets is reduced, the bull steepener move magnifies the transmission from the bond market to the stock market volatility. Another contribution of this chapter can be found within the volatility forecasting context. I uncover that the yield curve's level and slope volatility increase the stock market volatility, and the volatility of the curvature factor decreases the equity volatility. Moreover, including the yield curve factors' volatility in equity market volatility models improves the forecasting results within in-sample and out-of-sample windows.

The rest of the chapter is structured as follows. Section 4.2 reviews the literature, and Section 4.3 gives the theoretical intuition on the link between bond and stock market volatility. In Section 4.4, I provide the information regarding data and methodology by detailing the estimation strategy. In Section 4.5 I present the results of the empirical models. In Section 4.6 I provide a brief conclusion of this research.

4.2 Literature Review

I examine the impact of government bond market volatility on stock market volatility conditional on the shape of the yield curve. The changes in the yield curve reflect the macroeconomic expectations, and therefore the volatility of the yield curve during different phases of the yield curve shifts reflects precious information about market players. The interest rate changes have an impact on the security prices by both affecting expected cash flows and discount rates. I identify the link between interest rate and stock market volatility using intraday data, which paves the way to focus solely on the impact of the discount rate channel on stock prices. This approach concentrates on the yield curve movements to unveil whether the equity market volatility is associated with the bear or bull bond markets and/or steepening or flattening of the yield curve. The findings indicate that the transmission of volatility from bond markets to stock markets is represented by the shape factors of the yield curve, namely level, slope, and curvature.

In the dividend growth model, the variation in the stock prices can be attributed to the dividend flow and discount rates. In the earlier attempts to link the stock price volatility, Shiller (1981) states that the stock market is too volatile to be solely attributed to the variation in future real dividends, or cash flows while asserting that the high volatility can be justified by the movements in the interest rates. Therefore, the expectations regarding systematic factors, such as inflation and economic growth, are priced in stock market returns in the discounted cash flows channel. Since the seminal paper of Chen et al. (1986), the literature on the importance of systemic state variables, such as macroeconomic factors, on asset returns attempted to be associated. In this sense, the systematic factors influence stock returns by affecting expected cash flow and/or discount rate channels. In addition, the intertemporal asset pricing theory by Cox et al. (1985) state that the equilibrium asset prices depend on the state, underlying macroeconomic variables. In the theory, the discount rate is formed by depending on expected returns, and thus the price change can be reflected by discount rates from the variation in expected returns. Accordingly, the market volatility is also tried to be associated with the state variables, such as economic activity (e.g Officer (1973); Schwert (1989)). Furthermore, Cutler et al. (1989) assert that the innovations regarding macroeconomic news can explain up to one-third of the stock market variation. The indicators of both past and future systematic factors can explain the return volatility. Therefore, not only the realizations but also expectations on macroeconomic factors are effective on stock market volatility. Flannery & Protopapadakis (2015) find that exposures to the changes in macroeconomic factors are effective on equity market returns and conditional volatility. On the contrary, while trying to incorporate the squared bond yields and term premium in the conditional stock return volatility structure, Flannery & Protopapadakis (2015) observe those factors to be ineffective on the conditional volatility. There is a strong link between economic factors and stock market volatility in the short term and long term horizons (see e.g. Engle et al. (2013); Engle & Rangel (2008)). In addition, Engle & Rangel (2008) state that macroeconomic factors and their volatility, and short-term interest rates have a significant effect on equity market volatility.

Volatility is an important indicator for investors' decision-making and policymakers. I hypothesize that the stock market volatility is directly linked to the bond market dynamics that reflect the market participants' perceptions regarding growth expectations and risk premium. This framework depends on the extant literature focusing on the link between the stock market volatility and the interest rates[2].

The yield curve itself indeed provides more information than just showing a term structure of interest rates. In this fashion, Kessel (1971) finds the term structure of interest rates being synchronized with the business cycle. Moreover, Fama (1986) observes the shape of the yield curve changes with respect to economic activity that the curve is upward sloping during the strong economic activity episodes, while it turns out to be inverted and hump-shaped during recession periods[3]. Therefore, the information embedded in

[2]While there are some studies correlate the discount rate changes with the market volatility (see Chen et al. (1999)), some studies fail to provide significant evidence on public information flow led market volatility (see Berry & Howe (1994)).

[3]Fama (1986) asserts that the relationship between the term structure of interest rates and the business cycle is not always monotonic. This may be a result of consumption preferences of the economic agents to be stable, not high, during good times and preferring low consumption during recessions (Harvey (1988)).

the yield curve is used for predicting future economic activity (Harvey (1988); Stock & Watson (1989)). Indeed, the yield curve carries information value regarding not only consumption growth, or economic activity, but also inflation dynamics depending on inflation persistence(see e.g. Estrella & Mishkin (1997)). Wheelock & Wohar (2009) state that the persistence of inflation reflects the underlying monetary regime. In this study, I focus on the yield curve to reflect the economic growth dynamics depending on studies that show the forecasting power of the term structure of the yield curve for growth is independent of the current and future monetary policy (see e.g Estrella & Hardouvelis (1991); and Estrella & Mishkin (1997)). Thus, I can infer that the yield curve provides robust information regarding macroeconomic expectations.

Market prices reflect the information arrival from the market microstructure perspective. Ross (1989) shows that under no-arbitrage conditions the volatility of asset prices comes from the volatility of information flow. Similarly, Andersen (1996) presents that while daily returns are conditional normally distributed with information arrival, and variances exhibit the information arrival intensity. Therefore, the volatility process incorporates the information flow, while asset prices are adjusted based on available information. Engle et al. (1990) explain the volatility process from the perspective of the arrival of new information that causes clustering and the heterogeneous reaction of market participants. Also, Engle et al. (1990) assert that there exists the transmission of volatility across financial markets.

In traditional portfolio management, managers try to reduce the overall riskiness of stock and fixed income securities via portfolio diversification with stocks and bonds. Although diversification helps to reduce exposed portfolio risks, the benefits of diversification can be undermined by the volatility of asset classes. Therefore, the volatility connectedness between the stock and bond markets carries great importance for financial market participants. In this framework, Fleming et al. (1998) investigate the information and volatility linkages between the stock, bond, and money markets. Fleming et al. (1998) propose a model that shows the information flow to generate volatility linkages across markets, which is caused by fluctuations in investors' perceptions in all markets or perception changes in one market, and transmission of volatility through hedging demand[4].

I try to link the shifts in the shape of the government bond yield curve with macroeconomic expectations and risk premium. These framework hypotheses that changes in macroeconomic perceptions of market participants, due to the public or private information flows, cause the price formations in the government bonds in the short term, and risk premiums in the long term. Then, I use the volatility of the shape factors of the yield curve in explaining the stock market volatility during the different episodes

[4]Fleming et al. (1998)'s model forms a trading model, where trade is initiated by information flows. In a frictionless market, their model implied that hedging demand and speculative demand following any news-related trading activity causes volatility changes to be perfectly correlated across markets. However, in practice there exist position limits, capital constraints, and trading costs that may reduce the information-driven volatility spillover. Moreover, empirical results show that there are strong volatility spillovers across markets, but the volatility linkage is not perfectly correlated. Therefore, markets do not share the same information process.

of yield curve shifts with an assumption of those shifts are related to expectations on fundamentals. Although the implications of changes in the expectations are also priced in the stock market, and therefore in the stock return volatility. I focus on bond markets as a primary, and direct recipient of the modifications in macroeconomic perceptions. My approach depends on the impact of macroeconomic news releases on bond and stock markets. While, bond markets are found to be significantly affected by macroeconomic fundamentals (Fleming & Remolona (1997); Balduzzi et al. (2001); Green (2004); and Pasquariello & Vega (2007)), stock markets are evidenced to have weaker connectedness with the macroeconomic news (Boyd et al. (2005); and Andersen, Bollerslev, Diebold & Vega (2007*b*)). Therefore, I can infer that information flows from the changes in macroeconomic perceptions are priced in the stock markets through the discount factor channel that constitutes the grounding factor of volatility transmission of bonds, through pricing factors, via the yield curve shifts' episodes to stock markets.

4.3 Discounted Dividend Model

The determinants of stock prices can be attributed to three primary factors: the risk-free interest rate, expected dividend growth, and the risk premium (Boyd et al. (2005)). I can conceptualize this relationship considering the Gordon (constant) growth model.

$$P = \frac{D(1+g)}{k-g}. \tag{4.1}$$

In the Equation 4.1, P is the stock price, D is the current dividend, g is the expected dividend growth rate and k is the cost of capital, which consists of the risk-free interest rate and the equity premium.

In this paper, I investigate the transmission of bond market volatility to stock market volatility using intraday data. Since during intraday partitions, the current dividend and dividend growth rate will be unchanged, I change the Gordon model using $\tilde{D} = D(1+g)$ and $\tilde{k} = k - g$. Then, $P \cong \tilde{D}\tilde{k}^{-1}$.

In this context, I assume that the cost of capital, k, has a logarithmic-linear process, which incorporates the expectations of economic growth (output), g^e, (common) risk premium, ω^{rp}, hedge premium, ω^{hp}, and real rates, r. This model is similar to (Cieslak & Pang (2021)) that hypothesizes the common shocks moving both the stock markets and the yield curve are the innovations regarding monetary policy, economic fundamentals, and risk premium developments[5]. In addition to risk factors and economic fundamentals, real interest rate innovations are the major determinant of nominal interest rate variation and thus the discount rates (Campbell & Ammer (1993); and Fama (1990)).

$$\tilde{k}_t = (g_t^e)^{\alpha_1}(\omega_t^{rp})^{\alpha_2}(\omega_t^{hp})^{\alpha_3}(r_t)^{\alpha_4}e^{\epsilon_t}, \tag{4.2}$$

where I assume common risk premium and hedging premium are contemporaneously

[5]In this study, I aim to generalize the yield curve dynamics through the lens of economic fundamentals that are also the major driver of monetary policy decisions and shocks. Thus, I propose a theoretical framework that focuses only on economic growth expectations and the risk premiums.

orthogonal to each other. Then,

$$\log(\tilde{k}_t) \cong \alpha_0 + \alpha_1 \log(g_t^e) + \alpha_2 \log(\omega_t^{rp}) + \alpha_3 \log(\omega_t^{hp}) + \alpha_4 \log(r_t) + \epsilon_t. \tag{4.3}$$

The Gordon model holds even when the growth rates, interest rates, and risk premiums are not constant (Jagannathan et al. (2001), and Boyd et al. (2005)). Moreover, I transform Equation 4.1 into log-linear form as, $\log(P_t) \cong \log(\tilde{D}_t) - \log(\tilde{k}_t)$. Then,

$$\log(P_t) \cong \log(\tilde{D}_t) - \left(\alpha_0 + \alpha_1 \log(g_t^e) + \alpha_2 \log(\omega_t^{rp}) + \alpha_3 \log(\omega_t^{hp}) + \alpha_4 \log(r_t) + \epsilon_t\right), \tag{4.4}$$

and the one-period return of stock prices is calculated as follows:

$$\Delta(\log(P_t)) \cong \Delta(\log(\tilde{D}_t)) - \left(\alpha_1 \Delta(\log(g_t^e)) + \alpha_2 \Delta(\log(\omega_t^{rp})) + \alpha_3 \Delta(\log(\omega_t^{hp})) + \alpha_4 \Delta \log(r_t)) + \Delta(\epsilon_t)\right). \tag{4.5}$$

I use intraday data in order to approximate the continuous-time dynamics of asset price and returns, using discrete equidistant partitions. Within a short period of time, at intraday intervals, the change in dividend and real interest rate is economically negligible and does not affect the measurement of volatility, which paves us the way to ignore those developments using high-frequency data.

I follow the methodology of Andersen & Bollerslev (1998) for the estimation of realized volatility. As the intraday sampling frequency increases sufficiently, the cumulative sum of intraday returns converges to genuine unobserved volatility, which is the so-called realized volatility (RV) (Andersen & Bollerslev (1998); Andersen, Bollerslev, Diebold & Labys (2003); Barndorff-Nielsen & Shephard (2002, 2004)).

$$\begin{aligned} RV_p^2(t+h,h) = \sum_{i=1}^{n}\left(\Delta\log(P_{t+\frac{ih}{n}})\right)^2 \cong\ {\alpha_1}^2\sum_{i=1}^{n}\left(\Delta(\log(g^e_{t+\frac{ih}{n}}))\right)^2 + {\alpha_2}^2\sum_{i=1}^{n}\left(\Delta(\log(\omega^{rp}_{t+\frac{ih}{n}}))\right)^2 + \\ {\alpha_3}^2\sum_{i=1}^{n}\left(\Delta(\log(\omega^{hp}_{t+\frac{ih}{n}}))\right)^2 + 2\alpha_1\alpha_2\sum_{i=1}^{n}\left(\Delta(\log(g^e_{t+\frac{ih}{n}}))\Delta(\log(\omega^{rp}_{t+\frac{ih}{n}}))\right) + \\ 2\alpha_1\alpha_3\sum_{i=1}^{n}\left(\Delta(\log(g^e_{t+\frac{ih}{n}}))\Delta(\log(\omega^{hp}_{t+\frac{ih}{n}}))\right) + \sigma_\epsilon^2, \end{aligned} \tag{4.6}$$

and therefore, shortly the stock price variances can be represented by a combination of the variance of growth expectations and risk premium and their co-variances.

$$\sigma_p^2 \cong {\alpha_1}^2\sigma_{g^e}^2 + {\alpha_2}^2\sigma_{\omega^{rp}}^2 + {\alpha_3}^2\sigma_{\omega^{hp}}^2 + 2\alpha_1\alpha_2\sigma_{(g^e,\omega^{rp})} + 2\alpha_1\alpha_3\sigma_{(g^e,\omega^{hp})} + \sigma_\epsilon^2 \tag{4.7}$$

Therefore, the volatility of stock prices depends on volatility exposure of change in economic growth expectations, common risk premium and hedging premium, and the co-variances between economic growth expectations and risk premiums. The sign and magnitude of transmission of volatility from bond markets to stock markets depend on the co-variances between economic fundamentals and risk premiums[6]. This paper aims to use the changes in the shape factors of the yield curve in order to represent the underlying factors that move the bond markets. Thus, I try the joint modeling of stock market volatility and bond market volatility. There exists immense literature focusing on the identification of shocks that affect both stock price and bond returns, and also the volatility structure. In this context, Campbell & Ammer (1993) use a dynamic framework to account for the variance of stock price returns using both stock and bond markets using an accounting identity rather than studies focusing on stock market return variability in isolation of a single market (Campbell & Shiller (1988); Campbell (1991)). In a similar setting, Cieslak & Pang (2021) analyses the shock dynamics for stock and bond markets using variance decomposition. The findings reveal a crucial difference in the reaction of nominal yield changes with different maturities to economic fundamentals and risk premium shocks. It is reported that most of the 2-year yield change variation is resulted from the economic fundamental shocks, whereas 10-year yield variation is mostly caused by the risk premium shocks. Therefore, it can be inferred that the innovations in fundamentals are a short-term phenomenon, while risk premium shocks are related to the long end of the yield curve.

In this perspective, I can link the episodes of the shifts in the shape of the yield

[6]Taking α_1, α_2, α_3 given in Equation 4.7, co-variance terms determine the sign and power within the volatility structure since the variance terms are positive definite.

curve to the economic fundamental and risk premium shocks, whether the yield curve moves in bear flattener, bear steepener, bull flattener, or bull steepener. First of all, the bear flattener move corresponds to the yield curve shifting upwards while the short-term rates increase more. I associate the bear flattener with positive growth expectations and a negative risk premium. In a positive growth economy, $\Delta g^e > 0$, I expect the risk premium to decrease, $\Delta\omega^{rp} < 0$, and demand for hedging to decrease (less demand for long term bonds), $\Delta\omega^{hp} > 0$, where the risk premium shock dominates. In this context, the yields increase at the short end of the yield curve more than at the long end. Thus, the transmission of volatility from bond markets to stock markets is reduced due to negative co-variance between the growth expectations and risk premium, $\sigma_{(g^e,\omega^{rp})} < 0$ (see Equation 4.6 and 4.7). Moreover, when the yield curve moves in a bear steepener, there is an upward shift of the yield curve while the change in the short-term yields is less prominent than the change in the long term. Thus I can infer that the move in the yield curve is not caused by the growth expectations, Δg^e?, whereas either the common risk premium, $\omega^{rp} > 0$, or hedging premium $\Delta\omega^{hp} > 0$ is positive, or both. In this scenario, the transmission from bond markets to equity markets is positive but not primarily driven by the risk and expectation co-variances. Similarly, a bull flattener move in the yield curve is observed when the yields decrease on average while the decrease in the long-term yields is more eminent than the short term. The limited downward move in the short term indicates that there is only a little information I can infer from the short-term regarding growth expectations, Δg^e?. Likewise, since the interest rates are pushed downward on average along the maturity span, both risk premium and/or hedging premium (demand) decreases, $\Delta\omega^{rp} < 0$ and/or $\Delta\omega^{hp} < 0$. Therefore, the co-variances between growth expectations and risk premiums have a limited impact on the transmission of volatility through the yield curve to stock markets. Moreover, the bull steepener move in the yield curve is observed when the yields decrease on average while the decrease in the short-term yields is more prominent than in the long term. The decrease in the growth expectations, $\Delta g^e < 0$, can be inferred from the move since the dominance in the downward shift in the short end of the yield curve. In this environment, I observe that the risk premium increases, $\Delta\omega^{rp} > 0$, but the risk-averse behavior of market participants put heightened demand for long term government bonds, which can be reflected as an increase in hedging demand, and thus $\Delta\omega^{hp} < 0$. Therefore, the flight to safety behavior of financial markets to hedge themselves magnifies the volatility transmission from bond markets to stock markets.

4.4 Data and Methodology

4.4.1 Data

In this paper, I try to analyse whether the volatility in the term structure of interest rates influences the equity market volatility and this effect can be used in explaining volatile episodes of equity markets. In order to show the relationship between bond and equity market volatility, I depend on the analysis of major European markets. In this analysis, I use UK, Germany, France, and Switzerland sovereign bond markets, and equity markets' intraday data in the January 2005 –October 2019 period by relying on Thomson Reuters Tick History (TRTH) database. The bond maturity spectrum consists of 1-, 2-, 5-, 10-, 20- and 30-year assets. The dataset relies on quotes for "on-the-run", generic, instruments which are more liquid in terms off-the-run securities. To represent the equity markets, I use FTSE100 for the UK, DAX40 for Germany, CAC40 for France, and SSMI for Switzerland.

The intraday sampling frequency is 10-minutes for sovereign bond markets and 5-minutes for the equity markets. Using high-frequency data, there exists a trade-off between microstructure noise and liquidity. Therefore, I prefer to use different sampling frequencies in estimating volatility indicators. I provide a more comprehensive discussion of the optimal sampling frequency in Chapter 2.

In this study, the zero-coupon rates are obtained following Nelson & Siegel (1987), which led us to extract the intraday latent factors of the yield curve. Since the seminal paper of Litterman & Scheinkman (1991), which states the first three latent factors give level slope and curvature of the yield curve, the latent factor approaches gain immense popularity.

Using those developments, I define the bull (bear) bond market as the negative (positive) shift in the level factor, and flattener (steepener) of the curve is defined as a

Table 4.1: Yield Curve Shifts' Distribution

	Swiss	German	French	UK
Bear Flattening	21.08%	21.08%	13.19%	12.53%
Bear Steepening	27.50%	27.50%	33.53%	34.44%
Bull Flattening	28.08%	28.08%	38.08%	36.81%
Bull Steepening	23.33%	23.33%	15.19%	16.22%

decrease (increase) in the slope factor. I give more information on how I construct those factors in the next section.

The distribution of yield curve shifts is given in Table 4.1. According to the distribution of yield curve shape changes, the most frequent move that the yield curve exhibits are bull flattener, and that is followed by bear steepener. Therefore, I can infer that the expansionary monetary policies, especially after the Global Financial Crisis (GFC), put downward pressure on the yield curves by also limiting the term premium, which in turn flattened the yield curve. Also, when there is a bear market for the government bonds, this generally increased the risk premium and causes the yield curve to steepen. In terms of bull versus bear markets, although there are more bull days present in the sovereign bond markets in the estimation period, there is no clear dominance between the two distinct market forces.

The basic idea on how to compute realized indicators lies in the stochastic price process as following:

$$dlog(P_t) = \mu_t dt + \sigma_t dW_t, \tag{4.8}$$

where μ_t is the drift, and σ_t is the instantaneous volatility. W_t denotes the standard Brownian motion.

Then, daily integrated variance (IV) is defined as:

$$IV_t = \int_{t-1}^{t} \sigma_s^2 ds. \tag{4.9}$$

Having largely enough intraday partitions, the realized variance (RV) can be defined as the sum of squared high-frequency returns.

$$RV_t = \sum_{M}^{i} r_{t,i}^2, \tag{4.10}$$

where M is the number of intraday partitions, and $M = 1/\Delta$, as Δ is the intraday return period. The intraday return is calculated as $r_{t,i} = log(P_{t-1+i\Delta}) - log(P_{t-1+(i-1)\Delta})$ [7]

Barndorff-Nielsen & Shephard (2002) and Bollerslev et al. (2016) state that according to the asymptotic distribution theory the consistency of the realized estimators depend on the intraday sampling frequency, or number of partitions. In theory, the approximations of integrated variation and realized variance is sustained by infinite partitions, but in the empirical estimations M is limited. The resulting error between two are given as,

$$RV_t = IV_t + \eta_t,\ \eta_t \sim MN(0, 2\Delta IQ_t). \tag{4.11}$$

[7]I provide more theoretical foundations on realized variance indicators and high frequency distribution in Chapter 2

The integrated quarticity (IQ) is obtained by $IQ_t \equiv \int_{t-1}^{t} \sigma_s^4 ds$. This indicator can also be consistently estimated by the realized quarticity (RQ) under the sufficient number of intraday partitions.

$$RQ_t = \frac{M}{3} \sum_{M}^{i} r_{t,i}^4, \tag{4.12}$$

In this study, the aim is to show the relationship between the bond market and equity market volatility by controlling the different episodes of yield curve shifts. In Table 4.2, I give the descriptive statistics on not the raw data but the volatility's for the markets. I computed the volatility ($RV^{1/2}$) by the sum of squared returns for both the equity markets and the shape factors of the yield curve, separately.

4.4.2 Empirical models

In the HAR model of Corsi (2009), it is assumed that the heterogeneous markets hypothesis (HMH), which depends on market participants' non-homogeneity in terms of expectations and behavior, is valid. Therefore, the general pattern of volatility structure can be generated from three different frequencies. The high-frequency component for short-term traders is reflected by daily volatility, for medium-term traders by weekly volatility, and for investors focusing on long-term trends by monthly volatility. Although the HAR structure does not externally impose long memory in the volatility process, the cascade type model generates slow decaying memory for the forecast horizons. To

Table 4.2: Descriptive Statistics

	Switzerland				Germany			
	$RV^{1/2}_{equity}$	$RV^{1/2}_{level}$	$RV^{1/2}_{slope}$	$RV^{1/2}_{curvature}$	$RV^{1/2}_{equity}$	$RV^{1/2}_{level}$	$RV^{1/2}_{slope}$	$RV^{1/2}_{curvature}$
Mean	7.2%	1.8%	1.9%	1.3%	9.1%	1.8%	1.9%	1.3%
Median	6.0%	1.4%	1.2%	0.9%	7.8%	1.4%	1.2%	0.9%
St. Dev.	0.043	0.015	0.020	0.012	0.055	0.015	0.020	0.012
Min	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Max	64.7%	23.1%	27.3%	14.9%	73.7%	23.1%	27.3%	14.9%
Skewness	3.662	3.692	4.097	3.701	3.285	3.692	4.097	3.701
Kurtosis	26.946	30.006	32.867	26.192	23.526	30.006	32.867	26.192

	France				United Kingdom			
	$RV^{1/2}_{equity}$	$RV^{1/2}_{level}$	$RV^{1/2}_{slope}$	$RV^{1/2}_{curvature}$	$RV^{1/2}_{equity}$	$RV^{1/2}_{level}$	$RV^{1/2}_{slope}$	$RV^{1/2}_{curvature}$
Mean	7.2%	1.8%	1.9%	1.3%	9.1%	1.8%	1.9%	1.3%
Median	6.0%	1.4%	1.2%	0.9%	7.8%	1.4%	1.2%	0.9%
St. Dev.	0.043	0.015	0.020	0.012	0.055	0.015	0.020	0.012
Min	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Max	64.7%	23.1%	27.3%	14.9%	73.7%	23.1%	27.3%	14.9%
Skewness	3.662	3.692	4.097	3.701	3.285	3.692	4.097	3.701
Kurtosis	26.946	30.006	32.867	26.192	23.526	30.006	32.867	26.192

(1) The descriptive statistics are given for daily equity market and, bond markets' shape factors volatility. (2) Mean, median, minimum, and maximum statistics are given in percentage units. (3) The estimation period is between January 2015 and October 2019.

represent weekly and monthly trends, I use simple averages as below.

$$RV_{t_1:t_2} = \frac{1}{t_2 - t_1 + 1} \sum_{t=t_1}^{t_2} RV_t, \; where \; t_1 \leqslant t_2. \tag{4.13}$$

Then, weekly and monthly averages[8] are given in the Eq. (4.14) below:

$$RV_{t-5:t-2} = \frac{1}{4} \sum_{t=t-5}^{t-2} RV_t, \tag{4.14}$$

[8] I prefer to use non-coinciding periods in the HAR variables to avoid double counting lagged observations.

$$RV_{t-22:t-6} = \frac{1}{17} \sum_{t=t-22}^{t-6} RV_t. \tag{4.15}$$

Although. the seminal work of Corsi (2009) is able to cover short-term to long-term dynamics in volatility structure, using intraday data is prone to microstructure noise and forecasts are subject to measurement error. In order to alleviate these weaknesses, Bollerslev et al. (2016) introduce the HARQ model, which incorporates the realized quarticity into the HAR structure. Therefore, the coefficients of forecasting regression become time-varying which helps to reduce the estimation errors.

Then, HARQ-RV model [9] is given in Eq. (4.16):

$$RV_{t+h-1:t} = \beta_0 + \beta_d RV_{t-1} + \beta_{d1} RV_{t-1} * RQ_{t-1}^{1/2} + \beta_w RV_{t-5:t-2} + \beta_m RV_{t-22:t-6} + \epsilon_t, \tag{4.16}$$

where h corresponds to forecast horizon. I decompose the continuous and discontinuous part of RV using Barndorff-Nielsen & Shephard (2004) methodology. Then, I can employ extended HARQ models such as HARQ-RVJ model and HARQ-CJ model of Andersen, Bollerslev & Diebold (2007) with the discontinuous jump variations. The inclusion of jump parameters in the volatility forecasting regressions enable us to measure the possible magnitude of daily jumps on the future volatility and its significant life span

[9] For simplicity, I report the general form of HARQ model, while the estimations are conducted using realized volatility, $RV^{1/2}$, in exchange for realized variance, RV.

over the investment horizon.

I identify the significant jump series using jump ratio test of Huang & Tauchen (2005)[10]:

$$\hat{J}_t = I_{z_t > \psi_\alpha}(RV_t - BV_t)^+, \tag{4.17}$$

where ψ_α is the cumulative distribution function at α confidence level. In this paper, I choose $\alpha = 0.999$, which corresponds to a critical value of 3.0902. In addition $(RV_t - BV_t)^+$ stands for $\max(0, RV_t - BV_t)$ and $I_{z_t > \psi_\alpha}$ is the indicator function that takes values of unity when there is a significant jump.

Then, the continuous part quadratic variation accounts for the significant jumps given in Eq. (4.18).

$$\hat{C}_t = RV_t - \hat{J}_t. \tag{4.18}$$

I also compute weekly, $\hat{C}_{t\,t-5:t-2}$, and monthly, $\hat{C}_{t\,t-22:t-6}$, continuous variation series, $\hat{C}_t$ similar to Eq. (4.14) and Eq. (4.15).

$$\hat{C}_{t-5:t-2} = \frac{1}{4}\sum_{t=t-5}^{t-2} \hat{C}_t, \tag{4.19}$$

[10] I provide more detailed information on jump identification in Chapter 2.

$$\hat{C}_{t-22:t-6} = \frac{1}{17} \sum_{t=t-22}^{t-6} \hat{C}_t. \tag{4.20}$$

Therefore, it becomes natural to extend the HAR-RV model to include the effect of continuous and jump variation separately.

HARQ-RVJ model:

$$RV_{t+h-1:t} = \beta_0 + \beta_d RV_{t-1} + \beta_{d1} RV_{t-1} * RQ_{t-1}^{1/2} + \beta_w RV_{t-5:t-2} + \beta_m RV_{t-22:t-6} + \beta_j \hat{J}_{t-1} + \epsilon_t. \tag{4.21}$$

HARQ-CJ model:

$$RV_{t+h-1:t} = \beta_0 + \beta_d \hat{C}_{t-1} + \beta_{d1} C_{t-1} * RQ_{t-1}^{1/2} + \beta_w \hat{C}_{t-5:t-2} + \beta_m \hat{C}_{t-22:t-6} + \beta_j \hat{J}_{t-1} + \epsilon_t. \tag{4.22}$$

In the tables 4.3 to 4.14, I use following models that incorporates one-day lag of RV. Encompassing model with yield curve factors (HARQ-RV-YC model):

$$\begin{aligned} RV_{t+h-1:t} = \beta_0 &+ \sum_{i=1}^{4} \beta_{l_i} sd_{level,t-1} I_i + \sum_{i=1}^{4} \beta_{s_i} sd_{slope,t-1} I_i + \sum_{i=1}^{4} \beta_{c_i} sd_{curvature,t-1} I_i \\ &+\beta_d RV_{t-1} + \beta_{d1} RV_{t-1} * RQ_{t-1}^{1/2} + \beta_w RV_{t-5:t-2} + \beta_m RV_{t-22:t-6} + \epsilon_t, \end{aligned} \tag{4.23}$$

Encompassing model with yield curve factors (HARQ-RVJ-YC model):

$$RV_{t+h-1:t} = \beta_0 + \sum_{i=1}^{4} \beta_{l_i} sd_{level,t-1} I_i + \sum_{i=1}^{4} \beta_{s_i} sd_{slope,t-1} I_i + \sum_{i=1}^{4} \beta_{c_i} sd_{curvature,t-1} I_i$$
$$+\beta_d RV_{t-1} + \beta_{d1} RV_{t-1} * RQ_{t-1}^{1/2} + \beta_w RV_{t-5:t-2} + \beta_m RV_{t-22:t-6} + \beta_j \hat{J}_{t-1} + \epsilon_t, \tag{4.24}$$

Encompassing model with yield curve factors (HARQ-CJ-YC model):

$$RV_{t+h-1:t} = \beta_0 + \sum_{i=1}^{4} \beta_{l_i} sd_{level,t-1} I_i + \sum_{i=1}^{4} \beta_{s_i} sd_{slope,t-1} I_i + \sum_{i=1}^{4} \beta_{c_i} sd_{curvature,t-1} I_i$$
$$+\beta_d \hat{C}_{t-1} + \beta_{d1} C_{t-1} * RQ_{t-1}^{1/2} + \beta_w \hat{C}_{t-5:t-2} + \beta_m \hat{C}_{t-22:t-6} + \beta_j \hat{J}_{t-1} + \epsilon_t, \tag{4.25}$$

where sd_k, $k = [level, slope, curvature]$ shows the volatility of intraday sovereign bond yield curves. Also I_1 is the indicator function showing bear flattener yield curve,$\Delta level > 0$, $\Delta slope < 0$, I_2 is the indicator function showing bear steepener yield curve,$\Delta level > 0$, $\Delta slope > 0$, I_3 is the indicator function showing bull flattener yield curve,$\Delta level < 0$, $\Delta slope < 0$, and I_4 is the indicator function showing bull steepener yield curve, $\Delta level < 0$, $\Delta slope > 0$,.

4.5 Empirical analysis

4.5.1 In Sample Results

Tables 4.3 to 4.26 give the in-sample forecasting results that help us to test for the validity of volatility transmission from bond markets to stock markets framework. In the tables 4.3 to 4.14, I use following models that incorporates one-day lag of RV, $t-1$, while In the Tables 4.15 to 4.26, I use following models that incorporates two-day lag of RV, $t-2$ instead of one-day lag of RV. Since the effect of bond market shape factors can be captured by the daily lag of realized stock market volatility, two day lagged RV results are also given.

According to the volatility incorporated dividend growth model, I expect that β_{k_1} to be the weakest positively significant or strongest negatively significant, while β_{i_4} to be the strongest positively significant or weakest negatively significant coefficients for $k = [l, s, c]$. The results verify my theory that the bear flattening is the better environment for stock market volatility, while bull steepener is the worst plausible environment for the equity market volatility. This result is quite striking since it indicates that decreasing interest rates cause the stock market volatility to increase, and vice versa.

The empirical results are in line with the extended dividend growth model in Section 4.3 since the bear flattener moves contribution to the equity volatility is, generally, negative and insignificant. In addition, the positive coefficient is observed when the move is bull steepener.

Moreover, the sample forecasting results show that the volatility in the curvature of the yield curve helps stock market volatility to be tamed, especially when the yield curve shifts in a bear flattener move. This relationship fades away as the forecasting horizon increases.

4.5.2 Out of Sample Results

In this section, I provide the out-of-sample forecasting results of forecasting models. In comparing the forecasts using different models, I use the Diebold & Mariano (1995) test. I provide 200-day out-of-sample forecasting results for the models in 1-day, 5-day, and 22-day forecasting horizons. The results indicate that the inclusion of yield curve factors as explanatory variables for the HARQ models improves both in-sample and out-of-sample forecasting power. While, the baseline HARQ models, models without yield curve volatility indicators, bring better forecast to result in some cases, these findings are limited.

4.6 Conclusion

In this study, I aim to test whether the inclusion of yield curve volatility improves the stock market volatility forecasting. Using the foundations of the dividend growth model, I extend the model in order to incorporate and relate the shape of the yield curve that affects the transmission from bond markets to equity markets volatility. Strikingly, I

Table 4.3: Swiss Market (h=1)

	HAR-RV					HAR-RVJ					HAR-CJ				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
β_0	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
	(0.9)	(0.94)	(0.95)	(0.86)	(0.86)	(1.11)	(1.17)	(1.16)	(1.1)	(1.06)	(0.95)	(0.99)	(0.98)	(0.91)	(0.89)
β_{l1}	—	-0.18	—	—	-0.04	—	-0.18	—	—	-0.04	—	-0.18	—	—	-0.04
	—	(-1.25)	—	—	(-0.21)	—	(-1.3)	—	—	(-0.24)	—	(-1.31)	—	—	(-0.23)
β_{l2}	—	0.03	—	—	-0.15	—	0.02	—	—	-0.15	—	0.03	—	—	-0.14
	—	(0.28)	—	—	(-1.33)	—	(0.23)	—	—	(-1.3)	—	(0.26)	—	—	(-1.22)
β_{l3}	—	0.20	—	—	-0.13	—	0.21	—	—	-0.13	—	0.21	—	—	-0.14
	—	(1.57)	—	—	(-0.7)	—	(1.58)	—	—	(-0.7)	—	(1.56)	—	—	(-0.73)
β_{l4}	—	0.20	—	—	0.49	—	0.19	—	—	0.50	—	0.19	—	—	0.50
	—	(1.36)	—	—	(1.87)*	—	(1.34)	—	—	(1.9)*	—	(1.34)	—	—	(1.88)*
β_{s1}	—	—	-0.13	—	-0.10	—	—	-0.13	—	-0.10	—	—	-0.14	—	-0.10
	—	—	(-1.21)	—	(-0.59)	—	—	(-1.26)	—	(-0.59)	—	—	(-1.26)	—	(-0.61)
β_{s2}	—	—	0.09	—	0.24	—	—	0.08	—	0.23	—	—	0.09	—	0.22
	—	—	(0.88)	—	(1.65)*	—	—	(0.8)	—	(1.57)	—	—	(0.81)	—	(1.51)
β_{s3}	—	—	0.27	—	0.39	—	—	0.28	—	0.40	—	—	0.28	—	0.41
	—	—	(2.03)**	—	(1.96)*	—	—	(2.03)**	—	(1.96)*	—	—	(2.03)**	—	(2)**
β_{s4}	—	—	0.11	—	-0.23	—	—	0.10	—	-0.24	—	—	0.10	—	-0.24
	—	—	(1.38)	—	(-1.45)	—	—	(1.34)	—	(-1.53)	—	—	(1.34)	—	(-1.5)
β_{c1}	—	—	—	-0.35	—	—	—	—	-0.36	—	—	—	—	-0.35	—
	—	—	—	(-1.99)**	—	—	—	—	(-2.05)**	—	—	—	—	(-2)**	—
β_{c2}	—	—	—	-0.07	—	—	—	—	-0.08	—	—	—	—	-0.06	—
	—	—	—	(-0.6)	—	—	—	—	(-0.78)	—	—	—	—	(-0.6)	—
β_{c3}	—	—	—	0.16	—	—	—	—	0.16	—	—	—	—	0.17	—
	—	—	—	(1.29)	—	—	—	—	(1.29)	—	—	—	—	(1.36)	—
β_{c4}	—	—	—	-0.04	—	—	—	—	-0.05	—	—	—	—	-0.04	—
	—	—	—	(-0.34)	—	—	—	—	(-0.42)	—	—	—	—	(-0.36)	—
β_d	0.59	0.58	0.58	0.58	0.58	0.57	0.56	0.56	0.57	0.56	0.60	0.58	0.59	0.59	0.59
	(7.85)***	(7.58)***	(7.71)***	(7.82)***	(7.63)***	(7.76)***	(7.41)***	(7.58)***	(7.75)***	(7.44)***	(7.84)***	(7.52)***	(7.69)***	(7.83)***	(7.57)***
β_{d1}	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
	(-1.67)*	(-1.52)	(-1.52)	(-1.62)	(-1.58)	(-1.51)	(-1.34)	(-1.34)	(-1.44)	(-1.39)	(-1.73)*	(-1.57)	(-1.57)	(-1.68)*	(-1.62)
β_w	0.29	0.29	0.29	0.29	0.29	0.29	0.29	0.29	0.29	0.29	0.28	0.28	0.28	0.28	0.28
	(6.12)***	(6.06)***	(6.12)***	(6.29)***	(6.12)***	(6.13)***	(6.08)***	(6.14)***	(6.32)***	(6.15)***	(5.85)***	(5.8)***	(5.86)***	(6.03)***	(5.86)***
β_m	0.11	0.11	0.11	0.12	0.10	0.11	0.11	0.11	0.12	0.11	0.11	0.11	0.11	0.12	0.11
	(3.08)***	(2.95)***	(2.72)***	(3.22)***	(2.68)***	(3.28)***	(3.19)***	(2.95)***	(3.48)***	(2.92)***	(3.31)***	(3.24)***	(2.99)***	(3.5)***	(2.96)***
β_j	—	—	—	—	—	0.09	0.09	0.09	0.09	0.09	0.24	0.24	0.24	0.25	0.25
	—	—	—	—	—	(0.91)	(0.96)	(0.95)	(0.96)	(0.99)	(2.6)***	(2.65)***	(2.63)***	(2.66)***	(2.69)***
R^2	69%	69%	69%	69%	69%	69%	69%	69%	69%	69%	69%	69%	69%	69%	69%
QLIKE	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06
J-R^2	73%	73%	73%	72%	73%	72%	72%	72%	72%	72%	73%	73%	73%	73%	73%
J-QLIKE	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
C-R^2	69%	69%	69%	69%	69%	69%	69%	69%	69%	69%	69%	69%	69%	69%	69%
C-QLIKE	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06

Table 4.4: German Market (h=1)

	HAR-RV					HAR-RVJ					HAR-CJ				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
β_0	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
	(1.68)*	(1.84)*	(1.75)*	(1.68)*	(1.82)*	(1.56)	(1.72)*	(1.64)	(1.57)	(1.69)*	(1.67)*	(1.83)*	(1.74)*	(1.68)*	(1.8)*
β_{l1}	—	-0.32	—	—	-0.25	—	-0.31	—	—	-0.23	—	-0.32	—	—	-0.23
	—	(-1.91)*	—	—	(-0.95)	—	(-1.91)*	—	—	(-0.93)	—	(-1.97)**	—	—	(-0.94)
β_{l2}	—	-0.04	—	—	-0.19	—	-0.04	—	—	-0.17	—	-0.04	—	—	-0.18
	—	(-0.35)	—	—	(-1.18)	—	(-0.36)	—	—	(-1.05)	—	(-0.41)	—	—	(-1.11)
β_{l3}	—	0.21	—	—	-0.12	—	0.22	—	—	-0.10	—	0.22	—	—	-0.10
	—	(1.76)*	—	—	(-0.52)	—	(1.86)*	—	—	(-0.42)	—	(1.82)*	—	—	(-0.45)
β_{l4}	—	0.20	—	—	0.46	—	0.21	—	—	0.46	—	0.19	—	—	0.44
	—	(1.25)	—	—	(1.95)*	—	(1.31)	—	—	(1.96)**	—	(1.22)	—	—	(1.89)*
β_{s1}	—	—	-0.22	—	-0.06	—	—	-0.21	—	-0.06	—	—	-0.22	—	-0.07
	—	—	(-1.63)	—	(-0.25)	—	—	(-1.63)	—	(-0.27)	—	—	(-1.67)*	—	(-0.29)
β_{s2}	—	—	0.04	—	0.21	—	—	0.03	—	0.17	—	—	0.03	—	0.18
	—	—	(0.32)	—	(1)	—	—	(0.2)	—	(0.84)	—	—	(0.2)	—	(0.87)
β_{s3}	—	—	0.28	—	0.38	—	—	0.29	—	0.36	—	—	0.29	—	0.37
	—	—	(1.94)*	—	(1.37)	—	—	(1.96)*	—	(1.34)	—	—	(1.96)**	—	(1.36)
β_{s4}	—	—	0.12	—	-0.20	—	—	0.13	—	-0.20	—	—	0.12	—	-0.19
	—	—	(1.05)	—	(-1.1)	—	—	(1.05)	—	(-1.07)	—	—	(1)	—	(-1.06)
β_{c1}	—	—	—	-0.49	—	—	—	—	-0.48	—	—	—	—	-0.49	—
	—	—	—	(-2.15)**	—	—	—	—	(-2.16)**	—	—	—	—	(-2.2)**	—
β_{c2}	—	—	—	-0.08	—	—	—	—	-0.09	—	—	—	—	-0.10	—
	—	—	—	(-0.57)	—	—	—	—	(-0.67)	—	—	—	—	(-0.69)	—
β_{c3}	—	—	—	0.15	—	—	—	—	0.16	—	—	—	—	0.15	—
	—	—	—	(1.11)	—	—	—	—	(1.12)	—	—	—	—	(1.1)	—
β_{c4}	—	—	—	0.06	—	—	—	—	0.06	—	—	—	—	0.05	—
	—	—	—	(0.32)	—	—	—	—	(0.33)	—	—	—	—	(0.25)	—
β_d	0.53	0.52	0.52	0.52	0.52	0.56	0.55	0.55	0.56	0.55	0.58	0.57	0.57	0.57	0.57
	(7.6)***	(7.49)***	(7.62)***	(7.58)***	(7.58)***	(7.88)***	(7.82)***	(7.94)***	(7.9)***	(7.93)***	(8.14)***	(8.09)***	(8.22)***	(8.16)***	(8.2)***
β_{d1}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(-0.33)	(-0.2)	(-0.23)	(-0.24)	(-0.2)	(-0.79)	(-0.68)	(-0.71)	(-0.7)	(-0.68)	(-0.98)	(-0.88)	(-0.9)	(-0.9)	(-0.88)
β_w	0.26	0.27	0.27	0.27	0.27	0.25	0.26	0.26	0.26	0.26	0.25	0.25	0.25	0.25	0.25
	(4.28)***	(4.48)***	(4.54)***	(4.67)***	(4.58)***	(4.26)***	(4.46)***	(4.52)***	(4.65)***	(4.57)***	(4.04)***	(4.24)***	(4.3)***	(4.43)***	(4.34)***
β_m	0.15	0.15	0.14	0.15	0.14	0.14	0.14	0.14	0.15	0.14	0.15	0.14	0.14	0.15	0.14
	(4.39)***	(4.09)***	(3.9)***	(4.36)***	(3.94)***	(4.25)***	(3.94)***	(3.74)***	(4.22)***	(3.78)***	(4.25)***	(3.96)***	(3.77)***	(4.24)***	(3.81)***
β_j	—	—	—	—	—	-0.15	-0.15	-0.15	-0.14	-0.14	0.03	0.03	0.03	0.03	0.03
	—	—	—	—	—	(-3.26)***	(-3.39)***	(-3.35)***	(-3.31)***	(-3.36)***	(0.82)	(0.78)	(0.78)	(0.87)	(0.82)
R^2	68%	69%	69%	69%	69%	69%	69%	69%	69%	69%	69%	69%	69%	69%	69%
QLIKE	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06
J-R^2	57%	58%	58%	58%	58%	58%	59%	59%	59%	59%	59%	61%	61%	61%	61%
J-QLIKE	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09
C-R^2	70%	70%	70%	70%	70%	70%	70%	70%	70%	70%	70%	70%	70%	70%	70%
C-QLIKE	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.0

Table 4.5: French Market (h=1)

	HAR-RV					HAR-RVJ					HAR-CJ				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
β_0	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.01	-0.02	-0.01	-0.01	-0.02	-0.01
	(0.5)	(0.41)	(0.76)	(0.37)	(0.58)	(0.37)	(0.27)	(0.66)	(0.22)	(0.46)	(-0.95)	(-0.66)	(-0.42)	(-0.9)	(-0.53)
β_{l1}	—	0.11	—	—	-0.07	—	0.14	—	—	-0.03	—	0.10	—	—	-0.06
	—	(0.45)	—	—	(-0.22)	—	(0.54)	—	—	(-0.1)	—	(0.38)	—	—	(-0.18)
β_{l2}	—	-0.14	—	—	-0.14	—	-0.13	—	—	-0.13	—	-0.15	—	—	-0.15
	—	(-1.6)	—	—	(-1.05)	—	(-1.52)	—	—	(-1.03)	—	(-1.68)*	—	—	(-1.19)
β_{l3}	—	0.18	—	—	0.26	—	0.19	—	—	0.29	—	0.18	—	—	0.27
	—	(1.24)	—	—	(1.04)	—	(1.31)	—	—	(1.14)	—	(1.2)	—	—	(1.06)
β_{l4}	—	0.39	—	—	0.67	—	0.39	—	—	0.68	—	0.35	—	—	0.61
	—	(2.17)**	—	—	(2.34)***	—	(2.18)**	—	—	(2.43)***	—	(1.87)*	—	—	(2.16)**
β_{s1}	—	—	0.15	—	0.34	—	—	0.17	—	0.31	—	—	0.10	—	0.27
	—	—	(0.43)	—	(1.13)	—	—	(0.47)	—	(1.02)	—	—	(0.3)	—	(0.88)
β_{s2}	—	—	-0.33	—	-0.05	—	—	-0.33	—	-0.05	—	—	-0.34	—	-0.05
	—	—	(-2.43)***	—	(-0.25)	—	—	(-2.47)***	—	(-0.26)	—	—	(-2.57)***	—	(-0.24)
β_{s3}	—	—	0.13	—	-0.20	—	—	0.12	—	-0.23	—	—	0.11	—	-0.23
	—	—	(0.74)	—	(-0.54)	—	—	(0.7)	—	(-0.63)	—	—	(0.66)	—	(-0.64)
β_{s4}	—	—	0.40	—	-0.61	—	—	0.37	—	-0.65	—	—	0.32	—	-0.60
	—	—	(1.49)	—	-1.30	—	—	(1.4)	—	-1.38	—	—	(1.18)	—	-1.31
β_{c1}	—	—	—	0.00	—	—	—	—	0.05	—	—	—	—	0.01	—
	—	—	—	(0)	—	—	—	—	(0.19)	—	—	—	—	(0.03)	—
β_{c2}	—	—	—	-0.18	—	—	—	—	-0.18	—	—	—	—	-0.16	—
	—	—	—	(-1.42)	—	—	—	—	(-1.38)	—	—	—	—	(-1.25)	—
β_{c3}	—	—	—	0.33	—	—	—	—	0.35	—	—	—	—	0.37	—
	—	—	—	(1.58)	—	—	—	—	(1.67)*	—	—	—	—	(1.9)*	—
β_{c4}	—	—	—	0.35	—	—	—	—	0.34	—	—	—	—	0.30	—
	—	—	—	(1.54)	—	—	—	—	(1.51)	—	—	—	—	(1.38)	—
β_d	0.62	0.60	0.61	0.61	0.60	0.65	0.62	0.63	0.64	0.62	0.70	0.68	0.69	0.70	0.68
	(12.11)***	(12.56)***	(12.66)***	(12.37)***	(12.6)***	(12.22)***	(12.73)***	(12.77)***	(12.45)***	(12.8)***	(14.27)***	(13.65)***	(14.44)***	(14.42)***	(13.65)***
β_{d1}	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
	(-2.82)***	(-2.85)***	(-2.73)***	(-2.8)***	(-2.77)***	(-3.24)***	(-3.3)***	(-3.17)***	(-3.2)***	(-3.21)***	(-5.98)***	(-5.96)***	(-5.85)***	(-5.82)***	(-6.02)***
β_w	0.28	0.29	0.29	0.29	0.28	0.28	0.28	0.28	0.28	0.28	0.30	0.31	0.31	0.30	0.31
	(5.27)***	(5.26)***	(5.42)***	(5.42)***	(5.15)***	(5.13)***	(5.15)***	(5.31)***	(5.32)***	(5.05)***	(6.14)***	(6.1)***	(6.29)***	(6.29)***	(6.01)***
β_m	0.11	0.11	0.11	0.11	0.11	0.11	0.10	0.10	0.10	0.11	0.08	0.07	0.08	0.08	0.08
	(3.71)***	(3.71)***	(3.62)***	(3.62)***	(3.88)***	(3.42)***	(3.43)***	(3.37)***	(3.35)***	(3.61)***	(3.71)***	(3.14)***	(3.49)***	(3.58)***	(3.45)***
β_j	—	—	—	—	—	-0.14	-0.14	-0.14	-0.14	-0.14	0.05	0.04	0.05	0.04	0.04
	—	—	—	—	—	(-3.47)***	(-3.43)***	(-3.43)***	(-3.43)***	(-3.47)***	(1.31)	(1.1)	(1.28)	(1.23)	(1.04)
R^2	78%	78%	78%	78%	78%	78%	78%	78%	78%	78%	78%	78%	78%	78%	78%
QLIKE	0.23	0.15	0.27	0.46	0.20	0.21	0.25	0.26	0.12	0.22	0.36	0.35	0.37	0.36	0.84
J-R^2	67%	67%	67%	67%	67%	68%	68%	68%	68%	68%	68%	68%	68%	68%	68%
J-QLIKE	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04
C-R^2	79%	79%	79%	79%	79%	79%	79%	79%	79%	79%	79%	79%	79%	79%	79%
C-QLIKE	0.21	0.26	0.33	0.28	0.26	0.16	0.29	0.29	0.17	0.27	0.36	0.41	0.30	0.36	0.39

Table 4.6: UK Market (h=1)

	HAR-RV					HAR-RVJ					HAR-CJ				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
β_0	0.03	0.03	0.03	0.03	0.03	0.03	0.04	0.04	0.04	0.04	0.03	0.04	0.04	0.03	0.04
	(1.4)	(1.23)	(1.17)	(1.39)	(1.21)	(2.27)**	(2.09)**	(2.09)**	(2.28)**	(2.13)**	(1.59)	(1.48)	(1.49)	(1.57)	(1.52)
β_{l1}	—	0.12	—	—	-0.02	—	0.06	—	—	0.03	—	0.01	—	—	-0.02
	—	(1.16)	—	—	(-0.15)	—	(0.62)	—	—	(0.17)	—	(0.15)	—	—	(-0.13)
β_{l2}	—	0.07	—	—	-0.09	—	0.00	—	—	-0.13	—	0.00	—	—	-0.12
	—	(0.55)	—	—	(-0.85)	—	(0.04)	—	—	(-1.34)	—	(0)	—	—	(-1.22)
β_{l3}	—	0.18	—	—	0.29	—	0.14	—	—	0.26	—	0.14	—	—	0.27
	—	(1.54)	—	—	(1.88)*	—	(1.27)	—	—	(1.73)*	—	(1.33)	—	—	(1.81)*
β_{l4}	—	0.38	—	—	0.67	—	0.31	—	—	0.62	—	0.28	—	—	0.58
	—	(2.21)**	—	—	(2.92)***	—	(1.83)*	—	—	(2.56)***	—	(1.63)	—	—	(2.29)**
β_{s1}	—	—	0.11	—	0.23	—	—	-0.02	—	0.03	—	—	-0.08	—	0.03
	—	—	(0.75)	—	(1.02)	—	—	(-0.12)	—	(0.14)	—	—	(-0.54)	—	(0.12)
β_{s2}	—	—	0.04	—	0.27	—	—	-0.06	—	0.21	—	—	-0.07	—	0.18
	—	—	(0.26)	—	(1.46)	—	—	(-0.4)	—	(1.46)	—	—	(-0.53)	—	(1.26)
β_{s3}	—	—	0.12	—	-0.20	—	—	0.05	—	-0.24	—	—	0.04	—	-0.26
	—	—	(0.7)	—	(-0.9)	—	—	(0.32)	—	(-1.05)	—	—	(0.29)	—	(-1.12)
β_{s4}	—	—	0.31	—	-0.49	—	—	0.20	—	-0.54	—	—	0.16	—	-0.53
	—	—	(1.2)	—	(-1.4)	—	—	(0.74)	—	(-1.41)	—	—	(0.55)	—	(-1.3)
β_{c1}	—	—	—	0.04	—	—	—	—	-0.01	—	—	—	—	-0.06	—
	—	—	—	(0.36)	—	—	—	—	(-0.11)	—	—	—	—	(-0.56)	—
β_{c2}	—	—	—	0.02	—	—	—	—	-0.01	—	—	—	—	-0.02	—
	—	—	—	(0.25)	—	—	—	—	(-0.18)	—	—	—	—	(-0.31)	—
β_{c3}	—	—	—	0.08	—	—	—	—	0.07	—	—	—	—	0.07	—
	—	—	—	(0.87)	—	—	—	—	(0.72)	—	—	—	—	(0.72)	—
β_{c4}	—	—	—	0.31	—	—	—	—	0.27	—	—	—	—	0.23	—
	—	—	—	(1.55)	—	—	—	—	(1.3)	—	—	—	—	(1.07)	—
β_d	0.53	0.50	0.52	0.53	0.50	0.57	0.55	0.57	0.57	0.55	0.53	0.51	0.53	0.53	0.51
	(10.4)***	(10.23)***	(10.46)***	(10.46)***	(10.12)***	(10.05)***	(9.97)***	(10.33)***	(10.25)***	(9.75)***	(7.51)***	(7.42)***	(7.73)***	(7.63)***	(7.25)***
β_{d1}	-0.01	-0.01	-0.01	-0.01	-0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(-2.8)***	(-2.39)***	(-2.6)***	(-2.64)***	(-2.44)***	(-0.69)	(-0.35)	(-0.61)	(-0.61)	(-0.35)	(0.11)	(0.46)	(0.23)	(0.21)	(0.46)
β_w	0.30	0.30	0.30	0.30	0.30	0.29	0.28	0.28	0.28	0.29	0.40	0.40	0.40	0.40	0.40
	(6.43)***	(6.09)***	(6.14)***	(6.17)***	(5.98)***	(4.93)***	(4.73)***	(4.73)***	(4.75)***	(4.65)***	(4.84)***	(4.65)***	(4.62)***	(4.66)***	(4.55)***
β_m	0.15	0.14	0.14	0.14	0.14	0.11	0.11	0.11	0.11	0.11	0.04	0.04	0.04	0.04	0.04
	(3.86)***	(3.73)***	(3.8)***	(3.87)***	(3.71)***	(3.49)***	(3.32)***	(3.43)***	(3.47)***	(3.29)***	(1.92)*	(1.67)*	(1.91)*	(1.88)*	(1.73)*
β_j	—	—	—	—	—	-0.28	-0.28	-0.28	-0.28	-0.28	-0.06	-0.06	-0.06	-0.06	-0.06
	—	—	—	—	—	(-5.91)***	(-5.93)***	(-5.88)***	(-5.89)***	(-5.92)***	(-1.44)	(-1.52)	(-1.45)	(-1.44)	(-1.56)
R^2	65%	65%	65%	65%	65%	66%	67%	66%	66%	67%	67%	67%	67%	67%	67%
QLIKE	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
J-R^2	81%	81%	81%	81%	81%	82%	83%	83%	83%	83%	84%	84%	84%	84%	84%
J-QLIKE	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
C-R^2	64%	64%	64%	64%	64%	64%	64%	64%	64%	65%	64%	65%	64%	64%	65%
C-QLIKE	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03

Table 4.7: Swiss Market (h=5)

	HAR-RV					HAR-RVJ					HAR-CJ				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
β_0	0.04	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
	(1.79)*	(1.9)*	(1.97)**	(1.88)*	(2.06)**	(2.05)**	(2.18)**	(2.24)**	(2.18)**	(2.34)***	(2)**	(2.11)**	(2.18)**	(2.1)**	(2.27)**
β_{l1}	—	-0.12	—	—	-0.14	—	-0.12	—	—	-0.14	—	-0.12	—	—	-0.13
	—	(-1.24)	—	—	(-1.07)	—	(-1.28)	—	—	(-1.11)	—	(-1.24)	—	—	(-1.06)
β_{l2}	—	0.03	—	—	-0.26	—	0.03	—	—	-0.25	—	0.03	—	—	-0.24
	—	(0.35)	—	—	(-1.64)	—	(0.3)	—	—	(-1.64)	—	(0.36)	—	—	(-1.56)
β_{l3}	—	0.10	—	—	-0.13	—	0.11	—	—	-0.13	—	0.11	—	—	-0.13
	—	(1.16)	—	—	(-0.66)	—	(1.18)	—	—	(-0.66)	—	(1.22)	—	—	(-0.67)
β_{l4}	—	0.22	—	—	0.28	—	0.22	—	—	0.29	—	0.22	—	—	0.29
	—	(2.18)**	—	—	(1.8)*	—	(2.16)**	—	—	(1.82)*	—	(2.18)**	—	—	(1.8)*
β_{s1}	—	—	-0.04	—	0.04	—	—	-0.04	—	0.04	—	—	-0.04	—	0.04
	—	—	(-0.54)	—	(0.38)	—	—	(-0.58)	—	(0.39)	—	—	(-0.57)	—	(0.35)
β_{s2}	—	—	0.17	—	0.39	—	—	0.16	—	0.38	—	—	0.16	—	0.37
	—	—	(1.56)	—	(1.86)*	—	—	(1.56)	—	(1.89)*	—	—	(1.59)	—	(1.86)*
β_{s3}	—	—	0.19	—	0.29	—	—	0.20	—	0.29	—	—	0.20	—	0.30
	—	—	(2.1)**	—	(1.45)	—	—	(2.09)**	—	(1.46)	—	—	(2.12)**	—	(1.49)
β_{s4}	—	—	0.18	—	-0.02	—	—	0.18	—	-0.04	—	—	0.18	—	-0.03
	—	—	(2.03)**	—	(-0.18)	—	—	(2)**	—	(-0.26)	—	—	(2.01)**	—	(-0.22)
β_{c1}	—	—	—	-0.28	—	—	—	—	-0.28	—	—	—	—	-0.27	—
	—	—	—	(-2.4)***	—	—	—	—	(-2.43)***	—	—	—	—	(-2.31)**	—
β_{c2}	—	—	—	-0.09	—	—	—	—	-0.10	—	—	—	—	-0.08	—
	—	—	—	(-0.79)	—	—	—	—	(-0.95)	—	—	—	—	(-0.76)	—
β_{c3}	—	—	—	-0.02	—	—	—	—	-0.02	—	—	—	—	-0.01	—
	—	—	—	(-0.22)	—	—	—	—	(-0.2)	—	—	—	—	(-0.08)	—
β_{c4}	—	—	—	0.04	—	—	—	—	0.03	—	—	—	—	0.04	—
	—	—	—	(0.26)	—	—	—	—	(0.21)	—	—	—	—	(0.26)	—
β_d	0.51	0.50	0.50	0.51	0.50	0.50	0.49	0.48	0.49	0.49	0.51	0.50	0.50	0.51	0.50
	(5.85)***	(5.61)***	(5.75)***	(5.81)***	(5.66)***	(6.05)***	(5.74)***	(5.9)***	(6.01)***	(5.76)***	(5.97)***	(5.67)***	(5.83)***	(5.93)***	(5.7)***
β_{d1}	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
	(-2.39)***	(-2.23)**	(-2.22)**	(-2.34)***	(-2.22)**	(-2.2)**	(-2.03)**	(-2.03)**	(-2.14)**	(-2.02)**	(-2.27)**	(-2.1)**	(-2.1)**	(-2.21)**	(-2.09)**
β_w	0.33	0.33	0.33	0.33	0.33	0.33	0.33	0.33	0.33	0.33	0.32	0.32	0.32	0.32	0.32
	(6.22)***	(6.14)***	(6.13)***	(6.32)***	(6.08)***	(6.33)***	(6.24)***	(6.23)***	(6.44)***	(6.18)***	(6.02)***	(5.94)***	(5.93)***	(6.11)***	(5.89)***
β_m	0.15	0.14	0.13	0.15	0.13	0.15	0.14	0.13	0.15	0.13	0.15	0.14	0.14	0.16	0.13
	(3.18)***	(3)***	(2.74)***	(3.26)***	(2.69)***	(3.33)***	(3.17)***	(2.9)***	(3.44)***	(2.85)***	(3.37)***	(3.21)***	(2.93)***	(3.47)***	(2.88)***
β_j	—	—	—	—	—	0.08	0.09	0.08	0.09	0.09	0.22	0.22	0.21	0.22	0.22
	—	—	—	—	—	(0.9)	(0.93)	(0.91)	(0.93)	(0.94)	(2.17)**	(2.2)**	(2.19)**	(2.2)**	(2.23)**
R^2	71%	71%	71%	71%	72%	71%	72%	72%	71%	72%	71%	71%	71%	71%	72%
QLIKE	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
J-R^2	66%	66%	67%	66%	67%	66%	66%	67%	66%	67%	66%	66%	67%	66%	67%
J-QLIKE	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
C-R^2	72%	73%	73%	73%	73%	72%	73%	73%	73%	73%	72%	73%	73%	72%	73%
C-QLIKE	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02

Table 4.8: German Market (h=5)

	HAR-RV					HAR-RVJ					HAR-CJ				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
β_0	0.07	0.07	0.07	0.07	0.08	0.07	0.07	0.07	0.07	0.08	0.07	0.07	0.08	0.08	0.08
	(2.25)**	(2.23)**	(2.39)***	(2.19)**	(2.56)***	(2.17)**	(2.16)**	(2.32)**	(2.12)**	(2.48)***	(2.4)***	(2.36)***	(2.52)***	(2.32)**	(2.69)***
β_{l1}	—	-0.18	—	—	-0.31	—	-0.17	—	—	-0.30	—	-0.18	—	—	-0.30
	—	(-1.57)	—	—	(-1.86)*	—	(-1.52)	—	—	(-1.83)*	—	(-1.63)	—	—	(-1.81)*
β_{l2}	—	0.04	—	—	-0.32	—	0.04	—	—	-0.30	—	0.04	—	—	-0.31
	—	(0.37)	—	—	(-1.49)	—	(0.37)	—	—	(-1.42)	—	(0.34)	—	—	(-1.47)
β_{l3}	—	0.20	—	—	-0.27	—	0.21	—	—	-0.25	—	0.21	—	—	-0.26
	—	(1.55)	—	—	(-0.94)	—	(1.63)	—	—	(-0.88)	—	(1.63)	—	—	(-0.89)
β_{l4}	—	0.27	—	—	0.31	—	0.28	—	—	0.31	—	0.26	—	—	0.30
	—	(2.13)**	—	—	(1.45)	—	(2.15)**	—	—	(1.44)	—	(2.02)**	—	—	(1.39)
β_{s1}	—	—	-0.05	—	0.14	—	—	-0.04	—	0.14	—	—	-0.05	—	0.12
	—	—	(-0.49)	—	(0.9)	—	—	(-0.45)	—	(0.9)	—	—	(-0.56)	—	(0.81)
β_{s2}	—	—	0.24	—	0.50	—	—	0.23	—	0.47	—	—	0.23	—	0.48
	—	—	(1.36)	—	(1.49)	—	—	(1.31)	—	(1.43)	—	—	(1.32)	—	(1.47)
β_{s3}	—	—	0.37	—	0.57	—	—	0.37	—	0.56	—	—	0.37	—	0.56
	—	—	(2.25)**	—	(1.63)	—	—	(2.29)**	—	(1.62)	—	—	(2.31)**	—	(1.63)
β_{s4}	—	—	0.25	—	0.01	—	—	0.25	—	0.01	—	—	0.24	—	0.01
	—	—	(2.05)**	—	(0.03)	—	—	(2.04)**	—	(0.05)	—	—	(1.95)*	—	(0.04)
β_{c1}	—	—	—	-0.33	—	—	—	—	-0.32	—	—	—	—	-0.34	—
	—	—	—	(-2.22)**	—	—	—	—	(-2.23)**	—	—	—	—	(-2.32)**	—
β_{c2}	—	—	—	-0.05	—	—	—	—	-0.06	—	—	—	—	-0.06	—
	—	—	—	(-0.34)	—	—	—	—	(-0.41)	—	—	—	—	(-0.45)	—
β_{c3}	—	—	—	0.12	—	—	—	—	0.12	—	—	—	—	0.12	—
	—	—	—	(0.69)	—	—	—	—	(0.7)	—	—	—	—	(0.7)	—
β_{c4}	—	—	—	0.16	—	—	—	—	0.16	—	—	—	—	0.14	—
	—	—	—	(0.94)	—	—	—	—	(0.94)	—	—	—	—	(0.83)	—
β_d	0.44	0.43	0.43	0.44	0.43	0.47	0.46	0.46	0.47	0.46	0.48	0.47	0.46	0.47	0.47
	(5.67)***	(5.67)***	(5.71)***	(5.66)***	(5.73)***	(5.92)***	(5.95)***	(5.99)***	(5.92)***	(6.02)***	(5.86)***	(5.88)***	(5.92)***	(5.87)***	(5.95)***
β_{d1}	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
	(-1.46)	(-1.36)	(-1.4)	(-1.37)	(-1.34)	(-1.83)*	(-1.74)*	(-1.79)*	(-1.73)*	(-1.72)*	(-1.98)**	(-1.88)*	(-1.92)*	(-1.87)*	(-1.85)*
β_w	0.31	0.31	0.30	0.31	0.31	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30
	(4.95)***	(5)***	(4.94)***	(5.12)***	(4.98)***	(4.95)***	(5)***	(4.93)***	(5.12)***	(4.98)***	(4.91)***	(4.97)***	(4.92)***	(5.1)***	(4.95)***
β_m	0.20	0.20	0.19	0.20	0.19	0.20	0.19	0.18	0.20	0.18	0.20	0.20	0.18	0.20	0.18
	(4.99)***	(4.72)***	(4.34)***	(5)***	(4.29)***	(4.98)***	(4.7)***	(4.31)***	(4.99)***	(4.26)***	(4.83)***	(4.58)***	(4.19)***	(4.85)***	(4.14)***
β_j	—	—	—	—	—	-0.11	-0.11	-0.11	-0.11	-0.11	0.03	0.03	0.03	0.03	0.03
	—	—	—	—	—	(-2.86)***	(-2.95)***	(-2.97)***	(-2.9)***	(-2.9)***	(0.89)	(0.81)	(0.84)	(0.93)	(0.92)
R^2	71%	71%	72%	71%	72%	71%	72%	72%	72%	72%	72%	72%	72%	72%	72%
QLIKE	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
J-R^2	63%	63%	63%	63%	64%	63%	64%	64%	64%	64%	65%	65%	65%	65%	65%
J-QLIKE	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
C-R^2	72%	72%	72%	72%	73%	72%	72%	72%	72%	73%	72%	73%	73%	72%	73%
C-QLIKE	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03

Table 4.9: French Market (h=5)

	HAR-RV					HAR-RVJ					HAR-CJ				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
β_0	0.03	0.03	0.03	0.02	0.03	0.03	0.03	0.03	0.02	0.03	0.00	0.00	0.00	-0.01	0.00
	(2.68)***	(1.98)**	(2.07)**	(1.9)*	(1.86)*	(2.48)***	(1.78)*	(1.94)*	(1.67)*	(1.71)*	(-0.04)	(0.15)	(0.28)	(-0.3)	(0.2)
β_{l1}	—	-0.04	—	—	-0.15	—	-0.01	—	—	-0.11	—	-0.06	—	—	-0.15
	—	(-0.18)	—	—	(-0.67)	—	(-0.04)	—	—	(-0.5)	—	(-0.3)	—	—	(-0.64)
β_{l2}	—	-0.08	—	—	-0.10	—	-0.07	—	—	-0.10	—	-0.09	—	—	-0.12
	—	(-0.7)	—	—	(-0.72)	—	(-0.63)	—	—	(-0.71)	—	(-0.76)	—	—	(-0.83)
β_{l3}	—	0.12	—	—	0.16	—	0.13	—	—	0.19	—	0.11	—	—	0.16
	—	(0.89)	—	—	(0.86)	—	(0.98)	—	—	(1.01)	—	(0.83)	—	—	(0.87)
β_{l4}	—	0.40	—	—	0.56	—	0.40	—	—	0.58	—	0.34	—	—	0.49
	—	(1.56)	—	—	(1.7)*	—	(1.57)	—	—	(1.75)*	—	(1.33)	—	—	(1.45)
β_{s1}	—	—	-0.07	—	0.22	—	—	-0.05	—	0.19	—	—	-0.13	—	0.15
	—	—	(-0.22)	—	(0.84)	—	—	(-0.16)	—	(0.72)	—	—	(-0.41)	—	(0.55)
β_{s2}	—	—	-0.18	—	0.02	—	—	-0.18	—	0.02	—	—	-0.19	—	0.03
	—	—	(-1.1)	—	(0.1)	—	—	(-1.14)	—	(0.1)	—	—	(-1.16)	—	(0.11)
β_{s3}	—	—	0.10	—	-0.10	—	—	0.09	—	-0.14	—	—	0.09	—	-0.12
	—	—	(0.51)	—	(-0.33)	—	—	(0.47)	—	(-0.46)	—	—	(0.44)	—	(-0.41)
β_{s4}	—	—	0.51	—	-0.36	—	—	0.48	—	-0.40	—	—	0.42	—	-0.34
	—	—	(1.21)	—	(-0.82)	—	—	(1.16)	—	(-0.92)	—	—	(1.03)	—	(-0.76)
β_{c1}	—	—	—	-0.02	—	—	—	—	0.04	—	—	—	—	-0.02	—
	—	—	—	(-0.09)	—	—	—	—	(0.13)	—	—	—	—	(-0.08)	—
β_{c2}	—	—	—	0.01	—	—	—	—	0.01	—	—	—	—	0.04	—
	—	—	—	(0.03)	—	—	—	—	(0.07)	—	—	—	—	(0.23)	—
β_{c3}	—	—	—	0.36	—	—	—	—	0.38	—	—	—	—	0.41	—
	—	—	—	(1.48)	—	—	—	—	(1.57)	—	—	—	—	(1.81)*	—
β_{c4}	—	—	—	0.45	—	—	—	—	0.44	—	—	—	—	0.41	—
	—	—	—	(1.31)	—	—	—	—	(1.28)	—	—	—	—	(1.21)	—
β_d	0.52	0.50	0.51	0.51	0.50	0.55	0.53	0.54	0.54	0.53	0.63	0.61	0.62	0.62	0.62
	(7.75)***	(7.32)***	(7.83)***	(7.74)***	(7.34)***	(7.6)***	(7.29)***	(7.71)***	(7.64)***	(7.32)***	(8.45)***	(7.81)***	(8.42)***	(8.41)***	(7.88)***
β_{d1}	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.02	-0.02	-0.02	-0.02	-0.02
	(-2.65)***	(-2.36)***	(-2.49)***	(-2.62)***	(-2.39)***	(-2.86)***	(-2.59)***	(-2.71)***	(-2.86)***	(-2.61)***	(-3.42)***	(-3.1)***	(-3.23)***	(-3.38)***	(-3.15)***
β_w	0.34	0.34	0.34	0.34	0.34	0.33	0.33	0.33	0.33	0.33	0.37	0.38	0.38	0.38	0.38
	(5.9)***	(5.83)***	(6.04)***	(6.05)***	(5.84)***	(5.65)***	(5.62)***	(5.8)***	(5.84)***	(5.63)***	(6.62)***	(6.57)***	(6.81)***	(6.77)***	(6.58)***
β_m	0.16	0.16	0.15	0.15	0.16	0.15	0.15	0.15	0.15	0.15	0.11	0.10	0.10	0.10	0.10
	(4.39)***	(4.33)***	(4.18)***	(4.27)***	(4.37)***	(4.23)***	(4.17)***	(4.03)***	(4.11)***	(4.23)***	(3.32)***	(2.97)***	(3.06)***	(3.21)***	(3.02)***
β_j	—	—	—	—	—	-0.16	-0.16	-0.16	-0.16	-0.16	-0.01	-0.01	0.00	-0.01	-0.01
	—	—	—	—	—	(-3.89)***	(-3.97)***	(-4)***	(-3.95)***	(-4.02)***	(-0.2)	(-0.19)	(-0.14)	(-0.24)	(-0.22)
R^2	80%	81%	81%	81%	81%	81%	81%	81%	81%	81%	81%	81%	81%	81%	81%
QLIKE	0.36	0.37	0.36	0.36	0.36	0.35	0.36	0.35	0.35	0.36	0.43	0.43	0.43	0.43	0.43
J-R^2	78%	78%	78%	78%	78%	79%	79%	79%	79%	79%	79%	79%	79%	79%	79%
J-QLIKE	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
C-R^2	81%	81%	81%	81%	81%	81%	81%	81%	81%	81%	81%	81%	81%	81%	81%
C-QLIKE	0.38	0.39	0.38	0.38	0.39	0.37	0.38	0.37	0.37	0.38	0.46	0.46	0.46	0.46	0.46

Table 4.10: UK Market (h=5)

	HAR-RV					HAR-RVJ					HAR-CJ				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
β_0	0.05	0.04	0.04	0.05	0.04	0.05	0.05	0.05	0.05	0.05	0.06	0.06	0.06	0.06	0.06
	(2.14)**	(1.79)*	(1.7)*	(2.14)**	(1.71)*	(2.67)***	(2.44)***	(2.4)***	(2.73)***	(2.41)***	(2.77)***	(2.76)***	(2.66)***	(2.89)***	(2.7)***
β_{l1}	—	0.04	—	—	-0.27	—	-0.01	—	—	-0.23	—	-0.04	—	—	-0.28
	—	(0.38)	—	—	(-1.16)	—	(-0.06)	—	—	(-0.93)	—	(-0.39)	—	—	(-1.03)
β_{l2}	—	0.16	—	—	0.04	—	0.10	—	—	0.01	—	0.11	—	—	0.03
	—	(0.89)	—	—	(0.36)	—	(0.66)	—	—	(0.05)	—	(0.67)	—	—	(0.22)
β_{l3}	—	0.24	—	—	0.32	—	0.21	—	—	0.29	—	0.23	—	—	0.31
	—	(1.25)	—	—	(1.14)	—	(1.16)	—	—	(1.09)	—	(1.22)	—	—	(1.11)
β_{l4}	—	0.43	—	—	0.44	—	0.37	—	—	0.40	—	0.35	—	—	0.38
	—	(2.05)**	—	—	(1.51)	—	(1.83)*	—	—	(1.37)	—	(1.76)*	—	—	(1.28)
β_{s1}	—	—	0.14	—	0.57	—	—	0.03	—	0.40	—	—	-0.02	—	0.42
	—	—	(0.69)	—	(1.48)	—	—	(0.14)	—	(0.96)	—	—	(-0.09)	—	(0.94)
β_{s2}	—	—	0.23	—	0.25	—	—	0.14	—	0.20	—	—	0.13	—	0.17
	—	—	(0.94)	—	(0.94)	—	—	(0.69)	—	(0.87)	—	—	(0.69)	—	(0.74)
β_{s3}	—	—	0.29	—	-0.08	—	—	0.24	—	-0.12	—	—	0.26	—	-0.12
	—	—	(1.3)	—	(-0.34)	—	—	(1.19)	—	(-0.46)	—	—	(1.3)	—	(-0.44)
β_{s4}	—	—	0.54	—	0.03	—	—	0.44	—	-0.02	—	—	0.42	—	-0.01
	—	—	(1.89)*	—	(0.08)	—	—	(1.57)	—	(-0.04)	—	—	(1.51)	—	(-0.03)
β_{c1}	—	—	—	0.00	—	—	—	—	-0.05	—	—	—	—	-0.09	—
	—	—	—	(0.01)	—	—	—	—	(-0.39)	—	—	—	—	(-0.8)	—
β_{c2}	—	—	—	0.13	—	—	—	—	0.10	—	—	—	—	0.09	—
	—	—	—	(1.55)	—	—	—	—	(1.31)	—	—	—	—	(1.23)	—
β_{c3}	—	—	—	0.16	—	—	—	—	0.15	—	—	—	—	0.16	—
	—	—	—	(1.74)*	—	—	—	—	(1.65)*	—	—	—	—	(1.77)*	—
β_{c4}	—	—	—	0.45	—	—	—	—	0.41	—	—	—	—	0.37	—
	—	—	—	(2.53)***	—	—	—	—	(2.23)**	—	—	—	—	(2.07)**	—
β_d	0.48	0.45	0.46	0.47	0.45	0.51	0.49	0.50	0.50	0.49	0.47	0.44	0.46	0.46	0.44
	(7.45)***	(6.61)***	(7.4)***	(7.5)***	(6.53)***	(7.68)***	(7.12)***	(7.81)***	(7.78)***	(7.02)***	(5.01)***	(4.43)***	(4.97)***	(5.03)***	(4.38)***
β_{d1}	-0.01	-0.01	-0.01	-0.01	-0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(-1.85)*	(-1.51)	(-1.81)*	(-1.78)*	(-1.53)	(-0.58)	(-0.42)	(-0.53)	(-0.52)	(-0.44)	(-0.12)	(0.01)	(-0.06)	(-0.06)	(-0.01)
β_w	0.30	0.30	0.29	0.29	0.29	0.28	0.28	0.28	0.28	0.28	0.43	0.43	0.43	0.43	0.43
	(7.29)***	(7.03)***	(7.08)***	(7.17)***	(6.81)***	(6.02)***	(5.82)***	(5.84)***	(5.9)***	(5.68)***	(6.43)***	(6.16)***	(6.18)***	(6.22)***	(5.92)***
β_m	0.20	0.20	0.20	0.20	0.19	0.18	0.17	0.17	0.17	0.17	0.05	0.05	0.05	0.05	0.05
	(4.24)***	(4.21)***	(4.26)***	(4.28)***	(4.2)***	(4.21)***	(4.05)***	(4.14)***	(4.23)***	(4.03)***	(1.92)*	(1.6)	(1.78)*	(1.85)*	(1.62)
β_j	—	—	—	—	—	-0.24	-0.24	-0.24	-0.24	-0.24	-0.06	-0.07	-0.06	-0.06	-0.06
	—	—	—	—	—	(-3.18)***	(-3.25)***	(-3.2)***	(-3.14)***	(-3.19)***	(-0.93)	(-0.96)	(-0.93)	(-0.93)	(-0.91)
R^2	68%	69%	69%	69%	69%	69%	70%	70%	70%	70%	70%	70%	70%	70%	70%
QLIKE	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
J-R^2	70%	70%	70%	70%	70%	71%	71%	71%	71%	71%	72%	72%	72%	72%	72%
J-QLIKE	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.03	0.04	0.04	0.04	0.03	0.03
C-R^2	69%	69%	69%	69%	69%	69%	70%	70%	70%	70%	69%	70%	69%	69%	70%
C-QLIKE	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03

Table 4.11: Swiss Market (h=22)

	HAR-RV					HAR-RVJ					HAR-CJ				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
β_0	0.14	0.14	0.15	0.14	0.14	0.14	0.14	0.15	0.15	0.15	0.14	0.14	0.15	0.15	0.15
	(4.44)***	(4.46)***	(4.45)***	(4.59)***	(4.27)***	(4.52)***	(4.54)***	(4.51)***	(4.68)***	(4.33)***	(4.52)***	(4.52)***	(4.5)***	(4.66)***	(4.31)***
β_{l1}	—	0.03	—	—	-0.04	—	0.03	—	—	-0.05	—	0.03	—	—	-0.04
	—	(0.34)	—	—	(-0.29)	—	(0.32)	—	—	(-0.32)	—	(0.29)	—	—	(-0.28)
β_{l2}	—	0.05	—	—	-0.22	—	0.05	—	—	-0.22	—	0.05	—	—	-0.21
	—	(0.51)	—	—	(-1.38)	—	(0.49)	—	—	(-1.37)	—	(0.52)	—	—	(-1.31)
β_{l3}	—	0.10	—	—	0.04	—	0.10	—	—	0.04	—	0.10	—	—	0.04
	—	(1.21)	—	—	(0.21)	—	(1.22)	—	—	(0.21)	—	(1.26)	—	—	(0.22)
β_{l4}	—	0.34	—	—	0.37	—	0.34	—	—	0.38	—	0.33	—	—	0.37
	—	(2.48)***	—	—	(1.44)	—	(2.48)***	—	—	(1.46)	—	(2.47)***	—	—	(1.44)
β_{s1}	—	—	0.05	—	0.08	—	—	0.04	—	0.08	—	—	0.04	—	0.07
	—	—	(0.56)	—	(0.69)	—	—	(0.54)	—	(0.7)	—	—	(0.5)	—	(0.65)
β_{s2}	—	—	0.14	—	0.35	—	—	0.13	—	0.34	—	—	0.14	—	0.34
	—	—	(1.44)	—	(1.82)*	—	—	(1.43)	—	(1.83)*	—	—	(1.45)	—	(1.8)*
β_{s3}	—	—	0.11	—	0.08	—	—	0.12	—	0.08	—	—	0.12	—	0.08
	—	—	(1.3)	—	(0.41)	—	—	(1.3)	—	(0.42)	—	—	(1.31)	—	(0.42)
β_{s4}	—	—	0.24	—	-0.01	—	—	0.24	—	-0.02	—	—	0.24	—	-0.02
	—	—	(1.89)*	—	(-0.05)	—	—	(1.88)*	—	(-0.08)	—	—	(1.86)*	—	(-0.07)
β_{c1}	—	—	—	-0.16	—	—	—	—	-0.16	—	—	—	—	-0.16	—
	—	—	—	(-1.38)	—	—	—	—	(-1.42)	—	—	—	—	(-1.35)	—
β_{c2}	—	—	—	-0.20	—	—	—	—	-0.21	—	—	—	—	-0.20	—
	—	—	—	(-1.64)	—	—	—	—	(-1.73)*	—	—	—	—	(-1.58)	—
β_{c3}	—	—	—	-0.15	—	—	—	—	-0.15	—	—	—	—	-0.13	—
	—	—	—	(-1.18)	—	—	—	—	(-1.18)	—	—	—	—	(-1.07)	—
β_{c4}	—	—	—	0.07	—	—	—	—	0.06	—	—	—	—	0.07	—
	—	—	—	(0.34)	—	—	—	—	(0.32)	—	—	—	—	(0.34)	—
β_d	0.41	0.40	0.40	0.42	0.40	0.41	0.39	0.40	0.41	0.39	0.41	0.40	0.40	0.42	0.40
	(4.72)***	(4.55)***	(4.58)***	(4.71)***	(4.53)***	(4.6)***	(4.4)***	(4.44)***	(4.59)***	(4.38)***	(4.66)***	(4.46)***	(4.5)***	(4.64)***	(4.43)***
β_{d1}	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
	(-2.27)**	(-2.15)**	(-2.14)**	(-2.27)**	(-2.1)**	(-2.12)**	(-2)**	(-1.99)**	(-2.11)**	(-1.95)*	(-2.14)**	(-2.02)**	(-2.02)**	(-2.13)**	(-1.97)**
β_w	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.26	0.26	0.26	0.26	0.26
	(4.14)***	(4.05)***	(4.02)***	(4.15)***	(4.01)***	(4.17)***	(4.09)***	(4.05)***	(4.19)***	(4.04)***	(3.98)***	(3.89)***	(3.86)***	(3.98)***	(3.85)***
β_m	0.19	0.18	0.17	0.19	0.17	0.19	0.18	0.17	0.19	0.17	0.20	0.18	0.18	0.20	0.18
	(3.07)***	(2.79)***	(2.69)***	(3.1)***	(2.69)***	(3.11)***	(2.82)***	(2.73)***	(3.14)***	(2.73)***	(3.17)***	(2.89)***	(2.79)***	(3.2)***	(2.8)***
β_j	—	—	—	—	—	0.05	0.05	0.04	0.05	0.05	0.15	0.15	0.15	0.16	0.15
	—	—	—	—	—	(0.71)	(0.71)	(0.66)	(0.74)	(0.71)	(2.22)**	(2.23)**	(2.19)**	(2.26)**	(2.24)**
R^2	60%	60%	60%	60%	60%	60%	60%	60%	60%	60%	60%	60%	60%	60%	60%
QLIKE	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
J-R^2	63%	64%	64%	63%	64%	63%	64%	64%	63%	64%	63%	64%	64%	63%	64%
J-QLIKE	0.03	0.03	0.03	0.04	0.03	0.03	0.03	0.03	0.04	0.03	0.03	0.03	0.03	0.04	0.03
C-R^2	59%	60%	60%	59%	60%	59%	60%	60%	59%	60%	59%	60%	60%	59%	60%
C-QLIKE	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03

Table 4.12: German Market (h=22)

	HAR-RV					HAR-RVJ					HAR-CJ				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
β_0	0.20	0.21	0.21	0.21	0.21	0.20	0.20	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.22
	(6.04)***	(5.78)***	(5.91)***	(5.98)***	(5.51)***	(5.96)***	(5.71)***	(5.85)***	(5.92)***	(5.42)***	(6.23)***	(5.94)***	(6.06)***	(6.18)***	(5.63)***
β_{l1}	—	0.07	—	—	-0.25	—	0.08	—	—	-0.24	—	0.07	—	—	-0.24
	—	(0.52)	—	—	(-1.37)	—	(0.6)	—	—	(-1.32)	—	(0.52)	—	—	(-1.29)
β_{l2}	—	0.10	—	—	-0.22	—	0.10	—	—	-0.20	—	0.10	—	—	-0.21
	—	(0.66)	—	—	(-1.05)	—	(0.65)	—	—	(-0.97)	—	(0.64)	—	—	(-1.03)
β_{l3}	—	0.14	—	—	0.00	—	0.15	—	—	0.02	—	0.16	—	—	0.01
	—	(1.16)	—	—	(-0.01)	—	(1.24)	—	—	(0.05)	—	(1.25)	—	—	(0.05)
β_{l4}	—	0.48	—	—	0.47	—	0.49	—	—	0.47	—	0.48	—	—	0.46
	—	(2.39)***	—	—	(1.17)	—	(2.4)***	—	—	(1.17)	—	(2.32)**	—	—	(1.14)
β_{s1}	—	—	0.12	—	0.29	—	—	0.12	—	0.28	—	—	0.11	—	0.27
	—	—	(1.2)	—	(2.13)**	—	—	(1.24)	—	(2.1)**	—	—	(1.15)	—	(2.01)**
β_{s2}	—	—	0.22	—	0.42	—	—	0.21	—	0.39	—	—	0.21	—	0.41
	—	—	(1.37)	—	(1.43)	—	—	(1.32)	—	(1.36)	—	—	(1.34)	—	(1.42)
β_{s3}	—	—	0.19	—	0.19	—	—	0.20	—	0.18	—	—	0.20	—	0.18
	—	—	(1.81)*	—	(0.74)	—	—	(1.86)*	—	(0.7)	—	—	(1.89)*	—	(0.71)
β_{s4}	—	—	0.36	—	0.04	—	—	0.36	—	0.04	—	—	0.36	—	0.04
	—	—	(2.26)**	—	(0.11)	—	—	(2.26)**	—	(0.12)	—	—	(2.18)**	—	(0.12)
β_{c1}	—	—	—	-0.08	—	—	—	—	-0.07	—	—	—	—	-0.09	—
	—	—	—	(-0.59)	—	—	—	—	(-0.51)	—	—	—	—	(-0.65)	—
β_{c2}	—	—	—	-0.17	—	—	—	—	-0.18	—	—	—	—	-0.19	—
	—	—	—	(-1.24)	—	—	—	—	(-1.32)	—	—	—	—	(-1.36)	—
β_{c3}	—	—	—	-0.12	—	—	—	—	-0.12	—	—	—	—	-0.12	—
	—	—	—	(-0.96)	—	—	—	—	(-0.95)	—	—	—	—	(-0.98)	—
β_{c4}	—	—	—	0.24	—	—	—	—	0.24	—	—	—	—	0.22	—
	—	—	—	(1.09)	—	—	—	—	(1.08)	—	—	—	—	(1)	—
β_d	0.29	0.28	0.28	0.29	0.28	0.31	0.30	0.31	0.31	0.30	0.32	0.30	0.31	0.31	0.30
	(4.34)***	(4.33)***	(4.27)***	(4.3)***	(4.38)***	(4.52)***	(4.52)***	(4.46)***	(4.48)***	(4.57)***	(4.5)***	(4.5)***	(4.44)***	(4.46)***	(4.54)***
β_{d1}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(-0.64)	(-0.57)	(-0.6)	(-0.6)	(-0.55)	(-0.93)	(-0.87)	(-0.89)	(-0.89)	(-0.84)	(-1)	(-0.94)	(-0.96)	(-0.96)	(-0.91)
β_w	0.28	0.27	0.27	0.27	0.27	0.27	0.27	0.26	0.27	0.27	0.28	0.27	0.27	0.27	0.27
	(4.91)***	(4.79)***	(4.66)***	(4.86)***	(4.66)***	(4.92)***	(4.79)***	(4.65)***	(4.86)***	(4.66)***	(4.96)***	(4.82)***	(4.69)***	(4.89)***	(4.68)***
β_m	0.25	0.24	0.23	0.25	0.23	0.25	0.23	0.22	0.25	0.22	0.25	0.23	0.22	0.24	0.22
	(4.75)***	(4.34)***	(4.14)***	(4.69)***	(4.17)***	(4.73)***	(4.31)***	(4.12)***	(4.67)***	(4.15)***	(4.62)***	(4.22)***	(4.03)***	(4.57)***	(4.06)***
β_j	—	—	—	—	—	-0.10	-0.10	-0.10	-0.10	-0.10	0.00	-0.01	-0.01	0.00	-0.01
	—	—	—	—	—	(-2.88)***	(-2.95)***	(-2.96)***	(-2.92)***	(-2.92)***	(-0.14)	(-0.34)	(-0.26)	(-0.17)	(-0.25)
R^2	61%	62%	62%	61%	62%	62%	62%	62%	62%	62%	62%	62%	62%	62%	62%
QLIKE	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
J-R^2	50%	51%	51%	50%	51%	50%	52%	51%	51%	52%	51%	53%	52%	52%	53%
J-QLIKE	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
C-R^2	63%	63%	63%	63%	63%	63%	63%	63%	63%	63%	63%	63%	63%	63%	63%
C-QLIKE	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03

Table 4.13: French Market (h=22)

	HAR-RV					HAR-RVJ					HAR-CJ				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
β_0	0.09	0.07	0.09	0.07	0.08	0.09	0.07	0.09	0.07	0.08	0.06	0.04	0.06	0.04	0.05
	(4.75)***	(2.83)***	(4.13)***	(3.62)***	(3.46)***	(4.69)***	(2.74)***	(4.07)***	(3.54)***	(3.39)***	(2.09)**	(1.42)	(2.11)**	(1.5)	(1.81)*
β_{l1}	—	0.29	—	—	0.32	—	0.31	—	—	0.34	—	0.24	—	—	0.29
	—	(1.45)	—	—	(1)	—	(1.55)	—	—	(1.09)	—	(1.24)	—	—	(0.96)
β_{l2}	—	0.25	—	—	0.36	—	0.25	—	—	0.36	—	0.23	—	—	0.35
	—	(1.6)	—	—	(1.64)	—	(1.64)	—	—	(1.67)*	—	(1.52)	—	—	(1.6)
β_{l3}	—	0.37	—	—	0.62	—	0.38	—	—	0.64	—	0.36	—	—	0.60
	—	(2.45)***	—	—	(2.7)***	—	(2.49)***	—	—	(2.76)***	—	(2.38)***	—	—	(2.55)***
β_{l4}	—	0.51	—	—	0.49	—	0.51	—	—	0.50	—	0.44	—	—	0.37
	—	(2)**	—	—	(1.4)	—	(1.99)**	—	—	(1.43)	—	(1.74)*	—	—	(1.03)
β_{s1}	—	—	0.07	—	-0.19	—	—	0.08	—	-0.21	—	—	0.00	—	-0.23
	—	—	(0.27)	—	(-0.46)	—	—	(0.32)	—	(-0.52)	—	—	(-0.01)	—	(-0.57)
β_{s2}	—	—	-0.04	—	-0.35	—	—	-0.04	—	-0.35	—	—	-0.03	—	-0.33
	—	—	(-0.2)	—	(-1.06)	—	—	(-0.22)	—	(-1.08)	—	—	(-0.15)	—	(-1)
β_{s3}	—	—	0.08	—	-0.61	—	—	0.07	—	-0.64	—	—	0.09	—	-0.57
	—	—	(0.41)	—	(-1.83)*	—	—	(0.38)	—	(-1.9)*	—	—	(0.47)	—	(-1.63)
β_{s4}	—	—	0.42	—	-0.10	—	—	0.40	—	-0.13	—	—	0.35	—	0.01
	—	—	(1.15)	—	(-0.26)	—	—	(1.1)	—	(-0.34)	—	—	(0.98)	—	(0.04)
β_{c1}	—	—	—	0.41	—	—	—	—	0.45	—	—	—	—	0.38	—
	—	—	—	(1.59)	—	—	—	—	(1.72)*	—	—	—	—	(1.54)	—
β_{c2}	—	—	—	0.43	—	—	—	—	0.43	—	—	—	—	0.48	—
	—	—	—	(1.67)*	—	—	—	—	(1.7)*	—	—	—	—	(1.86)*	—
β_{c3}	—	—	—	0.58	—	—	—	—	0.59	—	—	—	—	0.65	—
	—	—	—	(2.02)**	—	—	—	—	(2.1)**	—	—	—	—	(2.33)***	—
β_{c4}	—	—	—	0.66	—	—	—	—	0.65	—	—	—	—	0.61	—
	—	—	—	(1.82)*	—	—	—	—	(1.79)*	—	—	—	—	(1.73)*	—
β_d	0.47	0.44	0.46	0.46	0.43	0.49	0.46	0.48	0.48	0.45	0.62	0.58	0.61	0.61	0.58
	(7.14)***	(6.7)***	(7.07)***	(7.15)***	(6.71)***	(7.08)***	(6.67)***	(7.01)***	(7.13)***	(6.66)***	(9.23)***	(8.42)***	(9.03)***	(9.3)***	(8.39)***
β_{d1}	-0.02	-0.01	-0.01	-0.02	-0.01	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02
	(-3)***	(-2.89)***	(-2.97)***	(-3.12)***	(-2.79)***	(-3.08)***	(-2.98)***	(-3.04)***	(-3.22)***	(-2.88)***	(-3.88)***	(-3.78)***	(-3.85)***	(-4.06)***	(-3.7)***
β_w	0.27	0.28	0.27	0.27	0.28	0.27	0.28	0.27	0.27	0.28	0.34	0.35	0.34	0.34	0.35
	(5.27)***	(5.29)***	(5.33)***	(5.42)***	(5.26)***	(5.15)***	(5.19)***	(5.21)***	(5.31)***	(5.17)***	(7.22)***	(7.17)***	(7.31)***	(7.37)***	(7.22)***
β_m	0.24	0.23	0.23	0.23	0.24	0.23	0.23	0.23	0.23	0.23	0.14	0.12	0.13	0.13	0.12
	(4.48)***	(4.4)***	(4.41)***	(4.42)***	(4.53)***	(4.44)***	(4.35)***	(4.36)***	(4.37)***	(4.49)***	(3.17)***	(2.73)***	(3)***	(3.06)***	(2.8)***
β_j	—	—	—	—	—	-0.11	-0.11	-0.10	-0.11	-0.11	0.03	0.01	0.03	0.02	0.01
	—	—	—	—	—	(-2.89)***	(-3.03)***	(-2.9)***	(-3.07)***	(-3.13)***	(0.78)	(0.4)	(0.82)	(0.59)	(0.27)
R^2	73%	74%	73%	74%	74%	73%	74%	74%	74%	74%	73%	73%	73%	73%	73%
QLIKE	0.46	0.47	0.47	0.46	0.47	0.46	0.47	0.47	0.46	0.47	0.50	0.51	0.51	0.50	0.51
J-R^2	62%	63%	63%	62%	63%	62%	63%	63%	63%	63%	63%	63%	63%	62%	63%
J-QLIKE	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
C-R^2	74%	74%	74%	74%	75%	74%	74%	74%	74%	75%	73%	74%	73%	74%	74%
C-QLIKE	0.51	0.52	0.51	0.51	0.51	0.51	0.52	0.51	0.51	0.51	0.55	0.56	0.55	0.55	0.55

Table 4.14: UK Market (h=22)

	HAR-RV					HAR-RVJ					HAR-CJ				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
β_0	0.05	0.04	0.04	0.05	0.04	0.05	0.05	0.05	0.05	0.05	0.06	0.06	0.06	0.06	0.06
	(2.14)**	(1.79)*	(1.7)*	(2.14)**	(1.71)*	(2.67)***	(2.44)***	(2.4)***	(2.73)***	(2.41)***	(2.77)***	(2.76)***	(2.66)***	(2.89)***	(2.7)***
β_{l1}	—	0.18	—	—	0.08	—	0.15	—	—	0.11	—	0.12	—	—	0.04
	—	(1.5)	—	—	(0.38)	—	(1.35)	—	—	(0.48)	—	(1.05)	—	—	(0.18)
β_{l2}	—	0.35	—	—	0.50	—	0.32	—	—	0.48	—	0.33	—	—	0.50
	—	(2.15)**	—	—	(1.93)*	—	(2.06)**	—	—	(1.79)*	—	(2.05)**	—	—	(1.81)*
β_{l3}	—	0.40	—	—	0.45	—	0.38	—	—	0.44	—	0.41	—	—	0.45
	—	(2.16)**	—	—	(1.76)*	—	(2.15)**	—	—	(1.73)*	—	(2.19)**	—	—	(1.69)*
β_{l4}	—	0.49	—	—	0.31	—	0.46	—	—	0.29	—	0.45	—	—	0.28
	—	(2.89)***	—	—	(1.38)	—	(2.79)***	—	—	(1.28)	—	(2.75)***	—	—	(1.17)
β_{s1}	—	—	0.08	—	0.13	—	—	0.02	—	0.04	—	—	-0.01	—	0.09
	—	—	(0.4)	—	(0.45)	—	—	(0.09)	—	(0.11)	—	—	(-0.06)	—	(0.25)
β_{s2}	—	—	0.24	—	-0.29	—	—	0.19	—	-0.31	—	—	0.20	—	-0.33
	—	—	(1.29)	—	(-0.83)	—	—	(1.12)	—	(-0.9)	—	—	(1.12)	—	(-0.91)
β_{s3}	—	—	0.34	—	-0.13	—	—	0.31	—	-0.14	—	—	0.35	—	-0.12
	—	—	(1.42)	—	(-0.42)	—	—	(1.34)	—	(-0.47)	—	—	(1.46)	—	(-0.37)
β_{s4}	—	—	0.50	—	0.26	—	—	0.44	—	0.24	—	—	0.44	—	0.24
	—	—	(1.82)*	—	(0.67)	—	—	(1.61)	—	(0.59)	—	—	(1.6)	—	(0.58)
β_{c1}	—	—	—	0.13	—	—	—	—	0.10	—	—	—	—	0.06	—
	—	—	—	(0.95)	—	—	—	—	(0.74)	—	—	—	—	(0.45)	—
β_{c2}	—	—	—	0.34	—	—	—	—	0.33	—	—	—	—	0.32	—
	—	—	—	(2.68)***	—	—	—	—	(2.55)***	—	—	—	—	(2.36)***	—
β_{c3}	—	—	—	0.40	—	—	—	—	0.40	—	—	—	—	0.41	—
	—	—	—	(2.67)***	—	—	—	—	(2.65)***	—	—	—	—	(2.68)***	—
β_{c4}	—	—	—	0.50	—	—	—	—	0.48	—	—	—	—	0.45	—
	—	—	—	(2.89)***	—	—	—	—	(2.72)***	—	—	—	—	(2.59)***	—
β_d	0.46	0.41	0.45	0.44	0.41	0.48	0.43	0.47	0.46	0.43	0.45	0.40	0.44	0.44	0.41
	(4.91)***	(4.6)***	(4.62)***	(4.71)***	(4.64)***	(4.99)***	(4.76)***	(4.72)***	(4.8)***	(4.79)***	(5.05)***	(4.71)***	(4.8)***	(4.89)***	(4.72)***
β_{d1}	-0.02	-0.01	-0.02	-0.02	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
	(-2.7)***	(-2.38)***	(-2.55)***	(-2.56)***	(-2.4)***	(-1.85)*	(-1.63)	(-1.79)*	(-1.77)*	(-1.63)	(-1.49)	(-1.25)	(-1.42)	(-1.4)	(-1.24)
β_w	0.25	0.26	0.25	0.25	0.26	0.24	0.25	0.24	0.24	0.25	0.39	0.39	0.38	0.38	0.39
	(3.84)***	(3.84)***	(3.74)***	(3.82)***	(3.75)***	(3.71)***	(3.71)***	(3.62)***	(3.69)***	(3.63)***	(6.16)***	(6.08)***	(5.97)***	(6.07)***	(5.8)***
β_m	0.23	0.21	0.22	0.22	0.21	0.21	0.20	0.20	0.20	0.20	0.08	0.07	0.08	0.08	0.07
	(3.43)***	(3.27)***	(3.39)***	(3.4)***	(3.32)***	(3.19)***	(3.02)***	(3.14)***	(3.15)***	(3.07)***	(1.86)*	(1.59)	(1.78)*	(1.75)*	(1.57)
β_j	—	—	—	—	—	-0.15	-0.14	-0.14	-0.14	-0.14	-0.01	-0.01	-0.01	-0.01	-0.01
	—	—	—	—	—	(-2.44)***	(-2.42)***	(-2.43)***	(-2.37)***	(-2.37)***	(-0.14)	(-0.23)	(-0.15)	(-0.15)	(-0.21)
R^2	61%	61%	61%	61%	61%	61%	62%	61%	61%	62%	60%	61%	60%	61%	61%
QLIKE	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04
J-R^2	59%	60%	59%	59%	60%	59%	60%	59%	59%	60%	58%	59%	58%	58%	59%
J-QLIKE	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
C-R^2	61%	62%	62%	62%	62%	62%	62%	62%	62%	62%	61%	61%	61%	61%	61%
C-QLIKE	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03

Table 4.15: Swiss Market (h=1)

	HAR-RV					HAR-RVJ					HAR-CJ				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
β_0	0.02	0.01	0.02	0.02	0.01	0.02	0.01	0.02	0.01	0.01	0.02	0.01	0.02	0.02	0.01
	(0.91)	(0.55)	(0.89)	(0.65)	(0.45)	(0.82)	(0.45)	(0.78)	(0.57)	(0.34)	(0.87)	(0.46)	(0.82)	(0.58)	(0.36)
β_{l1}	—	0.11	—	—	0.30	—	0.09	—	—	0.26	—	0.10	—	—	0.27
	—	(0.69)	—	—	(1.45)	—	(0.59)	—	—	(1.33)	—	(0.68)	—	—	(1.37)
β_{l2}	—	0.31	—	—	0.15	—	0.29	—	—	0.15	—	0.31	—	—	0.17
	—	(2.38)***	—	—	(0.99)	—	(2.26)**	—	—	(0.93)	—	(2.33)***	—	—	(1.02)
β_{l3}	—	0.52	—	—	0.24	—	0.51	—	—	0.22	—	0.53	—	—	0.24
	—	(3.47)***	—	—	(1.1)	—	(3.37)***	—	—	(1.01)	—	(3.45)***	—	—	(1.12)
β_{l4}	—	0.50	—	—	0.91	—	0.48	—	—	0.93	—	0.49	—	—	0.93
	—	(2.87)***	—	—	(3.29)***	—	(2.81)***	—	—	(3.34)***	—	(2.86)***	—	—	(3.34)***
β_{s1}	—	—	-0.01	—	-0.15	—	—	-0.02	—	-0.15	—	—	-0.01	—	-0.14
	—	—	(-0.06)	—	(-0.85)	—	—	(-0.19)	—	(-0.84)	—	—	(-0.12)	—	(-0.82)
β_{s2}	—	—	0.25	—	0.21	—	—	0.22	—	0.18	—	—	0.23	—	0.17
	—	—	(1.91)*	—	(1.29)	—	—	(1.72)*	—	(1.06)	—	—	(1.76)*	—	(0.96)
β_{s3}	—	—	0.44	—	0.31	—	—	0.44	—	0.33	—	—	0.46	—	0.32
	—	—	(2.81)***	—	(1.32)	—	—	(2.78)***	—	(1.37)	—	—	(2.82)***	—	(1.36)
β_{s4}	—	—	0.23	—	-0.33	—	—	0.22	—	-0.37	—	—	0.22	—	-0.36
	—	—	(2.12)**	—	(-1.78)*	—	—	(2.07)**	—	(-2)**	—	—	(2.1)**	—	(-1.95)*
β_{c1}	—	—	—	-0.16	—	—	—	—	-0.17	—	—	—	—	-0.15	—
	—	—	—	(-0.85)	—	—	—	—	(-0.98)	—	—	—	—	(-0.89)	—
β_{c2}	—	—	—	0.08	—	—	—	—	0.04	—	—	—	—	0.06	—
	—	—	—	(0.62)	—	—	—	—	(0.35)	—	—	—	—	(0.48)	—
β_{c3}	—	—	—	0.36	—	—	—	—	0.36	—	—	—	—	0.40	—
	—	—	—	(2.43)***	—	—	—	—	(2.4)***	—	—	—	—	(2.54)***	—
β_{c4}	—	—	—	0.21	—	—	—	—	0.19	—	—	—	—	0.20	—
	—	—	—	(1.46)	—	—	—	—	(1.39)	—	—	—	—	(1.47)	—
β_d	0.43	0.42	0.43	0.43	0.42	0.43	0.42	0.43	0.43	0.42	0.44	0.44	0.44	0.44	0.43
	(4.43)***	(4.28)***	(4.35)***	(4.33)***	(4.23)***	(4.58)***	(4.42)***	(4.5)***	(4.48)***	(4.38)***	(4.59)***	(4.44)***	(4.5)***	(4.5)***	(4.39)***
β_{d1}	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.02	-0.02	-0.02	-0.02
	(-1.83)*	(-1.81)*	(-1.81)*	(-1.83)*	(-1.78)*	(-2.08)**	(-2.05)**	(-2.06)**	(-2.07)**	(-2.03)**	(-2.07)**	(-2.06)**	(-2.05)**	(-2.08)**	(-2.03)**
β_w	0.39	0.38	0.38	0.38	0.38	0.39	0.38	0.38	0.38	0.38	0.38	0.37	0.38	0.38	0.38
	(7.02)***	(6.74)***	(6.89)***	(6.83)***	(6.96)***	(6.99)***	(6.71)***	(6.88)***	(6.83)***	(6.96)***	(6.41)***	(6.18)***	(6.33)***	(6.26)***	(6.39)***
β_m	0.18	0.15	0.15	0.17	0.15	0.18	0.15	0.15	0.17	0.15	0.18	0.15	0.15	0.18	0.16
	(3.95)***	(3.26)***	(3.06)***	(3.72)***	(3.1)***	(4.03)***	(3.44)***	(3.25)***	(3.89)***	(3.3)***	(4.11)***	(3.48)***	(3.29)***	(3.95)***	(3.33)***
β_j	—	—	—	—	—	0.22	0.22	0.22	0.22	0.22	0.23	0.22	0.23	0.23	0.23
	—	—	—	—	—	(2.76)***	(2.78)***	(2.79)***	(2.82)***	(2.83)***	(2.8)***	(2.83)***	(2.83)***	(2.86)***	(2.87)***
R	62%	63%	63%	63%	63%	63%	64%	63%	63%	64%	63%	63%	63%	63%	63%
QLIKE	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06
J-R	68%	68%	68%	68%	68%	69%	69%	69%	69%	69%	69%	69%	69%	69%	69%
J-QLIKE	0.06	0.06	0.06	0.06	0.06	0.05	0.06	0.05	0.05	0.06	0.05	0.05	0.05	0.05	0.05
C-R	62%	63%	63%	62%	63%	62%	63%	63%	62%	63%	62%	62%	62%	62%	63%
C-QLIKE	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07

Table 4.16: German Market (h=1)

	HAR-RV					HAR-RVJ					HAR-CJ				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
β_0	0.07	0.06	0.07	0.07	0.06	0.07	0.06	0.07	0.06	0.06	0.07	0.06	0.07	0.07	0.06
	(2.55)***	(2.13)**	(2.47)***	(2.31)**	(2.1)**	(2.54)***	(2.13)**	(2.48)***	(2.3)**	(2.1)**	(2.76)***	(2.28)**	(2.64)***	(2.48)***	(2.26)**
β_{l1}	—	0.04	—	—	0.25	—	0.04	—	—	0.25	—	0.03	—	—	0.29
	—	(0.17)	—	—	(0.76)	—	(0.17)	—	—	(0.75)	—	(0.13)	—	—	(0.91)
β_{l2}	—	0.29	—	—	0.20	—	0.29	—	—	0.19	—	0.28	—	—	0.19
	—	(1.8)*	—	—	(1.14)	—	(1.8)*	—	—	(1.13)	—	(1.77)*	—	—	(1.11)
β_{l3}	—	0.59	—	—	0.30	—	0.59	—	—	0.29	—	0.60	—	—	0.31
	—	(3.58)***	—	—	(1.11)	—	(3.6)***	—	—	(1.12)	—	(3.53)***	—	—	(1.17)
β_{l4}	—	0.49	—	—	0.82	—	0.49	—	—	0.82	—	0.48	—	—	0.78
	—	(2.36)***	—	—	(2.93)***	—	(2.36)***	—	—	(2.91)***	—	(2.33)***	—	—	(2.85)***
β_{s1}	—	—	-0.05	—	-0.18	—	—	-0.05	—	-0.18	—	—	-0.07	—	-0.22
	—	—	(-0.33)	—	(-0.67)	—	—	(-0.34)	—	(-0.67)	—	—	(-0.42)	—	(-0.85)
β_{s2}	—	—	0.21	—	0.12	—	—	0.21	—	0.13	—	—	0.20	—	0.12
	—	—	(1.25)	—	(0.65)	—	—	(1.25)	—	(0.65)	—	—	(1.21)	—	(0.64)
β_{s3}	—	—	0.52	—	0.33	—	—	0.52	—	0.34	—	—	0.53	—	0.33
	—	—	(2.75)***	—	(1.05)	—	—	(2.75)***	—	(1.05)	—	—	(2.72)***	—	(1.03)
β_{s4}	—	—	0.24	—	-0.27	—	—	0.24	—	-0.27	—	—	0.24	—	-0.24
	—	—	(1.46)	—	(-1.01)	—	—	(1.46)	—	(-1.01)	—	—	(1.45)	—	(-0.97)
β_{c1}	—	—	—	-0.30	—	—	—	—	-0.30	—	—	—	—	-0.32	—
	—	—	—	(-1.1)	—	—	—	—	(-1.1)	—	—	—	—	(-1.18)	—
β_{c2}	—	—	—	0.02	—	—	—	—	0.02	—	—	—	—	0.01	—
	—	—	—	(0.1)	—	—	—	—	(0.11)	—	—	—	—	(0.07)	—
β_{c3}	—	—	—	0.39	—	—	—	—	0.39	—	—	—	—	0.39	—
	—	—	—	(2.11)**	—	—	—	—	(2.11)**	—	—	—	—	(2.07)**	—
β_{c4}	—	—	—	0.21	—	—	—	—	0.21	—	—	—	—	0.19	—
	—	—	—	(0.85)	—	—	—	—	(0.85)	—	—	—	—	(0.81)	—
β_d	0.39	0.38	0.38	0.38	0.38	0.39	0.38	0.38	0.38	0.38	0.42	0.42	0.42	0.42	0.41
	(3.96)***	(4.05)***	(4.07)***	(4.07)***	(4.09)***	(3.96)***	(4.05)***	(4.07)***	(4.07)***	(4.09)***	(4.25)***	(4.34)***	(4.35)***	(4.36)***	(4.39)***
β_{d1}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(-0.63)	(-0.69)	(-0.67)	(-0.68)	(-0.65)	(-0.63)	(-0.68)	(-0.66)	(-0.67)	(-0.65)	(-1.13)	(-1.22)	(-1.19)	(-1.19)	(-1.2)
β_w	0.29	0.28	0.28	0.29	0.28	0.29	0.28	0.28	0.29	0.28	0.28	0.27	0.28	0.28	0.28
	(3.65)***	(3.66)***	(3.76)***	(3.95)***	(3.8)***	(3.64)***	(3.66)***	(3.75)***	(3.94)***	(3.8)***	(3.48)***	(3.49)***	(3.58)***	(3.77)***	(3.63)***
β_m	0.24	0.22	0.22	0.24	0.22	0.24	0.22	0.22	0.24	0.22	0.24	0.22	0.22	0.24	0.22
	(5.68)***	(4.71)***	(4.42)***	(5.24)***	(4.57)***	(5.66)***	(4.71)***	(4.42)***	(5.23)***	(4.56)***	(5.64)***	(4.71)***	(4.42)***	(5.25)***	(4.56)***
β_j	—	—	—	—	—	0.02	0.01	0.01	0.02	0.01	0.02	0.01	0.01	0.02	0.01
	—	—	—	—	—	(0.42)	(0.15)	(0.32)	(0.42)	(0.18)	(0.5)	(0.22)	(0.39)	(0.5)	(0.24)
R	62%	62%	62%	62%	63%	62%	62%	62%	62%	63%	62%	63%	63%	62%	63%
QLIKE	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06
J-R	51%	53%	53%	52%	53%	51%	53%	53%	52%	53%	52%	54%	53%	53%	54%
J-QLIKE	0.10	0.10	0.10	0.10	0.10	0.10	0.09	0.09	0.10	0.09	0.10	0.09	0.09	0.10	0.09
C-R	63%	63%	63%	63%	64%	63%	63%	63%	63%	64%	63%	64%	63%	63%	64%
C-QLIKE	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06

Table 4.17: French Market (h=1)

	HAR-RV					HAR-RVJ					HAR-CJ				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
β_0	0.03	-0.01	0.01	0.02	-0.01	0.03	-0.01	0.01	0.02	-0.01	0.00	-0.03	-0.02	-0.01	-0.03
	(2.64)***	(-0.56)	(0.51)	(1.7)*	(-0.42)	(2.59)***	(-0.56)	(0.47)	(1.68)*	(-0.43)	(-0.2)	(-1.77)*	(-1.1)	(-0.75)	(-1.63)
β_{l1}	—	0.60	—	—	0.63	—	0.59	—	—	0.62	—	0.56	—	—	0.61
	—	(2.41)***	—	—	(2)**	—	(2.36)***	—	—	(1.93)*	—	(2.25)**	—	—	(1.89)*
β_{l2}	—	0.34	—	—	0.31	—	0.34	—	—	0.31	—	0.33	—	—	0.31
	—	(2.96)***	—	—	(1.98)**	—	(2.9)***	—	—	(1.96)*	—	(2.92)***	—	—	(1.95)*
β_{l3}	—	0.66	—	—	0.67	—	0.65	—	—	0.66	—	0.67	—	—	0.66
	—	(4.01)***	—	—	(2.47)***	—	(3.97)***	—	—	(2.44)***	—	(4.08)***	—	—	(2.49)***
β_{l4}	—	0.95	—	—	1.15	—	0.94	—	—	1.15	—	0.93	—	—	1.11
	—	(4.43)***	—	—	(3.93)***	—	(4.42)***	—	—	(3.92)***	—	(4.36)***	—	—	(3.79)***
β_{s1}	—	—	0.62	—	-0.10	—	—	0.60	—	-0.09	—	—	0.54	—	-0.13
	—	—	(1.76)*	—	(-0.32)	—	—	(1.74)*	—	(-0.29)	—	—	(1.59)	—	(-0.39)
β_{s2}	—	—	0.22	—	0.03	—	—	0.22	—	0.03	—	—	0.19	—	0.01
	—	—	(1.38)	—	(0.15)	—	—	(1.38)	—	(0.16)	—	—	(1.3)	—	(0.04)
β_{s3}	—	—	0.66	—	-0.07	—	—	0.66	—	-0.06	—	—	0.69	—	-0.01
	—	—	(3.06)***	—	(-0.16)	—	—	(3.05)***	—	(-0.14)	—	—	(3.27)***	—	(-0.03)
β_{s4}	—	—	1.10	—	-0.46	—	—	1.11	—	-0.45	—	—	1.08	—	-0.40
	—	—	(3.24)***	—	(-0.94)	—	—	(3.25)***	—	(-0.92)	—	—	(3.24)***	—	(-0.85)
β_{c1}	—	—	—	0.19	—	—	—	—	0.17	—	—	—	—	0.14	—
	—	—	—	(0.75)	—	—	—	—	(0.67)	—	—	—	—	(0.58)	—
β_{c2}	—	—	—	0.06	—	—	—	—	0.06	—	—	—	—	0.08	—
	—	—	—	(0.34)	—	—	—	—	(0.32)	—	—	—	—	(0.49)	—
β_{c3}	—	—	—	0.56	—	—	—	—	0.55	—	—	—	—	0.64	—
	—	—	—	(2.2)**	—	—	—	—	(2.15)**	—	—	—	—	(2.55)***	—
β_{c4}	—	—	—	0.75	—	—	—	—	0.74	—	—	—	—	0.74	—
	—	—	—	(2.79)***	—	—	—	—	(2.79)***	—	—	—	—	(2.89)***	—
β_d	0.40	0.39	0.41	0.40	0.39	0.41	0.39	0.41	0.40	0.39	0.52	0.49	0.51	0.52	0.49
	(5.38)***	(5.34)***	(5.56)***	(5.49)***	(5.31)***	(5.41)***	(5.35)***	(5.59)***	(5.51)***	(5.33)***	(6.07)***	(5.88)***	(6.22)***	(6.16)***	(5.86)***
β_{d1}	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
	(-1.27)	(-1.3)	(-1.42)	(-1.38)	(-1.27)	(-1.26)	(-1.3)	(-1.41)	(-1.36)	(-1.27)	(-2.5)***	(-2.33)***	(-2.53)***	(-2.59)***	(-2.29)**
β_w	0.36	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.42	0.43	0.42	0.42	0.43
	(5.79)***	(5.97)***	(5.97)***	(5.93)***	(5.99)***	(5.69)***	(5.92)***	(5.86)***	(5.83)***	(5.94)***	(5.99)***	(6.29)***	(6.16)***	(6.1)***	(6.3)***
β_m	0.21	0.19	0.19	0.20	0.19	0.21	0.19	0.19	0.20	0.19	0.13	0.09	0.11	0.12	0.10
	(6.49)***	(5.89)***	(5.88)***	(6.26)***	(6.06)***	(6.5)***	(5.89)***	(5.9)***	(6.27)***	(6.06)***	(4.13)***	(2.91)***	(3.39)***	(3.95)***	(3.04)***
β_j	—	—	—	—	—	0.06	0.03	0.06	0.05	0.03	0.06	0.03	0.06	0.05	0.03
	—	—	—	—	—	(1.46)	(0.77)	(1.44)	(1.35)	(0.72)	(1.41)	(0.74)	(1.4)	(1.31)	(0.7)
R	73%	74%	73%	73%	74%	73%	74%	73%	73%	74%	72%	73%	73%	73%	73%
QLIKE	0.38	0.40	0.39	0.37	0.40	0.37	0.39	0.39	0.37	0.39	0.46	0.46	0.46	0.45	0.46
J-R	64%	64%	64%	64%	64%	64%	64%	64%	65%	64%	64%	63%	64%	64%	63%
J-QLIKE	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.05	0.05	0.05	0.05	0.05
C-R	73%	74%	74%	73%	74%	73%	74%	74%	73%	74%	73%	74%	73%	73%	74%
C-QLIKE	0.40	0.41	0.42	0.39	0.41	0.40	0.41	0.42	0.39	0.41	0.49	0.49	0.49	0.49	0.49

Table 4.18: UK Market (h=1)

	HAR-RV					HAR-RVJ					HAR-CJ				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
β_0	0.07	0.05	0.06	0.07	0.05	0.06	0.05	0.05	0.06	0.05	0.08	0.06	0.07	0.08	0.06
	(2.76)***	(2.27)**	(2.63)***	(2.84)***	(2.33)***	(2.58)***	(2.11)**	(2.4)***	(2.63)***	(2.16)**	(2.63)***	(2.3)**	(2.49)***	(2.66)***	(2.33)**
β_{l1}	—	0.44	—	—	0.24	—	0.44	—	—	0.22	—	0.33	—	—	0.12
	—	(4.02)***	—	—	(1.51)	—	(3.97)***	—	—	(1.34)	—	(3.19)***	—	—	(0.68)
β_{l2}	—	0.52	—	—	0.29	—	0.51	—	—	0.27	—	0.47	—	—	0.27
	—	(2.43)***	—	—	(2.06)**	—	(2.51)***	—	—	(2.06)**	—	(2.6)***	—	—	(2.16)**
β_{l3}	—	0.51	—	—	0.62	—	0.50	—	—	0.61	—	0.47	—	—	0.58
	—	(3.51)***	—	—	(3.52)***	—	(3.51)***	—	—	(3.49)***	—	(3.83)***	—	—	(3.54)***
β_{l4}	—	0.78	—	—	1.29	—	0.77	—	—	1.26	—	0.69	—	—	1.16
	—	(3.98)***	—	—	(4.24)***	—	(3.96)***	—	—	(4.35)***	—	(3.82)***	—	—	(4.1)***
β_{s1}	—	—	0.41	—	0.33	—	—	0.42	—	0.36	—	—	0.28	—	0.33
	—	—	(2.68)***	—	(1.37)	—	—	(2.73)***	—	(1.47)	—	—	(2.01)**	—	(1.3)
β_{s2}	—	—	0.57	—	0.42	—	—	0.54	—	0.41	—	—	0.50	—	0.35
	—	—	(1.72)*	—	(1.44)	—	—	(1.77)*	—	(1.46)	—	—	(1.76)*	—	(1.4)
β_{s3}	—	—	0.43	—	-0.19	—	—	0.43	—	-0.19	—	—	0.40	—	-0.20
	—	—	(2.01)**	—	(-0.79)	—	—	(2.01)**	—	(-0.78)	—	—	(2.04)**	—	(-0.76)
β_{s4}	—	—	0.61	—	-0.85	—	—	0.61	—	-0.82	—	—	0.53	—	-0.78
	—	—	(2.11)**	—	(-2.03)**	—	—	(2.14)**	—	(-2.04)**	—	—	(1.91)*	—	(-1.97)**
β_{c1}	—	—	—	0.10	—	—	—	—	0.11	—	—	—	—	0.00	—
	—	—	—	(0.74)	—	—	—	—	(0.81)	—	—	—	—	(0)	—
β_{c2}	—	—	—	0.21	—	—	—	—	0.20	—	—	—	—	0.16	—
	—	—	—	(1.49)	—	—	—	—	(1.54)	—	—	—	—	(1.38)	—
β_{c3}	—	—	—	0.15	—	—	—	—	0.15	—	—	—	—	0.11	—
	—	—	—	(1.38)	—	—	—	—	(1.41)	—	—	—	—	(1.17)	—
β_{c4}	—	—	—	0.38	—	—	—	—	0.39	—	—	—	—	0.30	—
	—	—	—	(1.72)*	—	—	—	—	(1.79)*	—	—	—	—	(1.4)	—
β_d	0.31	0.27	0.29	0.30	0.27	0.33	0.28	0.30	0.32	0.28	0.33	0.29	0.31	0.32	0.29
	(3.45)***	(3.01)***	(3.19)***	(3.38)***	(2.94)***	(3.82)***	(3.31)***	(3.53)***	(3.75)***	(3.21)***	(3.42)***	(3.08)***	(3.26)***	(3.39)***	(2.98)***
β_{d1}	0.00	0.00	0.00	0.00	0.00	-0.01	0.00	0.00	-0.01	0.00	0.00	0.01	0.00	0.00	0.01
	(-0.56)	(-0.22)	(-0.37)	(-0.48)	(-0.22)	(-0.77)	(-0.38)	(-0.56)	(-0.69)	(-0.37)	(0.31)	(0.5)	(0.4)	(0.34)	(0.48)
β_w	0.36	0.34	0.35	0.35	0.35	0.35	0.34	0.34	0.34	0.34	0.46	0.44	0.44	0.46	0.44
	(6.04)***	(5.95)***	(5.88)***	(5.89)***	(5.93)***	(6.2)***	(6.05)***	(6.03)***	(6.06)***	(6)***	(6.89)***	(6.76)***	(6.55)***	(6.73)***	(6.73)***
β_m	0.24	0.21	0.22	0.23	0.21	0.24	0.21	0.22	0.23	0.21	0.09	0.07	0.09	0.09	0.07
	(4.57)***	(4.43)***	(4.58)***	(4.6)***	(4.37)***	(4.6)***	(4.44)***	(4.6)***	(4.63)***	(4.38)***	(4.91)***	(4)***	(4.71)***	(4.83)***	(4.08)***
β_j	—	—	—	—	—	0.07	0.06	0.07	0.07	0.05	0.05	0.04	0.05	0.05	0.04
	—	—	—	—	—	(1.81)*	(1.6)	(1.97)**	(1.89)*	(1.62)	(1.36)	(1.08)	(1.37)	(1.39)	(1.06)
R	60%	60%	60%	60%	61%	60%	61%	60%	60%	61%	62%	62%	62%	62%	63%
QLIKE	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04
J-R	70%	71%	70%	70%	72%	73%	74%	73%	73%	74%	73%	74%	73%	73%	74%
J-QLIKE	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04
C-R	58%	59%	59%	58%	59%	58%	59%	59%	58%	59%	61%	61%	61%	61%	61%
C-QLIKE	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04

Table 4.19: Swiss Market (h=5)

	HAR-RV					HAR-RVJ					HAR-CJ				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
β_0	0.05	0.05	0.06	0.05	0.05	0.05	0.04	0.05	0.05	0.05	0.05	0.05	0.06	0.05	0.05
	(2)**	(1.78)*	(2.16)**	(1.94)*	(1.86)*	(1.87)*	(1.66)*	(2)**	(1.83)*	(1.73)*	(2.07)**	(1.81)*	(2.2)**	(1.99)**	(1.89)*
β_{l1}	—	0.11	—	—	0.14	—	0.09	—	—	0.11	—	0.10	—	—	0.12
	—	(1.08)	—	—	(0.97)	—	(0.92)	—	—	(0.77)	—	(1.04)	—	—	(0.85)
β_{l2}	—	0.26	—	—	-0.02	—	0.24	—	—	-0.02	—	0.25	—	—	0.00
	—	(2.32)**	—	—	(-0.12)	—	(2.24)**	—	—	(-0.14)	—	(2.3)**	—	—	(-0.01)
β_{l3}	—	0.36	—	—	0.19	—	0.36	—	—	0.17	—	0.38	—	—	0.19
	—	(3.94)***	—	—	(0.9)	—	(3.8)***	—	—	(0.84)	—	(3.91)***	—	—	(0.93)
β_{l4}	—	0.46	—	—	0.59	—	0.44	—	—	0.61	—	0.45	—	—	0.61
	—	(3.7)***	—	—	(3.51)***	—	(3.78)***	—	—	(3.57)***	—	(3.83)***	—	—	(3.55)***
β_{s1}	—	—	0.06	—	-0.01	—	—	0.05	—	0.00	—	—	0.05	—	0.00
	—	—	(0.77)	—	(-0.05)	—	—	(0.64)	—	(0.01)	—	—	(0.73)	—	(0.01)
β_{s2}	—	—	0.29	—	0.37	—	—	0.27	—	0.34	—	—	0.28	—	0.34
	—	—	(2.29)**	—	(1.7)*	—	—	(2.26)**	—	(1.67)*	—	—	(2.27)**	—	(1.6)
β_{s3}	—	—	0.33	—	0.21	—	—	0.34	—	0.23	—	—	0.35	—	0.22
	—	—	(3.41)***	—	(0.99)	—	—	(3.33)***	—	(1.06)	—	—	(3.4)***	—	(1.04)
β_{s4}	—	—	0.29	—	-0.09	—	—	0.27	—	-0.12	—	—	0.27	—	-0.11
	—	—	(2.53)***	—	(-0.54)	—	—	(2.53)***	—	(-0.73)	—	—	(2.54)***	—	(-0.68)
β_{c1}	—	—	—	-0.13	—	—	—	—	-0.14	—	—	—	—	-0.13	—
	—	—	—	(-1.18)	—	—	—	—	(-1.34)	—	—	—	—	(-1.19)	—
β_{c2}	—	—	—	0.03	—	—	—	—	0.00	—	—	—	—	0.01	—
	—	—	—	(0.25)	—	—	—	—	(-0.03)	—	—	—	—	(0.1)	—
β_{c3}	—	—	—	0.14	—	—	—	—	0.14	—	—	—	—	0.17	—
	—	—	—	(1.33)	—	—	—	—	(1.32)	—	—	—	—	(1.54)	—
β_{c4}	—	—	—	0.23	—	—	—	—	0.21	—	—	—	—	0.22	—
	—	—	—	(1.51)	—	—	—	—	(1.44)	—	—	—	—	(1.48)	—
β_d	0.38	0.38	0.38	0.38	0.37	0.38	0.38	0.38	0.38	0.37	0.38	0.37	0.38	0.38	0.37
	(3.83)***	(3.75)***	(3.8)***	(3.8)***	(3.73)***	(3.96)***	(3.87)***	(3.92)***	(3.94)***	(3.85)***	(3.92)***	(3.83)***	(3.86)***	(3.9)***	(3.79)***
β_{d1}	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
	(-2.44)***	(-2.39)***	(-2.4)***	(-2.45)***	(-2.37)***	(-2.7)***	(-2.64)***	(-2.66)***	(-2.7)***	(-2.63)***	(-2.63)***	(-2.58)***	(-2.58)***	(-2.64)***	(-2.56)***
β_w	0.39	0.39	0.39	0.39	0.39	0.39	0.39	0.39	0.39	0.39	0.40	0.39	0.39	0.40	0.40
	(5.97)***	(5.75)***	(5.74)***	(5.74)***	(5.77)***	(5.94)***	(5.73)***	(5.74)***	(5.74)***	(5.77)***	(5.61)***	(5.42)***	(5.42)***	(5.41)***	(5.44)***
β_m	0.20	0.17	0.17	0.19	0.17	0.20	0.17	0.17	0.19	0.17	0.20	0.18	0.17	0.20	0.17
	(3.84)***	(3.26)***	(3.01)***	(3.67)***	(3.03)***	(3.88)***	(3.36)***	(3.13)***	(3.78)***	(3.14)***	(3.92)***	(3.39)***	(3.15)***	(3.8)***	(3.17)***
β_j	—	—	—	—	—	0.20	0.20	0.19	0.20	0.20	0.21	0.20	0.20	0.21	0.20
	—	—	—	—	—	(2.12)**	(2.13)**	(2.14)**	(2.15)**	(2.17)**	(2.13)**	(2.15)**	(2.16)**	(2.16)**	(2.18)**
R	67%	67%	67%	67%	68%	67%	68%	68%	68%	68%	67%	68%	67%	67%	68%
QLIKE	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
J-R	61%	62%	62%	61%	62%	63%	64%	64%	63%	64%	62%	63%	63%	62%	63%
J-QLIKE	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04
C-R	68%	69%	69%	68%	69%	68%	69%	69%	68%	69%	68%	69%	68%	68%	69%
C-QLIKE	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03

Table 4.20: German Market (h=5)

	HAR-RV					HAR-RVJ					HAR-CJ				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
β_0	0.08	0.08	0.09	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.09	0.08	0.09	0.08	0.08
	(2.49)***	(2.16)**	(2.53)***	(2.29)**	(2.38)***	(2.47)***	(2.16)**	(2.53)***	(2.27)**	(2.38)***	(2.65)***	(2.28)**	(2.66)***	(2.43)***	(2.51)***
β_{l1}	—	0.07	—	—	0.05	—	0.07	—	—	0.05	—	0.05	—	—	0.08
	—	(0.42)	—	—	(0.24)	—	(0.41)	—	—	(0.22)	—	(0.32)	—	—	(0.4)
β_{l2}	—	0.27	—	—	-0.07	—	0.27	—	—	-0.07	—	0.26	—	—	-0.08
	—	(1.63)	—	—	(-0.32)	—	(1.62)	—	—	(-0.33)	—	(1.59)	—	—	(-0.39)
β_{l3}	—	0.49	—	—	0.06	—	0.49	—	—	0.06	—	0.50	—	—	0.07
	—	(3.31)***	—	—	(0.2)	—	(3.25)***	—	—	(0.19)	—	(3.28)***	—	—	(0.23)
β_{l4}	—	0.49	—	—	0.58	—	0.49	—	—	0.58	—	0.47	—	—	0.54
	—	(2.84)***	—	—	(2.28)**	—	(2.86)***	—	—	(2.27)**	—	(2.76)***	—	—	(2.21)**
β_{s1}	—	—	0.06	—	0.04	—	—	0.06	—	0.04	—	—	0.04	—	0.00
	—	—	(0.52)	—	(0.24)	—	—	(0.51)	—	(0.25)	—	—	(0.37)	—	(0.03)
β_{s2}	—	—	0.36	—	0.46	—	—	0.36	—	0.47	—	—	0.36	—	0.47
	—	—	(1.73)*	—	(1.41)	—	—	(1.74)*	—	(1.42)	—	—	(1.73)*	—	(1.45)
β_{s3}	—	—	0.55	—	0.52	—	—	0.55	—	0.52	—	—	0.55	—	0.51
	—	—	(3.14)***	—	(1.44)	—	—	(3.12)***	—	(1.44)	—	—	(3.14)***	—	(1.43)
β_{s4}	—	—	0.34	—	-0.04	—	—	0.34	—	-0.04	—	—	0.33	—	-0.02
	—	—	(2.21)**	—	(-0.16)	—	—	(2.22)**	—	(-0.16)	—	—	(2.16)**	—	(-0.11)
β_{c1}	—	—	—	-0.21	—	—	—	—	-0.21	—	—	—	—	-0.23	—
	—	—	—	(-1.11)	—	—	—	—	(-1.12)	—	—	—	—	(-1.25)	—
β_{c2}	—	—	—	0.02	—	—	—	—	0.02	—	—	—	—	0.02	—
	—	—	—	(0.13)	—	—	—	—	(0.14)	—	—	—	—	(0.1)	—
β_{c3}	—	—	—	0.30	—	—	—	—	0.30	—	—	—	—	0.30	—
	—	—	—	(1.7)*	—	—	—	—	(1.69)*	—	—	—	—	(1.69)*	—
β_{c4}	—	—	—	0.28	—	—	—	—	0.28	—	—	—	—	0.26	—
	—	—	—	(1.34)	—	—	—	—	(1.35)	—	—	—	—	(1.27)	—
β_d	0.31	0.30	0.30	0.30	0.30	0.31	0.30	0.30	0.30	0.30	0.34	0.33	0.34	0.34	0.33
	(3.25)***	(3.27)***	(3.29)***	(3.29)***	(3.3)***	(3.24)***	(3.27)***	(3.29)***	(3.29)***	(3.29)***	(3.45)***	(3.48)***	(3.48)***	(3.49)***	(3.49)***
β_{d1}	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
	(-1.39)	(-1.43)	(-1.43)	(-1.43)	(-1.43)	(-1.39)	(-1.43)	(-1.43)	(-1.43)	(-1.43)	(-1.79)*	(-1.82)*	(-1.82)*	(-1.82)*	(-1.82)*
β_w	0.36	0.36	0.36	0.37	0.36	0.36	0.36	0.36	0.37	0.36	0.37	0.36	0.36	0.37	0.36
	(4.71)***	(4.7)***	(4.66)***	(4.87)***	(4.73)***	(4.67)***	(4.67)***	(4.63)***	(4.82)***	(4.7)***	(4.69)***	(4.67)***	(4.64)***	(4.85)***	(4.72)***
β_m	0.27	0.25	0.24	0.26	0.24	0.27	0.25	0.24	0.26	0.24	0.26	0.25	0.24	0.26	0.24
	(6.17)***	(5.33)***	(4.91)***	(5.88)***	(4.97)***	(6.13)***	(5.32)***	(4.9)***	(5.85)***	(4.96)***	(5.94)***	(5.17)***	(4.74)***	(5.69)***	(4.8)***
β_j	—	—	—	—	—	0.02	0.01	0.02	0.02	0.01	0.02	0.01	0.02	0.02	0.02
	—	—	—	—	—	(0.52)	(0.29)	(0.43)	(0.53)	(0.38)	(0.6)	(0.36)	(0.5)	(0.61)	(0.45)
R	67%	67%	67%	67%	67%	67%	67%	67%	67%	67%	67%	68%	68%	67%	68%
QLIKE	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
J-R	58%	59%	59%	59%	59%	59%	59%	60%	59%	60%	60%	61%	61%	61%	61%
J-QLIKE	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
C-R	68%	68%	68%	68%	68%	68%	68%	68%	68%	68%	68%	68%	69%	68%	69%
C-QLIKE	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03

Table 4.21: French Market (h=5)

	HAR-RV					HAR-RVJ					HAR-CJ				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
β_0	0.04	0.01	0.02	0.03	0.01	0.04	0.01	0.02	0.03	0.01	0.00	-0.02	-0.01	-0.01	-0.02
	(2.93)***	(0.48)	(1.03)	(1.74)*	(0.45)	(2.95)***	(0.48)	(1.04)	(1.75)*	(0.46)	(-0.09)	(-1.03)	(-0.66)	(-0.6)	(-1)
β_{l1}	—	0.34	—	—	0.37	—	0.35	—	—	0.38	—	0.30	—	—	0.36
	—	(1.59)	—	—	(1.61)	—	(1.59)	—	—	(1.61)	—	(1.42)	—	—	(1.52)
β_{l2}	—	0.28	—	—	0.23	—	0.28	—	—	0.23	—	0.26	—	—	0.23
	—	(1.74)*	—	—	(1.72)*	—	(1.74)*	—	—	(1.72)*	—	(1.68)*	—	—	(1.69)*
β_{l3}	—	0.49	—	—	0.48	—	0.49	—	—	0.48	—	0.50	—	—	0.47
	—	(3.15)***	—	—	(2.3)**	—	(3.12)***	—	—	(2.29)**	—	(3.21)***	—	—	(2.3)**
β_{l4}	—	0.83	—	—	0.98	—	0.84	—	—	0.98	—	0.81	—	—	0.94
	—	(2.89)***	—	—	(2.91)***	—	(2.87)***	—	—	(2.9)***	—	(2.83)***	—	—	(2.78)***
β_{s1}	—	—	0.30	—	-0.07	—	—	0.30	—	-0.08	—	—	0.22	—	-0.12
	—	—	(0.86)	—	(-0.27)	—	—	(0.86)	—	(-0.3)	—	—	(0.65)	—	(-0.46)
β_{s2}	—	—	0.21	—	0.07	—	—	0.21	—	0.07	—	—	0.17	—	0.04
	—	—	(0.86)	—	(0.31)	—	—	(0.86)	—	(0.3)	—	—	(0.75)	—	(0.16)
β_{s3}	—	—	0.51	—	0.00	—	—	0.51	—	0.00	—	—	0.53	—	0.03
	—	—	(2.05)**	—	(0.01)	—	—	(2.05)**	—	(-0.01)	—	—	(2.17)**	—	(0.1)
β_{s4}	—	—	1.05	—	-0.31	—	—	1.05	—	-0.31	—	—	1.01	—	-0.29
	—	—	(2.09)**	—	(-0.67)	—	—	(2.09)**	—	(-0.69)	—	—	(2.06)**	—	(-0.65)
β_{c1}	—	—	—	0.15	—	—	—	—	0.16	—	—	—	—	0.13	—
	—	—	—	(0.57)	—	—	—	—	(0.57)	—	—	—	—	(0.48)	—
β_{c2}	—	—	—	0.17	—	—	—	—	0.17	—	—	—	—	0.19	—
	—	—	—	(0.62)	—	—	—	—	(0.62)	—	—	—	—	(0.74)	—
β_{c3}	—	—	—	0.55	—	—	—	—	0.55	—	—	—	—	0.64	—
	—	—	—	(1.92)*	—	—	—	—	(1.91)*	—	—	—	—	(2.27)**	—
β_{c4}	—	—	—	0.77	—	—	—	—	0.77	—	—	—	—	0.76	—
	—	—	—	(1.97)**	—	—	—	—	(1.97)**	—	—	—	—	(2.03)**	—
β_d	0.38	0.36	0.38	0.38	0.36	0.38	0.36	0.38	0.38	0.36	0.51	0.48	0.50	0.50	0.49
	(4.46)***	(4.31)***	(4.54)***	(4.52)***	(4.33)***	(4.47)***	(4.31)***	(4.55)***	(4.53)***	(4.32)***	(5.43)***	(5.16)***	(5.47)***	(5.47)***	(5.18)***
β_{d1}	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.02	-0.02	-0.02	-0.02	-0.02
	(-1.96)*	(-1.9)*	(-2.06)**	(-2.06)**	(-1.93)*	(-1.96)*	(-1.91)*	(-2.06)**	(-2.07)**	(-1.93)*	(-2.88)***	(-2.69)***	(-2.88)***	(-2.96)***	(-2.71)***
β_w	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.47	0.47	0.47	0.47	0.47
	(6.18)***	(6.48)***	(6.46)***	(6.4)***	(6.53)***	(6.23)***	(6.54)***	(6.51)***	(6.44)***	(6.6)***	(6.96)***	(7.26)***	(7.2)***	(7.13)***	(7.29)***
β_m	0.22	0.21	0.21	0.21	0.21	0.22	0.21	0.21	0.21	0.21	0.15	0.12	0.13	0.14	0.12
	(5.84)***	(5.33)***	(5.27)***	(5.59)***	(5.35)***	(5.84)***	(5.33)***	(5.27)***	(5.59)***	(5.35)***	(3.89)***	(3.1)***	(3.33)***	(3.77)***	(3.11)***
β_j	—	—	—	—	—	0.00	-0.02	0.00	-0.01	-0.02	0.00	-0.02	0.00	-0.01	-0.02
	—	—	—	—	—	(-0.13)	(-0.66)	(-0.07)	(-0.25)	(-0.7)	(-0.09)	(-0.58)	(-0.03)	(-0.21)	(-0.61)
R	77%	78%	77%	77%	78%	77%	78%	77%	77%	78%	77%	78%	77%	77%	78%
QLIKE	0.39	0.41	0.41	0.39	0.41	0.39	0.41	0.41	0.39	0.41	0.47	0.47	0.47	0.46	0.47
J-R	76%	76%	77%	77%	76%	76%	76%	77%	77%	76%	76%	75%	76%	76%	75%
J-QLIKE	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
C-R	77%	78%	78%	77%	78%	77%	78%	78%	77%	78%	77%	78%	77%	77%	78%
C-QLIKE	0.42	0.44	0.44	0.42	0.44	0.42	0.44	0.44	0.42	0.44	0.50	0.51	0.51	0.50	0.51

Table 4.22: UK Market (h=5)

	HAR-RV					HAR-RVJ					HAR-CJ				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
β_0	0.05	0.04	0.04	0.05	0.04	0.05	0.04	0.04	0.05	0.03	0.06	0.04	0.05	0.06	0.04
	(2.24)**	(1.32)	(1.52)	(2.15)**	(1.29)	(2.09)**	(1.26)	(1.42)	(2.01)**	(1.22)	(2.59)***	(1.69)*	(1.82)*	(2.49)***	(1.63)
β_{l1}	—	0.29	—	—	-0.07	—	0.29	—	—	-0.09	—	0.21	—	—	-0.17
	—	(2.24)**	—	—	(-0.32)	—	(2.22)**	—	—	(-0.41)	—	(1.72)*	—	—	(-0.68)
β_{l2}	—	0.51	—	—	0.34	—	0.49	—	—	0.33	—	0.48	—	—	0.33
	—	(1.89)*	—	—	(2.17)**	—	(1.89)*	—	—	(2.18)**	—	(1.94)*	—	—	(2.29)**
β_{l3}	—	0.50	—	—	0.58	—	0.49	—	—	0.57	—	0.50	—	—	0.56
	—	(2.33)***	—	—	(1.99)**	—	(2.29)**	—	—	(1.95)*	—	(2.39)***	—	—	(1.91)*
β_{l4}	—	0.72	—	—	0.93	—	0.71	—	—	0.91	—	0.67	—	—	0.86
	—	(3.01)***	—	—	(2.9)***	—	(3.01)***	—	—	(2.85)***	—	(2.99)***	—	—	(2.85)***
β_{s1}	—	—	0.36	—	0.65	—	—	0.37	—	0.68	—	—	0.26	—	0.67
	—	—	(1.73)*	—	(1.76)*	—	—	(1.78)*	—	(1.82)*	—	—	(1.32)	—	(1.63)
β_{s2}	—	—	0.61	—	0.33	—	—	0.59	—	0.32	—	—	0.58	—	0.29
	—	—	(1.56)	—	(0.93)	—	—	(1.57)	—	(0.92)	—	—	(1.63)	—	(0.9)
β_{s3}	—	—	0.53	—	-0.09	—	—	0.53	—	-0.09	—	—	0.54	—	-0.07
	—	—	(2.03)**	—	(-0.37)	—	—	(2.03)**	—	(-0.37)	—	—	(2.15)**	—	(-0.26)
β_{s4}	—	—	0.73	—	-0.30	—	—	0.73	—	-0.28	—	—	0.69	—	-0.26
	—	—	(2.29)**	—	(-0.83)	—	—	(2.31)**	—	(-0.76)	—	—	(2.25)**	—	(-0.74)
β_{c1}	—	—	—	0.04	—	—	—	—	0.05	—	—	—	—	-0.05	—
	—	—	—	(0.33)	—	—	—	—	(0.4)	—	—	—	—	(-0.38)	—
β_{c2}	—	—	—	0.26	—	—	—	—	0.26	—	—	—	—	0.23	—
	—	—	—	(2.06)**	—	—	—	—	(2.1)**	—	—	—	—	(2.05)**	—
β_{c3}	—	—	—	0.21	—	—	—	—	0.22	—	—	—	—	0.20	—
	—	—	—	(2.11)**	—	—	—	—	(2.14)**	—	—	—	—	(2.13)**	—
β_{c4}	—	—	—	0.49	—	—	—	—	0.49	—	—	—	—	0.42	—
	—	—	—	(2.38)***	—	—	—	—	(2.43)***	—	—	—	—	(2.13)**	—
β_d	0.38	0.34	0.36	0.37	0.34	0.40	0.35	0.37	0.39	0.35	0.36	0.33	0.34	0.36	0.33
	(5.33)***	(5.1)***	(5.2)***	(5.32)***	(5.02)***	(5.48)***	(5.2)***	(5.38)***	(5.49)***	(5.11)***	(3.94)***	(3.65)***	(3.84)***	(3.91)***	(3.62)***
β_{d1}	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
	(-2.07)**	(-1.57)	(-1.75)*	(-1.96)**	(-1.53)	(-2.33)**	(-1.72)*	(-1.96)*	(-2.21)**	(-1.67)*	(-1.06)	(-0.72)	(-0.86)	(-0.99)	(-0.71)
β_w	0.32	0.31	0.31	0.31	0.31	0.31	0.30	0.30	0.31	0.30	0.51	0.49	0.49	0.50	0.49
	(6.18)***	(6.27)***	(6.16)***	(6.17)***	(6.15)***	(5.84)***	(5.91)***	(5.82)***	(5.84)***	(5.79)***	(7.38)***	(7.49)***	(7.35)***	(7.23)***	(7.36)***
β_m	0.27	0.24	0.25	0.26	0.24	0.27	0.24	0.25	0.26	0.24	0.09	0.07	0.08	0.09	0.07
	(4.76)***	(4.69)***	(4.8)***	(4.79)***	(4.66)***	(4.78)***	(4.7)***	(4.82)***	(4.81)***	(4.69)***	(3.18)***	(2.4)***	(2.9)***	(3.08)***	(2.44)***
β_j	—	—	—	—	—	0.06	0.05	0.06	0.06	0.05	0.05	0.03	0.04	0.04	0.03
	—	—	—	—	—	(1.86)*	(1.44)	(1.84)*	(1.89)*	(1.48)	(1.23)	(0.85)	(1.12)	(1.22)	(0.88)
R	64%	65%	65%	65%	66%	65%	65%	65%	65%	66%	65%	66%	65%	65%	66%
QLIKE	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
J-R	67%	68%	68%	68%	69%	69%	69%	69%	69%	70%	69%	69%	70%	69%	70%
J-QLIKE	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04
C-R	64%	65%	64%	64%	65%	64%	65%	64%	64%	65%	65%	65%	65%	65%	65%
C-QLIKE	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03

Table 4.23: Swiss Market (h=22)

	HAR-RV					HAR-RVJ					HAR-CJ				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
β_0	0.14	0.14	0.15	0.15	0.14	0.14	0.14	0.15	0.14	0.14	0.14	0.14	0.15	0.15	0.14
	(4.4)***	(4.14)***	(4.42)***	(4.41)***	(3.96)***	(4.32)***	(4.07)***	(4.34)***	(4.34)***	(3.88)***	(4.38)***	(4.09)***	(4.38)***	(4.37)***	(3.9)***
β_{l1}	—	0.20	—	—	0.16	—	0.18	—	—	0.14	—	0.19	—	—	0.15
	—	(1.84)*	—	—	(1.05)	—	(1.79)*	—	—	(0.92)	—	(1.81)*	—	—	(0.97)
β_{l2}	—	0.22	—	—	-0.04	—	0.20	—	—	-0.04	—	0.21	—	—	-0.03
	—	(1.91)*	—	—	(-0.25)	—	(1.81)*	—	—	(-0.27)	—	(1.87)*	—	—	(-0.16)
β_{l3}	—	0.29	—	—	0.29	—	0.29	—	—	0.28	—	0.31	—	—	0.30
	—	(3.31)***	—	—	(1.3)	—	(3.29)***	—	—	(1.27)	—	(3.38)***	—	—	(1.34)
β_{l4}	—	0.51	—	—	0.58	—	0.50	—	—	0.59	—	0.50	—	—	0.59
	—	(3.47)***	—	—	(2.13)**	—	(3.52)***	—	—	(2.16)**	—	(3.5)***	—	—	(2.16)**
β_{s1}	—	—	0.12	—	0.04	—	—	0.11	—	0.05	—	—	0.11	—	0.04
	—	—	(1.33)	—	(0.33)	—	—	(1.28)	—	(0.37)	—	—	(1.28)	—	(0.36)
β_{s2}	—	—	0.23	—	0.34	—	—	0.21	—	0.32	—	—	0.22	—	0.31
	—	—	(2.16)**	—	(1.71)*	—	—	(2.08)**	—	(1.67)*	—	—	(2.1)**	—	(1.6)
β_{s3}	—	—	0.23	—	0.02	—	—	0.23	—	0.03	—	—	0.23	—	0.02
	—	—	(2.61)***	—	(0.11)	—	—	(2.58)***	—	(0.15)	—	—	(2.61)***	—	(0.12)
β_{s4}	—	—	0.32	—	-0.04	—	—	0.31	—	-0.06	—	—	0.31	—	-0.06
	—	—	(2.36)***	—	(-0.19)	—	—	(2.33)***	—	(-0.27)	—	—	(2.3)**	—	(-0.25)
β_{c1}	—	—	—	-0.05	—	—	—	—	-0.06	—	—	—	—	-0.05	—
	—	—	—	(-0.41)	—	—	—	—	(-0.52)	—	—	—	—	(-0.42)	—
β_{c2}	—	—	—	-0.11	—	—	—	—	-0.14	—	—	—	—	-0.12	—
	—	—	—	(-0.84)	—	—	—	—	(-1.06)	—	—	—	—	(-0.95)	—
β_{c3}	—	—	—	-0.01	—	—	—	—	-0.01	—	—	—	—	0.01	—
	—	—	—	(-0.14)	—	—	—	—	(-0.13)	—	—	—	—	(0.11)	—
β_{c4}	—	—	—	0.20	—	—	—	—	0.18	—	—	—	—	0.19	—
	—	—	—	(1.05)	—	—	—	—	(0.99)	—	—	—	—	(1.01)	—
β_d	0.33	0.33	0.33	0.33	0.33	0.33	0.33	0.33	0.33	0.32	0.33	0.33	0.33	0.33	0.32
	(3.47)***	(3.39)***	(3.42)***	(3.46)***	(3.37)***	(3.54)***	(3.45)***	(3.48)***	(3.54)***	(3.44)***	(3.41)***	(3.33)***	(3.35)***	(3.41)***	(3.3)***
β_{d1}	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
	(-2.61)***	(-2.55)***	(-2.57)***	(-2.61)***	(-2.53)***	(-2.79)***	(-2.72)***	(-2.74)***	(-2.79)***	(-2.71)***	(-2.67)***	(-2.62)***	(-2.62)***	(-2.67)***	(-2.6)***
β_w	0.32	0.31	0.31	0.31	0.31	0.32	0.31	0.31	0.31	0.31	0.32	0.31	0.31	0.31	0.31
	(3.79)***	(3.56)***	(3.54)***	(3.63)***	(3.54)***	(3.77)***	(3.56)***	(3.54)***	(3.63)***	(3.54)***	(3.63)***	(3.42)***	(3.4)***	(3.48)***	(3.41)***
β_m	0.22	0.19	0.19	0.22	0.19	0.22	0.19	0.19	0.22	0.19	0.23	0.20	0.20	0.23	0.20
	(3.54)***	(3)***	(2.91)***	(3.46)***	(2.93)***	(3.56)***	(3.03)***	(2.96)***	(3.5)***	(2.97)***	(3.58)***	(3.06)***	(2.99)***	(3.52)***	(3.01)***
β_j	—	—	—	—	—	0.15	0.14	0.14	0.15	0.14	0.15	0.14	0.14	0.15	0.14
	—	—	—	—	—	(2.16)**	(2.14)**	(2.13)**	(2.2)**	(2.16)**	(2.18)**	(2.17)**	(2.16)**	(2.22)**	(2.19)**
R	57%	58%	58%	57%	58%	58%	58%	58%	58%	58%	57%	58%	58%	57%	58%
QLIKE	0.04	0.03	0.03	0.04	0.03	0.04	0.03	0.03	0.04	0.03	0.04	0.03	0.03	0.04	0.03
J-R	60%	61%	61%	60%	61%	61%	62%	62%	61%	63%	60%	61%	61%	60%	62%
J-QLIKE	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04
C-R	57%	58%	57%	57%	58%	57%	58%	57%	57%	58%	57%	58%	57%	57%	58%
C-QLIKE	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03

Table 4.24: German Market (h=22)

	HAR-RV					HAR-RVJ					HAR-CJ				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
β_0	0.21	0.21	0.22	0.21	0.21	0.21	0.21	0.22	0.21	0.21	0.21	0.21	0.22	0.22	0.21
	(6.07)***	(5.48)***	(5.88)***	(5.92)***	(5.15)***	(6.11)***	(5.54)***	(5.93)***	(5.97)***	(5.2)***	(6.28)***	(5.64)***	(6.03)***	(6.12)***	(5.29)***
β_{l1}	—	0.24	—	—	-0.01	—	0.24	—	—	-0.01	—	0.23	—	—	0.02
	—	(1.47)	—	—	(-0.05)	—	(1.48)	—	—	(-0.03)	—	(1.41)	—	—	(0.09)
β_{l2}	—	0.26	—	—	-0.04	—	0.26	—	—	-0.04	—	0.25	—	—	-0.05
	—	(1.37)	—	—	(-0.17)	—	(1.37)	—	—	(-0.15)	—	(1.35)	—	—	(-0.22)
β_{l3}	—	0.34	—	—	0.22	—	0.35	—	—	0.23	—	0.35	—	—	0.24
	—	(2.31)**	—	—	(0.71)	—	(2.31)**	—	—	(0.73)	—	(2.33)***	—	—	(0.76)
β_{l4}	—	0.63	—	—	0.65	—	0.63	—	—	0.65	—	0.62	—	—	0.62
	—	(2.86)***	—	—	(1.53)	—	(2.86)***	—	—	(1.53)	—	(2.78)***	—	—	(1.48)
β_{s1}	—	—	0.19	—	0.22	—	—	0.19	—	0.22	—	—	0.18	—	0.19
	—	—	(1.69)*	—	(1.5)	—	—	(1.69)*	—	(1.49)	—	—	(1.57)	—	(1.32)
β_{s2}	—	—	0.30	—	0.39	—	—	0.30	—	0.38	—	—	0.29	—	0.39
	—	—	(1.68)*	—	(1.31)	—	—	(1.68)*	—	(1.3)	—	—	(1.68)*	—	(1.36)
β_{s3}	—	—	0.32	—	0.15	—	—	0.32	—	0.15	—	—	0.32	—	0.15
	—	—	(2.75)***	—	(0.58)	—	—	(2.76)***	—	(0.57)	—	—	(2.77)***	—	(0.55)
β_{s4}	—	—	0.43	—	0.00	—	—	0.43	—	0.00	—	—	0.42	—	0.01
	—	—	(2.48)***	—	(0.01)	—	—	(2.48)***	—	(0.01)	—	—	(2.41)***	—	(0.04)
β_{c1}	—	—	—	0.01	—	—	—	—	0.01	—	—	—	—	-0.02	—
	—	—	—	(0.03)	—	—	—	—	(0.04)	—	—	—	—	(-0.1)	—
β_{c2}	—	—	—	-0.13	—	—	—	—	-0.13	—	—	—	—	-0.13	—
	—	—	—	(-0.78)	—	—	—	—	(-0.79)	—	—	—	—	(-0.85)	—
β_{c3}	—	—	—	0.01	—	—	—	—	0.01	—	—	—	—	0.01	—
	—	—	—	(0.06)	—	—	—	—	(0.07)	—	—	—	—	(0.04)	—
β_{c4}	—	—	—	0.32	—	—	—	—	0.32	—	—	—	—	0.30	—
	—	—	—	(1.39)	—	—	—	—	(1.39)	—	—	—	—	(1.31)	—
β_d	0.19	0.19	0.20	0.20	0.19	0.19	0.19	0.20	0.20	0.19	0.22	0.22	0.22	0.22	0.22
	(2.73)***	(2.74)***	(2.75)***	(2.76)***	(2.78)***	(2.72)***	(2.74)***	(2.75)***	(2.76)***	(2.77)***	(2.91)***	(2.93)***	(2.93)***	(2.94)***	(2.96)***
β_{d1}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.01	-0.01	-0.01	-0.01	-0.01
	(-0.85)	(-0.88)	(-0.9)	(-0.89)	(-0.89)	(-0.85)	(-0.89)	(-0.9)	(-0.89)	(-0.9)	(-1.18)	(-1.21)	(-1.22)	(-1.21)	(-1.22)
β_w	0.32	0.31	0.31	0.32	0.31	0.32	0.31	0.31	0.32	0.31	0.32	0.31	0.31	0.32	0.31
	(4.53)***	(4.34)***	(4.2)***	(4.44)***	(4.24)***	(4.55)***	(4.37)***	(4.22)***	(4.45)***	(4.26)***	(4.59)***	(4.37)***	(4.22)***	(4.48)***	(4.27)***
β_m	0.30	0.27	0.26	0.29	0.26	0.30	0.27	0.26	0.29	0.26	0.29	0.27	0.26	0.29	0.26
	(5.81)***	(4.96)***	(4.75)***	(5.57)***	(4.81)***	(5.82)***	(4.98)***	(4.76)***	(5.58)***	(4.82)***	(5.62)***	(4.83)***	(4.62)***	(5.4)***	(4.67)***
β_j	—	—	—	—	—	-0.01	-0.02	-0.02	-0.01	-0.02	-0.01	-0.02	-0.02	-0.01	-0.02
	—	—	—	—	—	(-0.43)	(-0.74)	(-0.59)	(-0.49)	(-0.67)	(-0.36)	(-0.68)	(-0.52)	(-0.41)	(-0.6)
R	59%	60%	60%	59%	60%	59%	60%	60%	59%	60%	59%	60%	60%	60%	60%
QLIKE	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
J-R	49%	51%	50%	50%	51%	49%	51%	50%	50%	51%	50%	52%	51%	51%	52%
J-QLIKE	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
C-R	60%	61%	61%	60%	61%	60%	61%	61%	60%	61%	60%	61%	61%	60%	61%
C-QLIKE	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03

Table 4.25: French Market (h=22)

	HAR-RV					HAR-RVJ					HAR-CJ				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
β_0	0.09	0.05	0.08	0.07	0.06	0.09	0.05	0.08	0.07	0.06	0.05	0.02	0.04	0.03	0.03
	(4.7)***	(2.02)**	(3.38)***	(3.29)***	(2.53)***	(4.67)***	(2.02)**	(3.36)***	(3.28)***	(2.53)***	(1.8)*	(0.69)	(1.44)	(1.1)	(1.01)
β_{l1}	—	0.55	—	—	0.66	—	0.55	—	—	0.66	—	0.51	—	—	0.64
	—	(2.67)***	—	—	(2.08)**	—	(2.66)***	—	—	(2.09)**	—	(2.62)***	—	—	(2.16)**
β_{l2}	—	0.45	—	—	0.58	—	0.45	—	—	0.58	—	0.44	—	—	0.59
	—	(2.78)***	—	—	(2.64)***	—	(2.77)***	—	—	(2.63)***	—	(2.82)***	—	—	(2.7)***
β_{l3}	—	0.61	—	—	0.84	—	0.61	—	—	0.84	—	0.64	—	—	0.83
	—	(3.88)***	—	—	(3.6)***	—	(3.85)***	—	—	(3.58)***	—	(4.13)***	—	—	(3.59)***
β_{l4}	—	0.81	—	—	0.81	—	0.81	—	—	0.81	—	0.80	—	—	0.76
	—	(3.03)***	—	—	(2.31)**	—	(3.02)***	—	—	(2.31)**	—	(3.08)***	—	—	(2.16)**
β_{s1}	—	—	0.34	—	-0.37	—	—	0.34	—	-0.37	—	—	0.27	—	-0.40
	—	—	(1.23)	—	(-0.92)	—	—	(1.21)	—	(-0.92)	—	—	(0.99)	—	(-1.01)
β_{s2}	—	—	0.18	—	-0.37	—	—	0.18	—	-0.37	—	—	0.15	—	-0.41
	—	—	(0.8)	—	(-1.12)	—	—	(0.8)	—	(-1.12)	—	—	(0.71)	—	(-1.25)
β_{s3}	—	—	0.36	—	-0.57	—	—	0.36	—	-0.57	—	—	0.41	—	-0.49
	—	—	(1.71)*	—	(-1.65)*	—	—	(1.71)*	—	(-1.66)*	—	—	(1.91)*	—	(-1.4)
β_{s4}	—	—	0.81	—	-0.14	—	—	0.81	—	-0.15	—	—	0.78	—	-0.07
	—	—	(1.95)*	—	(-0.38)	—	—	(1.96)**	—	(-0.39)	—	—	(1.99)**	—	(-0.18)
β_{c1}	—	—	—	0.58	—	—	—	—	0.57	—	—	—	—	0.55	—
	—	—	—	(2.09)**	—	—	—	—	(2.07)**	—	—	—	—	(2.02)**	—
β_{c2}	—	—	—	0.50	—	—	—	—	0.50	—	—	—	—	0.53	—
	—	—	—	(1.7)*	—	—	—	—	(1.7)*	—	—	—	—	(1.87)*	—
β_{c3}	—	—	—	0.73	—	—	—	—	0.72	—	—	—	—	0.83	—
	—	—	—	(2.27)**	—	—	—	—	(2.25)**	—	—	—	—	(2.59)***	—
β_{c4}	—	—	—	0.91	—	—	—	—	0.91	—	—	—	—	0.91	—
	—	—	—	(2.29)**	—	—	—	—	(2.29)**	—	—	—	—	(2.41)***	—
β_d	0.38	0.36	0.38	0.38	0.36	0.38	0.36	0.38	0.38	0.35	0.53	0.50	0.53	0.53	0.50
	(5.33)***	(5.19)***	(5.39)***	(5.55)***	(5.17)***	(5.36)***	(5.19)***	(5.41)***	(5.57)***	(5.17)***	(6.93)***	(6.63)***	(6.93)***	(7.21)***	(6.57)***
β_{d1}	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.03	-0.03	-0.03	-0.03	-0.03
	(-2.96)***	(-2.85)***	(-3.03)***	(-3.18)***	(-2.84)***	(-2.96)***	(-2.85)***	(-3.03)***	(-3.18)***	(-2.84)***	(-3.96)***	(-3.74)***	(-3.96)***	(-4.2)***	(-3.71)***
β_w	0.32	0.31	0.31	0.31	0.31	0.31	0.31	0.31	0.31	0.31	0.41	0.41	0.41	0.40	0.41
	(5.12)***	(5.41)***	(5.26)***	(5.31)***	(5.36)***	(5.17)***	(5.47)***	(5.3)***	(5.36)***	(5.42)***	(7.09)***	(7.42)***	(7.25)***	(7.28)***	(7.42)***
β_m	0.28	0.26	0.27	0.27	0.26	0.28	0.26	0.27	0.27	0.26	0.16	0.13	0.15	0.15	0.14
	(5.44)***	(5)***	(5.14)***	(5.25)***	(5.12)***	(5.43)***	(5)***	(5.14)***	(5.25)***	(5.12)***	(3.72)***	(2.94)***	(3.33)***	(3.58)***	(3.02)***
β_j	—	—	—	—	—	0.02	0.00	0.03	0.02	-0.01	0.03	0.00	0.03	0.02	0.00
	—	—	—	—	—	(0.78)	(-0.01)	(0.82)	(0.51)	(-0.18)	(0.81)	(0.06)	(0.85)	(0.53)	(-0.08)
R	72%	72%	72%	72%	73%	72%	72%	72%	72%	73%	70%	71%	71%	71%	71%
QLIKE	0.47	0.48	0.48	0.47	0.48	0.47	0.48	0.48	0.47	0.48	0.52	0.52	0.52	0.51	0.52
J-R	60%	62%	61%	61%	62%	60%	62%	61%	61%	62%	60%	62%	61%	60%	62%
J-QLIKE	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
C-R	72%	73%	72%	73%	73%	72%	73%	72%	73%	73%	71%	72%	71%	72%	72%
C-QLIKE	0.52	0.53	0.53	0.52	0.52	0.52	0.53	0.53	0.52	0.52	0.57	0.57	0.57	0.56	0.57

Table 4.26: UK Market (h=22)

	HAR-RV					HAR-RVJ					HAR-CJ				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
β_0	0.11	0.09	0.10	0.10	0.09	0.10	0.08	0.09	0.10	0.09	0.12	0.10	0.10	0.11	0.10
	(2.67)***	(1.9)*	(2.28)**	(2.44)***	(2.03)**	(2.55)***	(1.84)*	(2.19)**	(2.33)***	(1.97)**	(2.97)***	(2.18)**	(2.54)***	(2.74)***	(2.32)**
β_{l1}	—	0.37	—	—	0.24	—	0.36	—	—	0.22	—	0.30	—	—	0.14
	—	(2.78)***	—	—	(1.07)	—	(2.76)***	—	—	(0.94)	—	(2.43)***	—	—	(0.58)
β_{l2}	—	0.58	—	—	0.71	—	0.56	—	—	0.70	—	0.57	—	—	0.71
	—	(2.77)***	—	—	(2.35)***	—	(2.78)***	—	—	(2.38)***	—	(2.91)***	—	—	(2.46)***
β_{l3}	—	0.59	—	—	0.65	—	0.58	—	—	0.64	—	0.60	—	—	0.64
	—	(2.97)***	—	—	(2.42)***	—	(2.92)***	—	—	(2.38)***	—	(3)***	—	—	(2.3)**
β_{l4}	—	0.70	—	—	0.67	—	0.69	—	—	0.65	—	0.68	—	—	0.63
	—	(3.79)***	—	—	(2.61)***	—	(3.78)***	—	—	(2.55)***	—	(3.83)***	—	—	(2.47)***
β_{s1}	—	—	0.24	—	0.16	—	—	0.25	—	0.20	—	—	0.18	—	0.23
	—	—	(1.2)	—	(0.55)	—	—	(1.27)	—	(0.65)	—	—	(0.92)	—	(0.68)
β_{s2}	—	—	0.47	—	-0.28	—	—	0.45	—	-0.29	—	—	0.47	—	-0.28
	—	—	(1.9)*	—	(-0.7)	—	—	(1.91)*	—	(-0.74)	—	—	(2.04)**	—	(-0.73)
β_{s3}	—	—	0.52	—	-0.15	—	—	0.51	—	-0.15	—	—	0.55	—	-0.11
	—	—	(2.04)**	—	(-0.51)	—	—	(2.03)**	—	(-0.5)	—	—	(2.15)**	—	(-0.34)
β_{s4}	—	—	0.62	—	-0.01	—	—	0.62	—	0.02	—	—	0.62	—	0.04
	—	—	(2.18)**	—	(-0.02)	—	—	(2.22)**	—	(0.05)	—	—	(2.23)**	—	(0.1)
β_{c1}	—	—	—	0.16	—	—	—	—	0.17	—	—	—	—	0.09	—
	—	—	—	(1.18)	—	—	—	—	(1.27)	—	—	—	—	(0.7)	—
β_{c2}	—	—	—	0.42	—	—	—	—	0.41	—	—	—	—	0.40	—
	—	—	—	(3)***	—	—	—	—	(3.01)***	—	—	—	—	(2.82)***	—
β_{c3}	—	—	—	0.45	—	—	—	—	0.45	—	—	—	—	0.45	—
	—	—	—	(3.02)***	—	—	—	—	(3.03)***	—	—	—	—	(2.94)***	—
β_{c4}	—	—	—	0.53	—	—	—	—	0.54	—	—	—	—	0.50	—
	—	—	—	(2.87)***	—	—	—	—	(2.96)***	—	—	—	—	(2.75)***	—
β_d	0.40	0.35	0.38	0.38	0.36	0.41	0.36	0.39	0.40	0.37	0.37	0.33	0.35	0.36	0.33
	(4.17)***	(4.02)***	(3.92)***	(4.04)***	(3.94)***	(4.21)***	(4.06)***	(3.97)***	(4.09)***	(3.98)***	(4.21)***	(4)***	(4.02)***	(4.11)***	(3.97)***
β_{d1}	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.01	-0.01	-0.01	-0.01
	(-2.86)***	(-2.54)***	(-2.59)***	(-2.72)***	(-2.5)***	(-3.01)***	(-2.63)***	(-2.73)***	(-2.87)***	(-2.6)***	(-2.48)***	(-2.03)**	(-2.24)**	(-2.37)***	(-2.03)**
β_w	0.27	0.26	0.26	0.27	0.26	0.26	0.25	0.25	0.25	0.25	0.45	0.43	0.43	0.44	0.43
	(3.5)***	(3.55)***	(3.44)***	(3.5)***	(3.48)***	(3.35)***	(3.41)***	(3.31)***	(3.35)***	(3.33)***	(5.89)***	(6.09)***	(5.82)***	(5.88)***	(5.81)***
β_m	0.27	0.24	0.26	0.26	0.24	0.27	0.24	0.26	0.26	0.24	0.11	0.09	0.10	0.10	0.09
	(4.09)***	(3.72)***	(3.99)***	(4.05)***	(3.76)***	(4.14)***	(3.77)***	(4.04)***	(4.1)***	(3.8)***	(2.43)***	(1.9)*	(2.27)**	(2.29)**	(1.89)*
β_j	—	—	—	—	—	0.07	0.06	0.07	0.07	0.06	0.06	0.04	0.05	0.06	0.04
	—	—	—	—	—	(2.88)***	(2.16)**	(2.71)***	(2.88)***	(2.14)**	(1.91)*	(1.32)	(1.76)*	(1.87)*	(1.33)
R	58%	60%	59%	59%	60%	59%	60%	59%	59%	60%	58%	59%	58%	58%	59%
QLIKE	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04
J-R	58%	60%	59%	59%	60%	60%	61%	60%	60%	61%	59%	60%	59%	59%	60%
J-QLIKE	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
C-R	58%	60%	59%	59%	60%	58%	60%	59%	59%	60%	58%	59%	58%	58%	59%
C-QLIKE	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04

Table 4.27: Out of Sample Forecasting Results

Table 4.28: Switzerland

	HAR-RV					HAR-RVJ					HAR-CJ				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
h=1	0.149	0.151	0.151	0.147	0.149	0.149	0.146	0.148	0.149	0.148	0.15	0.15	0.147	0.149	0.149
h=5	0.117	0.118	0.117	0.114^{a}	0.116	0.115	0.115	0.116	0.115	0.116	0.117	0.117	0.115	0.116^{a}	0.115^{a}
h=22	0.122	0.121	0.123	0.117^{a}	0.117^{a}	0.118	0.12	0.119	0.121^{b}	0.121^{b}	0.121	0.122^{b}	0.119^{a}	0.118^{a}	0.12

Table 4.29: Germany

	HAR-RV					HAR-RVJ					HAR-CJ				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
h=1	0.212	0.212^{a}	0.216	0.21	0.21	0.213	0.21	0.21	0.213	0.211	0.211	0.215	0.21	0.21	0.214
h=5	0.162	0.162^{a}	0.16	0.161	0.161	0.158	0.16	0.16	0.158	0.161	0.161	0.159	0.16	0.16	0.158
h=22	0.186	0.186^{b}	0.184	0.181^{a}	0.181^{a}	0.179	0.183	0.183	0.181	0.185	0.185	0.183	0.182^{a}	0.182^{a}	0.18

Table 4.30: France

	HAR-RV					HAR-RVJ					HAR-CJ				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
h=1	0.195	0.195	0.2	0.196	0.196	0.199	0.195	0.195	0.199	0.194	0.195	0.199	0.197	0.197	0.199
h=5	0.153	0.153^{b}	0.155	0.152	0.152	0.153	0.15	0.15	0.153	0.152	0.152	0.154	0.152	0.153	0.153
h=22	0.176	0.175^{a}	0.187	0.168	0.168	0.178	0.174	0.174	0.185	0.173	0.173	0.184	0.169	0.169	0.179

Table 4.31: United Kingdom

	HAR-RV					HAR-RVJ					HAR-CJ				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
h=1	0.125	0.125^{a}	0.129	0.128	0.128	0.13	0.127	0.126	0.129	0.125	0.125	0.128	0.13	0.129	0.131
h=5	0.104	0.104^{a}	0.105	0.103	0.102	0.102	0.102	0.102	0.103	0.102	0.102	0.103	0.103	0.103	0.103
h=22	0.126	0.125^{a}	0.131^{b}	0.115	0.114	0.119	0.12	0.119	0.124^{b}	0.12	0.119	0.125^{b}	0.115	0.115	0.119

(1) The table gives the mean squared errors for 200 days out of sample forecasting. (2) In each group, HAR-RV, HAR-RVJ and HAR-CJ, the forecasts are compared to the first column of the groups, baseline models. (3) ^{a} means the model's forecasting results are significantly better than the baseline according to Diebold & Mariano (1995) test in 95% confidence interval. (4) ^{b} corresponding to the baseline model provides better forecasts.

show that the transmission of volatility from the bond to equity markets is the highest when the yield curve moves in bull steepener and the transmission is limited as the curve demonstrates a bear flattener move. I try to explain these results by separating the risk premium and hedging premium following Cieslak & Pang (2021) that is inherent in the sovereign yield curves. In an extended HARQ framework, I empirically show the inclusion of yield curve volatility to help to get more robust forecasts and I provide the estimations that show the relationship is valid not only in theory but also in estimations.

To my knowledge, this is the first attempt to provide a theoretical background on the transmission of bond market volatility to stock market volatility from the yield curve's shape perspective in a testable HAR framework. Also, this study is the first to assert that while the bear flattener shift in the yield curve reduces the transmission and bull steepener move magnifies the volatility transmission to the stock markets. Moreover, the variation of latent yield curve factors has different effects on the equity market volatility. In addition, the results indicate that the inclusion of the yield curve shape factors' volatility in the equity market volatility forecasting models improves both the in-sample and out-of-sample forecasting power of the HAR-type models.

This study emphasizes the potency of risk premium and hedging premium in determining the transmission of volatility from bond markets to equity markets. The findings of this paper have important policy implications for policymakers and portfolio managers by uncovering the relationship between the shape of the yield curve and the equity market volatility.

Chapter 5

Concluding Remarks

In this thesis, I combine three different studies using the information embedded in the term structure of interest rates. Particularly, I provide analyses for the bond market volatility forecasting, monetary policy impact on the bond market and the representative capacity of bonds' yield curve fitting parameters as latent monetary policy factors, and the transmission channel of bond market volatility to equity market volatility conditional on the term structural changes.

In Chapter 2 of this thesis, I contribute to the literature from the volatility forecasting perspective by proposing a robust forecasting structure and also by investigating the bond market volatility reaction to the monetary policy. In this chapter, I examine the European government bond markets, Germany, France, Switzerland, and the UK, in the HAR (Corsi (2009)) model. I examine (1) whether the intraday jumps improve the forecasting efficacy in the European bond markets; (2) the bond market volatility jumps from the monetary policy perspective; and (3) whether the pre-announcement drift, widely known as pre-FOMC drift, is present in the volatility structure.

By investigating the European bond markets in the January 2005 and October 2019 period using intraday data in 10-minute intervals, I uncover the term structure of realized volatility and jumps for a set of maturities. There exists a mass literature on HAR models with different specifications using stock market and commodity market data (Bollerslev et al. (2018); Dueker (1997); Bollerslev et al. (2016); Bollerslev & Mikkelsen (1996); and Luo et al. (2022)), but the literature on the bond market volatility forecasting is limited and there is no consensus on whether the inclusion of jump parameter improves the forecasting ability of models (Andersen, Bollerslev & Diebold (2007); and Corsi et al. (2010)). I verify that the intraday jumps are effective and improve the forecasting power of HAR-type bond market volatility forecasting models. In addition, the effect of macroeconomic and monetary policy announcements is associated with the jumps as being one of the key drivers of volatility. In a similar fashion, I find the bond markets exhibit significant intraday jumps in almost %50 of monetary policy meetings on average. Furthermore, I investigate whether the pre-announcement drift is effective in the bond market volatility structure. To test the hypothesis, I test for the presence of a higher volatility transmission from 1-day lagged volatility to forecasting monetary policy announcement day volatility in the HAR model, which has auto-regressive construction. While Lucca & Moench (2015) find that there is no detectable drift of the markets in the US treasury bonds in the 1-day period before the FOMC announcements, I find that the pre-announcement effect is present in the European government bond volatility. I proceed with analysis by seeking the source of the drift and find that the pre-announcement drift in bond market volatility is stemming from the diffusive, or continuous, part of volatility and the jump variation. This phenomenon can be explained by the short memory of the jump process.

In Chapter 3, I try to quantify ECB's monetary policy shocks using German government bond data between January 2005 and October 2019 period. Since the central banks become more and more dependent on the unconventional policies due to zero lower bound of policy rates, not only the information on the policy rates but also the future path of interest rates for longer horizons and the information released on the security purchase programs gained great importance for the economic agents. Therefore, the conveyance of communication and signals for the QE programs are necessary to be measured by using alternative indicators. I assess (1) whether intraday yield curve fitting factors or the latent shape factors provide sufficient information in representing ECB policy dimensions; (2) whether the latent monetary policy factors impact asset prices; and (3) the effectiveness of monetary policy tools within each other.

I extract the monetary policy surprises using German bonds in the announcement windows of the ECB, which has a two-tier monetary policy announcement, the press release, and the following press conference. This feature of ECB policy communication paves the way for me to focus on the separate windows in estimating the policy surprises' effect on asset prices. In this study, I find that the latent shape factors, which are obtained by following the Nelson & Siegel (1987) model for curve fitting in the intra-day frequency, demonstrate higher variation around the policy announcement windows during communication days than on other days. I call those latent factors: target rate, forward guidance, and quantitative easing shocks. Also, the latent factors have a notable effect on, government interest rate spreads, euro exchange rate, corporate credit costs, and market-based inflation indicators. In addition, I find the QE shock has more power in affecting yield spreads and inflation indicators than target rate and forward guidance shocks.

In Chapter 4, I contribute to the literature by providing a framework that demonstrates the dynamics between the volatility of equity markets and fixed income markets. Since the changes in the term structure have the potential to reflect the current state and the expectations regarding the economy, the interest rate volatility can be used as a crucial input for asset pricing and volatility modeling. In this chapter, I use the high-frequency data on European government bond markets and equity markets of corresponding countries in estimations. I prefer to use sovereign bonds as a representative of fixed income markets since sovereign markets are direct recipients of the information flow concerning the economy and the expectations of economic agents. In this context, I aim (1) to demonstrate the theoretical relationship between equity and bond market volatility using discounted cash flow model; (2) to test whether the shape of the sovereign bonds affects the interest rate volatility transmission to equity markets; and (3) to test whether the information on the yield curve improves equity market volatility forecasting.

In this scope, I extend the discounted cash flow model in the intraday setting to extract the volatility dynamics between interest rates and equity markets. The discounted cash flow model asserts that the equity prices are affected by two major sources: expected cash flow and the discount rate. Since the expected cash flow is a long-term parameter and does not change between the intraday windows, the changes in the equity prices become only dependent on the changes in the discount rates and the underlying factors that affect the discount rates. Moreover, I show that the changes in the term structure of interest rates can be attributed to the growth expectations and risk premium, in general. Then, separating the risk premium into the (common) risk premium and hedging premium, by following Cieslak & Pang (2021), led us to identify the changes in the shape of the yield curve. I find that the magnitude of volatility transmission from the bond markets to equity markets depends on the term structure of interest rates. The yield curve moves in the bear flattener move the transmission is limited, while the bull steepener move magnifies the transmission. Moreover, I find that the inclusion of yield curve volatility with respect to the shape helps to improve the equity volatility forecasts in both in-sample and out-of-sample.

The analyses in this thesis are subject to some limitations. First, the use of high-frequency data in the analyses may cause the estimations to suffer from microstructure noise. I use intraday data with 10-minute intervals for the government bond markets and 5-minute intervals for the equity markets. The sampling frequency selection is made with respect to the availability of data and the market liquidity considerations. Although I provide some robustness checks in Chapter 2 and try to exploit the errors generated from microstructure noise in Chapter 4, finding the optimal sampling frequency provides an alternative solution to come with the noise. Second, in Chapters 2 and 4, I provide in-sample and out-of-sample forecasts for bond market volatility and equity market volatility, respectively. In comparing the forecasting models with different specifications, I use the Diebold & Mariano (1995) test, which enables us to construct pairwise comparison test statistics. Therefore, I prefer to compare the models with respect to the selected baseline model and specific forecasting horizon, but I do not determine which specification provides the best volatility forecasts for the markets. A multiple horizon test (such as Quaedvlieg (2021)) can be employed to overcome this limitation. Third, in Chapter 3, I extract the monetary policy surprises using German sovereign bonds from 1-year to 30-year maturities. Using these bond market data, I extract the intraday surprises, target rate, forward guidance, and QE, on the monetary policy announcement windows. The estimation results indicate the forward guidance to be the least effective surprise on asset prices. This result may be the direct outcome of data limitations. Since the monetary policy impact horizon is not effective on the distant maturity rates and the impact of forward guidance might be reflected by the securities that have less than 1-year maturity. To overcome this problem, another dataset that includes short term securities can be used, if available, as a robustness check,

My analyses provide valuable insights for the policymaker, especially from the market surveillance perspective. Firstly, the monetary policy announcements are the major determinant of bond market volatility, then the volatility of the pre-announcement days can be closely monitored as a nearly warning indicator of rising volatility during announcements. Also, since the intraday volatility jumps can be associated with the policy announcements, policymakers may scrutinize the communication frequency. Secondly, the findings emphasize the significance of quantitative easing shocks in stimulating inflation and lowering bond spreads. Thirdly, a deeper understanding of the equity market and bond market volatility sources can improve the monitoring ability of policymakers in reaching the financial stability objective.

Although I provide a complete picture in this thesis, all chapters are subject to development as future research. An immediate avenue for further research for Chapter 2 is to extend the analysis by considering the realized semivariances and signed jumps of Patton & Sheppard (2015). The extension of pre-announcement volatility drift with respect to the clustering of negative and positive returns has the potential to provide valuable insights into the sources of the drift. In addition, Chapter 3 is suitable to be developed by decomposing the monetary policy shocks into Odyssean versus Delphic shocks following Andrade & Ferroni (2021). The decomposed monetary policy shocks can unveil more information on the policy shocks' impact on asset prices. Another potential research can be produced by including the monetary policy decision in Chapter 4's volatility dynamics. In this perspective, I can use monetary policy shocks in order to quantify the magnitude of risk premium on the equity market volatility and decompose the common risk premium and hedging premium following an event study approach.

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