International channels of monetary policy transmission

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This dissertation is submitted for the degree of
Doctor of Philosophy in Finance and Economics

Birkbeck April 2020

To my father.

Declaration

I hereby declare that except where specific reference is made to the work of others, the contents of this dissertation are original and have not been submitted in whole or in part for consideration for any other degree or qualification in this, or any other university. This dissertation is my own work and contains nothing which is the outcome of work done in collaboration with others, except as specified in the text and Acknowledgements. This dissertation contains fewer than 65,000 words including appendices, bibliography, footnotes, tables and equations and has fewer than 150 figures.

Paul Wohlfarth
April 2020

Acknowledgements

I am indebted to my supervisor Prof. Ron Smith for his careful reading and help and comments provided. His support and guidance has been an invaluable asset throughout my PhD studies. Besides my supervisor, I would like to thank Prof. Yunus Aksoy for his help and comments as well as his continued support for my research. I would also like to thank members of the Department of Economics, Mathematics and Statistics at Birkbeck, University of London, as well as participants of the annual conferences of the Society for Computational Economics and Finance (CEF) in Milan 2018 and Ottawa 2019, the International Conferences on Economic Modelling and Data Science (EcoMOD) in Venice 2018 and Ponta Delgada 2019, and the annual conference of the Money Macro and Finance Research Group (MMF) in London 2019 for valuable comments and feedback.

Lastly, I thank my fellow PhD students and the students I taught for their questions, comments, and discussions, which have been a great inspiration for my research.

Parts of the chapter "Measuring the Impact of Monetary Policy Attention on Global Asset Volatility Using Search Data" of this thesis is published in Wohlfarth [2018b].

Abstract

This thesis investigates international channels of monetary policy transmission in global financial markets from empirical and theoretical perspectives. The main contributions are empirical, where the focus is on transmission at daily frequency allowing for the time-varying volatility by assets. Chapter 2 develops a daily measure for monetary policy attention, using GoogleTrends data. Policy attention, alongside interest rate futures, are used in an analysis of policy spill-overs on European and US money and capital markets. Policy mainly affects variances rather than means of processes. Chapter 3 extends the analysis to a multivariate framework, analysing dynamic covariances, filtered by Dynamic Conditional Correlations, BEKK, and the RiskMetrics long-memory exponential smoother. Policy affects both asset variances and covariances, domestically and internationally, supporting both signalling and portfolio rebalancing channels. Chapter 4 examines foreign exchange markets, focussing on covered interest parity (CIP) deviations, measured by cross-currency bases from swaps. CIP failure cannot be explained by risk alone, given observed bases widened in a relatively low-risk environment (2014-2016). Informed by preferred habitat theory of risk averse arbitrage, we empirically examine the impact of various factors on cross-currency bases of different maturities as well as co-movement between different currency bases. Findings highlight the role of policy and volatility and indicate the presence of time-varying market segmentation that is linked to volatility. Overall this dissertation suggests more complex international policy transmission effects than commonly assumed: Policy is transmitted via variances often onto particular market segments, creating a complex system of spill-over relationships. Volatility plays an important but not exclusive role, as it exacerbates the effect of policy asymmetry. Limits to arbitrage offers explanations for observed empirical findings.

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Chapter 1

Introduction

Policy transmission is at the heart of macroeconomic research. It evaluates policy effectiveness along a sequence of effects, following an impulse from a policy instrument to a policy target. There is a large body of literature describing various transmission channels through which monetary policy affects the real economy. The necessity to study monetary policy transmission has gained importance in the aftermath of the Global Financial Crisis (GFC), when traditional policy instruments became ineffective. Newly introduced *unconventional policy measures* such as quantitative easing, the expansion of central bank balance sheets through, predominantly, large-scale asset purchases, were not considered in traditional models evaluating policy. In 2014, then Federal Reserve (FED) Chairman Ben Bernanke famously referred to this as "[...] [quantitative easing] worked in practise but not in theory." By this time the FED had more than quadrupled the size of it's balance sheet in reaction to the GFC. So in fact Bernanke was admitting a poor understanding of monetary policy transmission at a time when there was unprecedented use of policy instruments. One crucial missing link in policy transmission are financial frictions: Traditional theory assumes that prices are cleared on complete markets. In reality, financial markets are incomplete and do not necessarily clear, causing market segmentation and failure of crucial no-arbitrage conditions. Understanding financial frictions is therefore at the heart of understanding policy transmission.

The problem of policy transmission becomes yet even more difficult, when viewed from a global point of view. The effect of monetary expansions was not limited to domestic markets but transmitted globally. Such policy spill-over effects were again observed in practice, but not satisfactorily explained in theory. Following traditional explanations policy effects should be largely absorbed by exchange rates. The initial global policy reaction to the GFC was relatively coordinated, which masked the effect of policy spill-overs. But over the last five years the FED initiated a policy contraction at a time when other central banks continued expansionary policy stances; most notably the ECB accelerated its policy expansion at the same time. This development of policy divergence caused global imbalances that were not absorbed by FX markets. The situation is so dramatic that the Bank of International Settlement (BIS) referred to it in its Quarterly Report of September 2015 as "dislocated markets" BIS [2015a]. There are two lead symptoms of this dislocation: A global shortage of USD liquidity and with it the persistence of substantial non-zero bases on cross-currency swap markets, an integral part of foreign exchange markets. Both indicate the same problem: Clearing of exchange rates is incomplete and cannot absorb asymmetries arising from policy. In this case, covered interest parity (CIP), a condition that requires differences between otherwise equal foreign and domestic assets to be absorbed by forward exchange rates, fails. This background highlights two closely related problems that increasingly enter research agendas in macroeconomics in general and monetary economics in particular:

Firstly, financial frictions, and with it an understanding of the role of financial markets in the wider economy, remain poorly understood. Here market segmentation takes a centre stage. Fixed income markets, that is capital markets for bonds of longer maturities and money markets for short run debt instruments (with typically lower than 18 months maturity), provide the first link for most policy transmission channels. These markets are segmented along maturities and credit quality. Traditional theory assumes representative agents that price assets in the market uniquely following e.g. the expectations theory of the term structure. Here the return of some asset would be explained by the expected path of short term instruments of the tenor of the asset. This implies that there are relatively little restrictions on investment decisions in the market. In fact fixed income market are highly institutionalised and regulated: E.g. pension and insurance funds are highly restricted on the debt quality they can hold, and assets and liabilities often need to be maturity-matched to meet regulatory requirements. One can then view the expectations theory of the term structure in an equivalent framework with heterogeneous agents, where markets are initially segmented, chiefly because of regulatory requirements, but unlimited arbitrage exists that profitably exploit and mitigate excess pricing premia. But here the assumption of unlimited arbitrage, i.e. of arbitrageurs having *deep pockets* is troubling. Preferred habitat theory relaxes this assumption and constrains the risk-taking capacity of arbitrageurs. In such an institutional view of fixed income pricing, market segmentation (and hence pricing) is therefore a function of the market structure, such as the regulatory environment, and risk. There have been major regulatory and structural changes following the GFC that profoundly affected the international fixed income market structure. This included reforms to the international banking regulation (Basel III) agreed by the Basel Comittee on Banking Supervision in November 2010, comprehensive US financial market reform (Dodd-Frank Act) in July 2010, and the review of the Markets in

Financial Instruments Directive (MiFiD II) in April 2010 in the European Union. Whilst we abstain from further discussion of financial market reforms after the GFC, as this would clearly be beyond the scope of this thesis, we argue that there was a profound change in the regulatory environment from 2010 on, that affected the market structure and the risk-taking capacity of arbitrageurs in the market.[1] This development therefore highlights the need to employ theoretical arguments that assume segmented markets with limits to arbitrage, such as preferred habitat theory.

Secondly, we are currently witnessing the unwinding of an unprecedented episode of global monetary expansion, which is insufficiently coordinated to avoid imbalances on global asset markets. This coincides with a lack of understanding of global transmission of monetary policy and the role of financial frictions on international asset markets. This thesis aims to explore these international channels of monetary policy transmission. Our approach is both theoretical and empirical. Throughout this thesis, an extended preferred habitat model will be used as workhorse theory, that allows to evaluate policy transmission onto fixed income markets in the presence of financial frictions. Frictions are here twofold: There is credit default risk and markets are segmented as a result of limits to arbitrage. Empirically we explore a case study of policy transmission between the US FED and the European Central Bank (ECB). This choice is due to similarities[2] in market structure and size between both currency areas. Size is particularly important in this respect as it directly affects the presence of spill-over effects onto other currency areas. This means that we can only accurately observe international policy transmission in a level playing field of equally sized objects of investigation. We further differ from much of previous research in that we estimate empirical results with daily data using conditional volatility models. Volatility is an important measure of risk on financial markets, which takes centre stage in several models of policy transmission. Empirically it is time-varying, due to the presence of volatility clustering. Conditional volatility models that explicitly model second moments to tackle this source of heteroskedasticity are a standard tool in financial econometrics but are hardly used in empirical macroeconomics. We employ daily data in our empirical analysis to be able to capture these volatility processes that would not be observed on lower frequencies and thereby policy transmission more accurately. This gain in accuracy of our estimates is not compromised by an increase in noise following the higher frequency of our data.

[1] An overview of global financial market reform after the GFC can be found in Duffie [2017].

[2] We do not neglect important differences between European and US American asset markets (e.g. differences in overall exposure of the financial system to bank lending). From a point of international policy comparison both currency areas are similar in a number of decisive factors, such as implemented monetary policy, exchange rate system, and size.

1.1 Literature on Preferred Habitat Theory and International Policy Transmission

This section gives a brief overview of the literature relating to all chapters of this thesis, i.e. the transmission of monetary policy, its link to preferred habitat theory, and a discussion of global policy spillovers.

Policy transmission has regained attention following the introduction of unconventional monetary policy measures. Whilst there is largely consensus about main transmission effects through signalling and portfolio rebalancing channels, there is ongoing debate on their relative contributions. This debate often presumes signalling and portfolio rebalancing as mutually exclusive but this may be misleading. Theoretical explanations can be found in the term structure literature with preferred habitat theory, which explains market segmentation through risk-averse arbitrage. Here, policy can affect local asset supply, a path of expected short term interest rates, and risk-taking behaviour. International transmission is traditionally assumed to be absorbed by foreign exchange markets. Policy independence and unrestricted capital flows, hence the absence of policy spill-overs, is here possible through a regime of freely floating exchange rates. This was questioned more recently, given empirical evidence on the existence of global financial cycles that appear to be related to US monetary policy. There is further ample evidence for spill-over effects between large and small currency unions, but the literature lacks evidence on transmission between similarly sized central banks.

1.1.1 Transmission Channels in the Context of Unconventional Policy

There is a vast literature on monetary policy transmission. Not all of these *transmission channels* are relevant for the purpose of our research and we hence restrict our focus to transmission channels that are particularly relevant in the context of policy measures widely implemented after the 2008 financial crisis. An overview of this episode of *unconventional policy*[3] is comprehensively discussed in Bhattarai and Neely [2018]. Accordingly, the most important unconventional policies were central bank communication through *forward guidance* and quantitative easing through asset purchases. Neely [2015] links two main transmission mechanisms: The portfolio rebalancing channel, which was originally based

[3]The term *unconventional policy* is commonly used to refer to the policy reaction when policy rates are at or close to the zero lower bound, and policy transmission via interest rate setting is hence compromised. This term can be seen a misnomer as there is neither consensus on what constitutes *conventional* nor whether the measures it refers to are unconventional. We henceforth use this term to refer to policy measures, other than interest rate policies, that followed the GFC.

on work by Tobin [1969] and Brunner and Meltzer [1973] among others, puts emphasis on investors objective to keep a balanced portfolio of assets. Accordingly, policy induced return changes for particular assets transmit onto other assets given a change in investors' portfolio weights that follows the change in relative prices. The importance of the portfolio rebalancing channel for unconventional policies is advocated in Gagnon et al. [2010], who evaluate Fed policy announcements in an event study using a Kim-Wright decomposition. Bauer and Rudebusch [2013] contest this view and propose the signalling channel as the main channel for policy transmission. Signalling is related to evidence provided in Gurkaynak et al. [2004], where an event study analysis of policy announcements revealed significant changes in forecasts of future policy rates. Therefore, credible signals of an extended period of low policy rates can affect the expected path of short term interest rates and with it expected term premia. This channel emphasises the effectiveness of forward-guidance policies, that aim at managing market expectations of future policy rates. It also more generally links to the importance of managing agents' expectations rather than actual policy interventions. Bauer and Rudebusch [2013] use this point for quantitative easing policies, highlighting the relatively small size of central bank asset purchases in the context of the overall fixed income market. However, this argument implicitly dismisses signalling effects of quantitative easing announcements that induce portfolio rebalancing behaviour. Evidence from Krishnamurthy and Vissing-Jorgensen [2007] highlights the importance of market segmentation, which is explicitly dismissed by Bauer and Rudebusch. Krishnamurthy and Vissing-Jorgensen [2011] support the presence of both, signalling and portfolio rebalancing and highlight the importance of considering market segmentation and expectations more generally. Joyce et al. [2011] argue in the same spirit using empirical evidence on the BoE's unconventional policies. Given the focus on policy expectations inherent in the signalling channel, it implies more general repercussions on policy measurement that we will discuss in the next chapter. Throughout the rest of this thesis we do not take the view that signalling and portfolio rebalancing channels are mutually exclusive but regard them as complements and as such they should be discussed jointly.

1.1.2 Preferred Habitat Theory

The arguments on transmission channels above are mostly empirical. Traditional models of policy transmission, such as Smets and Wouters [2003] do not feature unconventional policies, which imply the presence of financial frictions. One branch of the literature that introduces transmission channels in the presence of financial frictions uses preferred habitat theory. Preferred habitat theory was introduced by Modigliani and Sutch [1966] as a theory that captures elements of both, segmented markets and the expectations theory of the term structure. Market segmentation initially exists because investors have heterogeneous preferences for particular assets. This can be for several reason, such as differences in regulatory requirements across assets or market structural factors. Arbitrage exists but arbitrageurs do not have deep pockets and face budgetary constraints that depend on risk. This is commonly referred to as *risk-bearing capacity* or *leverage constraint*. Vayanos and Vila [2009] re-introduced preferred habitat theory in the context of monetary policy transmission, deriving equilibrium on fixed income markets in a term structure model with preferred habitat structure, where arbitrageurs are subject to constant risk aversion. Comparative static analysis shows that the expectations theory of the term structure only holds for risk neutral arbitrage. The explicit link between the expectations theory of the term structure and risk-neutral arbitrage sets limits to policy transmission via rate setting or forward guidance. Policy can mitigate this through direct asset purchases in market segments that face risk premia arising from limits to arbitrage. Altavilla et al. [2015] extend the model with a credit channel that arises from assuming that bonds are subject to credit risk. Policy, in particular asset purchases, are here effective through local supply effects and via compression of credit premia. As Greenwood and Vayanos [2014] argue, risk-averse arbitrage gives rise to portfolio-rebalancing behaviour as arbitrageurs update balanced arbitrage portfolios. However, this does not dismiss signalling as an expected path of risk-neutral interest rates enters pricing kernels directly in preferred habitat models. Furthermore, expectations and therefore signalling effects matter beyond a narrow definition of forward guidance. Preferred habitat theory thus provides a viable theoretical framework to explain recent unconventional monetary policy.

1.1.3 International Policy Transmission

An early treatment of the transmission of policy in open economies can be found in the *Mundell-Flemming Model* that goes back to independent work by Marcus Flemming and Robert Mundell in the early 1960s (Fleming [1962] Mundell [1960] Mundell [1961a] Mundell [1961b] Mundell [1963]). An important contribution of this model is a definition of conditions under which monetary policy can be independent: When either control of exchange rates is abandoned or international capital flows are being restricted. In the aftermath of the collapse of the Bretton-Woods System it has become consensus and common policy for major central banks to operate independently in a system of floating exchange rates. Hence freely floating exchange rates were seen as capable of absorbing policy spill-overs, allowing central banks to maintain independent policies. Recent policies are investigated in this spirit in Georgiadis and Gräb [2016], who consider transmission between the ECB and the Fed through foreign exchange (FX) markets. However, Rey [2015] argues that this *Mundellian*

Trilemma gives insufficient conditions for independent monetary policy. Rey emphasises the presence of global financial cycles, where globally monetary policy is dominated by few large central banks – in her case the US Fed – whilst other central banks are limited in their policy reaction. In this case, the Mundellian Trilemma, stating that from the policy objectives of targeting exchange rates, unrestricted capital flows and independent monetary policy only two can simultaneously be met, is insufficient – there are policy spill-overs despite largely unrestricted FX and capital markets. Miranda-Agrippino and Rey [2015] provide evidence for this, showing that global asset prices follow one common factor, that can be identified as the VIX volatility index. Increasingly evidence directly links this to US monetary policy (Gourinchas et al. [2019]).

The evidence on global financial cycles is also compelling from a theoretical point of view. The conditions proposed in the Mundell-Flemming Model implicitly assume fully integrated markets. This, as in some of the above literature, sees no role for portfolio rebalancing effects as featured in preferred habitat models. One can show that in a setting, where arbitrage is complete and risk-neutral, main interest parity conditions, uncovered and covered interest parity, hold and the Mundellian Trilemma can be sufficient for policy independence. But there is strong evidence for policy induced global portfolio rebalancing (Camanho et al. [2018]), market segmentation and restricted arbitrage that question that assumption.[4]

There is empirical evidence on policy transmission between freely floating currency areas. This literature mostly focusses on transmission between large and small central banks with Bauer and Neely [2014] and Neely [2015] being prominent examples. Rey [2016] approaches this in a similar vein using a multivariate framework of monetary transmission by fitting a VAR model with exogenous 2SLS identification to data on a group of economies with freely-floating exchange rates, using instruments similar to those applied in Gertler and Karadi [2015] [5] But size arguably matters for spill-over effects. Yet there is a distinct lack of research on direct transmission effects between large central banks.

1.1.4 Implications from the Literature

The literature on international policy transmission leaves important gaps, that we aim to address with this thesis. First, policy transmission needs to be analysed using higher data

[4] We consider the effect of risk averse aribtrage by developing a preferred habitat model of the Eurodollar swap market in Chapter 4.

[5] Gertler and Karadi use high-frequency surprise factors, following Gurkaynak et al. [2004], ie. surprises in FOMC announcements, measured in event-studies as response of different fed funds futures rates within 30 minute windows to individual announcements. The surprise factors received through this exercise are then in the first stage used as instruments for either a policy rate or a 1- or 2-year government bond. In the second stage, different market interest rates are regressed on the instruments.

frequencies. The crucial objective is here to measure sufficient information on volatility of asset returns. Hence related measurement issues will be the starting point of this thesis. Estimation of policy effects with models that cater for conditional heteroskedasticity, typically present in high-frequency financial data, is also scarce. We tackle this, estimating our empirical results with several conditional volatility models that allow us to get a better understanding of the role of risk, particularly volatility, in policy transmission. Lastly, whilst several transmission channels are being discussed in the literature, this discussion is largely empirical. Term structure models that use preferred habitat theory have been proposed to derive equilibrium returns in the presence of market segmentation and risk averse arbitrage. There are similar approaches, using limits to arbitrage on international swap markets to derive existing pricing puzzles. But there is, to our knowledge, no theory that integrates models that allow the analysis of domestic policy transmission into an open economy setting that addresses pricing puzzles observed on foreign exchange swap markets. We address this through extending a preferred habitat to an open economy setting that we then integrate into existing models on FX swap market pricing.

1.2 Thesis Structure

Based on the above, this thesis is structured in three main chapters as follows:

Chapter 1 addresses an important reason for the absence of high-frequency analyses of policy transmission: the lack of policy measures. Common policy measures either observe policy interventions directly – such as changes in main policy benchmark rates or balance sheet positions – or indirectly via policy announcements. The latter gained importance as central banks increasingly focussed on communication as a policy tool. Here increased transparency and the communication of monetary policy decisions and intentions were used to manage agents policy expectations. From a measurement perspective, this implied the need to measure changes to agents' expectations rather than simply observing policy interactions. For this policy announcements are analysed in event studies, where the immediate reaction of interest rate futures around announcements is measured and then accumulated to obtain monthly policy measures. We tackle policy measurement, introducing a new measure of monetary policy attention using Google online search data. This follows a similar logic to that of event studies, but does not limit the identification to a set of pre-defined policy events. Instead, it continuously observes indices of policy relevant searches on Google. We show that this measure is exogenous and identifies relevant policy events. We then apply attention indices in an analysis of policy spill-over effects onto a range of fixed-income assets between US and European markets. Findings show significant policy effects on variances but not means of asset processes. The analysis of international policy transmission in the first chapter uses univariate conditional volatility (GARCH) models for considered assets separately. The main focus here was to introduce high-frequency policy measures and to contrast policy transmisssion onto first and second moments of asset returns. But this assumed absence of cross-correlations between assets. Given the presence of policy transmission onto individual asset segments as well as portfolio-rebalancing effects this assumption is clearly too strong.

Chapter 2 relaxes this assumption and investigate dynamic covariances instead. For this, we first compare different methods to filter covariances. We estimate covariances using three filters: Dynamic Conditional Correlations (DCC), that allow efficient estimation of correlations between a large number of assets using variance-targeting. Variance targeting sacrifices dynamic updates of asset cross-correlations for the sake of efficiency, which is why we also employ covariances estimated with a multivariate GARCH extension, a BEKK model. This approach sacrifices computational efficiency and can therefore only be estimated in a pairwise setting. To tackle this, we also estimate covariances with a simple long-memory exponential smoother, that is multivariate, preserves the dynamic covariance structure, but is also relatively noisy. We then regress all covariances on policy attention and interest rate futures as policy measures. Our findings give a complex picture of domestic policy effects on variances and covariances as well as international spill overs. International transmission is bi-directional, i.e. US policy transmits onto European markets and vice versa. Policy attention is significant in most covariances. We believe this is because the measures capture information on policy beyond agents' expectations about the future path of short-term interest rates.[6] This is particularly important given the extended use of unconventional policies, especially large scale asset purchases, that target long-term interest rates directly. Our results give evidence for international policy transmission via portfolio rebalancing and signalling channels.Our evidence for policy spill-over effects was observed for dollarised assets. It therefore confirms the existence of international policy transmission effects that are not absorbed by foreign exchange markets.

In chapter 3 we turn our attention to the policy effects on foreign exchange markets. In particular we evaluate the role of policy in global imbalances and determinants affecting the ability of foreign exchange markets to absorb such imbalances. The CIP Puzzle, i.e. the unexplained post-crisis failure of Covered Interest Parity (CIP) on foreign exchange swap markets serves as vehicle for this investigation. FX swap markets govern the exchange

[6]There is a distincion between different concepts of policy attention, uncertainty, fear, and sentiment, some of which we refer to in the following chapter. For the purpose of this thesis, we largely abstain from applying this distinction, as these concepts are very closely related and reliable identification of empirical measures is hence difficult. Policy attention captures expectations more generally, which is sufficient for the purposes of this research.

of liquidity denominated in different currencies and are therefore an integral part of the functioning of FX markets. Here CIP is a crucial no-arbitrage condition as it dictates that, after hedging against expected changes in the exchange rate, otherwise equal assets pay equal returns. This condition held almost exactly before 2008 and failed thereafter. This has initially been explained with increased risk in the wake of the GFC, but persistent CIP failure in a relatively calm market environment from 2014 onwards questioned this. We first approach the CIP puzzle theoretically using preferred habitat theory. Market segmentation is explained endogenously with the limited risk-bearing capacity of arbitrageurs. This implies that there is a link between market risk and market segmentation, which causes frictions to market clearing. We extend our model, considering CIP in the presence of intermediation costs and traditional transaction costs. Here, the GFC has introduced credit risk, arising from foreign currency denomination of collateral, onto swap markets. Foreign currency balance sheet exposure is hence costly for banks, who typically act as arbitrageurs on the market, introducing no-arbitrage bounds around CIP. Again, limits to arbitrage and therefore volatility takes a centre stage in explaining fricitons to market clearing. Combining the two approaches then shows how diverging policy caused imbalances that, owing to imperfect arbitrage, persisted on foreign exchange markets. We empirically test this in two ways. We first consider co-movement between cross-currency swap bases of different tenors, providing evidence for the time-varying nature of market segmentation as well as its link to volatility. We then consider the effect of policy imbalances as well as volatility on cross currency bases. This provides evidence for the impact of the combination of policy asymmetry and volatility on FX swap markets. Policy attention measures show that, whilst imbalances are mostly driven by US policy, there is a significant impact of ECB policy.

1.3 Contributions

This thesis contributes to knowledge in several ways. Firstly, we introduce a new policy measure that allows bridging the gap between macro-economic policy evaluation and return processes, observed on financial markets. We show that this measure captures a larger amount of policy interaction, which is important in explaining pricing puzzles described in the macro-finance literature. We also document international policy transmission to an extent that was previously not visible. In particular, using high-frequency analyses shows how main policy effects are on asset return variances and not means. Considering dynamic covariances shows that policy affects asset cross-correlations in line with portfolio rebalancing theory, but that these effects are more complex than previously assumed. Lastly, we show that policy affects imbalances and clearing on foreign exchange markets directly. The latter can be explained using limits to arbitrage, commonly applied in preferred habitat theory, and policy effects on asset volatility, previously documented. This thesis therefore shows a far more wide-reaching impact of policy on global financial markets raising the need to reconsider global policy coordination in the absence of other regulatory frameworks.

Chapter 2

Measuring the Impact of Monetary Policy Attention on Global Asset Volatility Using Search Data

2.1 Introduction

What is monetary policy in an open economy? And how can we identify it empirically? An increasing focus on agents policy expectations and the need to observe policy on higher frequencies pose challenges for policy measurement. Policy makers increasingly focus on management of agents' expectations, most visibly through increased transparency about policy decisions. The introduction of explicit inflation targets, regular communication of policy decisions in press conferences and minutes of policy meetings, and the introduction of forward guidance as a policy tool give examples for this. Agents' expectations about policy have become a policy target but expectations are latent variables and hence not directly observable.

The literature addresses this with analyses of policy announcements in event-studies. Here policy surprises can be observed as changes on futures markets immediately after announcements. Identification follows a logic similar to that of revealed preferences: Agents reveal policy expectations with changes in trading behaviour when new information is discovered. But event studies rely on a set of pre-defined events around which surprise factors are observed. Typically, regular announcements of policy decisions, and in some cases other information, such as speeches or minutes of policy meetings, are used as event samples. These events are observed relatively infrequently so that surprise factors are accumulated to obtain monthly policy measures. Thus, whilst event studies tackle some of the latency of policy expectations, they do not allow the measurement of policy on higher than monthly frequencies.

Further challenges arise from an implicit sample selection bias in event studies: Event studies rely on a set of pre-defined policy events. Whilst this is useful for identification purposes, it is restrictive with respect to policy interactions and the definition of expectations. Having more precise definitions of expectations is particularly important, given the importance of policy on risk-taking behaviour. To analyse expectations in the context of risk-taking it is further important to distinguish uncertainty, sentiment, and attention.

In this chapter, we tackle this measurement problem, introducing a policy measure that addresses both, the latency and the frequency problems of policy measurement. For this, we introduce a daily measure of monetary policy attention, obtained as indices based on frequency of of search words entered on the Google search engine.[1] This uses the identifying assumption that agents react to policy surprises with increasing online searches for policy relevant search terms. In other words, online search behaviour reveals changes in agents' expectations. We apply our policy attention measures to data on policy transmission between FED and ECB from 2014 to mid 2016. We show that the indices can replicate a set of manually identified policy events, are exogenous, and give a plausible measure for monetary policy. We then study policy spill-over effects, captured by policy attention and short-run interest rate futures, in a set of conditional volatility (GARCH) models, finding significant policy transmission effects through variances of considered asset returns. Means largely follow random walks with drift, in line with the efficient market hypothesis. To build our empirical model, we use a modified version of a preferred habitat theory that features direct policy channels via an expected path of short term interest rates and indirect policy effects on return volatility that stem from changes to the risk-taking ability of arbitrageurs in the market. We will employ this model as theoretical workhorse throughout this thesis.

With this research we add to existing literature threefold: We introduce a new measure for monetary policy that allows measurement of policy attention and thereby revealed expectations on high frequencies. The measure should be understood as complementing existing identification by means of surprise factors. Our research further adds to the growing literature on the international transmission of monetary policy, documenting policy transmission on return volatility between two similarly sized central banks. Lastly, we adapt a preferred habitat model, where policy channels can be explained in the context of market segmentation and limits to arbitrage, to cater for global policy transmission.

[1]The data for this is freely available via Google Trends, but needs to be re-normalised to obtain daily measures. See section 2.4.1 for further details.

The next section gives an overview of the literature on policy measurement, followed by an introduction to our preferred-habitat model as well as a discussion of policy transmission channels in section 1.3. Section 1.4 gives an overview of the data used and explains the construction of our policy measures. We estimate policy effects in sections 1.5-1.7, followed by a conclusion.

2.2 Literature on Policy Measurement

The literature on monetary policy measurement largely evolved in two stages: First, a shift from traditional measures, such as interest rates and balance sheet positions, towards the study of policy announcements with event studies. Secondly, the availability of new measures from the big-data literature, such as search indices (predominantly used in labour economics), or risk-, sentiment, and uncertainty measures. These measures typically either employ text analyses based on news databases and sentiment dictionaries or new media sources, such as social media engagement and online searches. This latest generation of policy measures particularly address identification problems of second moments. Here, conditional volatility models give an empirical framework, where such policy measures enter variance processes and therefore entertain an understanding of policy effects on realised risk. But the distinction of different underlying concepts, such as uncertainty, sentiment, and attention is important and non-trivial.

Traditional analysis of policy uses simple interest rate or balance sheet measures, such as employed in Christiano et al. [2005]. Event studies evaluate pricing effects of announcements. They were first established in corporate finance, as a statistical tool to evaluate the impact of particular events on the price of a security. [2] Identification is here achieved through comparing the behaviour of a series in a control window preceding an event to that of a treatment window following the event. This rests on the assumption of event dominance, ie. the absence of other events causing the reaction in the treatment window.For monetary policy analysis event studies are commonly used to obtain surprise factors as introduced by Kuttner [2001] with prominent applications in Gurkaynak et al. [2004], Bernanke et al. [2004] and Bernanke and Kuttner [2005]. Here, a policy shock is identified through observing changes in policy-rate futures over narrow intra-day (typically 30-minutes) event windows. These factors can then be used as explanatory variables in ordinary regressions. However, the benefit of intra-day identification strategies is debated. Gurkaynak et al. [2004] compare the use of intra-day to daily event windows. Their results show only small changes in magnitude of the observed effects but led to a substantial increase in the model fit: Comparing a daily

[2] A review of applications of event studies in Finance can be found in Kothari and Warner [2004].

surprise factor using 3m-T-Bills, gives an R^2 of 56%, compared to 77% and 80% for intra-day data. Lucca and Moench [2015] observe an anticipative effect on equity markets prior to FOMC announcements, that they call "Pre-FOMC announcement drift". Whilst they cannot infer any significant drifts for money market futures or fixed income markets, it illustrates problems regarding intra-day identification. The question of how much information is reliably extracted within 30 minutes of monetary policy announcements adds to this. Event studies are further subject to a selection bias. Underlying event-datasets are typically based on a set of chosen key announcement and therefore omit policy that does not feature in selected event samples. Whilst using event studies is therefore beneficial for purposes of identifying the effect of certain policies with known announcement dates, restrictions with respect to policy interaction and propagation of policy effects questions the application to studying broader policy effects.

There are a number of policy measures from the big data literature that became available more recently. These measures can be classified by data sources into news- and web-based measures. News based measures analyse data available through news media using mainly text analysis of newspaper articles. Examples for this are news intensity indices, applied in Altavilla et al. [2015] and Krishnamurthy and Vissing-Jorgensen [2011]. Here news data is used to qualify a set of events and thereby sharpen identification. Whilst this approach qualifies selection of given events it again relies on a definition of policy events and thereby limits possible policy interactions. Measures of policy sentiment and uncertainty, in contrast, are continuously observed irrespective of some definition of an event sample. Da et al. [2015], propose a news coverage index based on data gathered through the news database Factiva to construct an index for investor sentiment. Sentiment can be established based on sentiment dictionaries that are commonly used in text-analysis. Such dictionaries then map words into particular definitions of sentiment (Wilson et al. [2005]). A seminal paper on measurement of policy uncertainty is Bloom [2009], who highlight the importance of uncertainty shocks for the macro-economy. Baker et al. [2016] build on this with the introduction of Economic Policy Uncertainty (EPU) indices, measuring investor sentiment based on newspaper coverage. Web based data uses information on sentiment or expectations revealed by online activity. One approach is to observe online search behaviour on Google, available via GoogleTrends. Seminal papers on using GoogleTrends data can be found in labour economics and the Now-Casting literature (Choi and Varian [2012] and Carrière-Swallow and Labbé [2013]). Da et al. [2015] develop a sentiment index based on Google Trends data, called FEARS [3] index. Lucca and Trebbi [2009] use Google data to develop monetary policy sentiment indices. Rather than Google trends data, they use

[3] Financial and Economic Attitudes Revealed by Search

Google searches as a news database and therefore do not observe agents' reactions to news. Further applications in sentiment analysis use social media such as Kouloumpis et al. [2011] for twitter, and Ortigosa et al. [2014] for facebook. Whilst these measures give useful information for sentiment analysis, samples are restricted to agents that post regular content on social media. The Google search engine covers almost the entirety of the global search engine market[4], so it is the main tool for online research. In this respect, Google data is less prone to sample bias than social media.

We build on this literature, introducing a measure of monetary policy attention based on Google Trends data. The literature on studying attention has been pioneered by Kahneman [1973] who describes attention as a scarce cognitive resource. Attention is not directly observable and is therefore creating difficult measurement problems. In the literature proxies such as observable trade sizes have been used to capture investor attention (Barber et al. [2008]). Da et al. [2011] proposed a direct measure of investor attention using Google data. Here Google searches can be understood as revealed attention similar to the treatment of revealed preferences (Samuelson [1938]). Da et al. [2011] find that Google data leads alternative measures of attention for a number of stocks investigated. We extend this approach to measure policy attention. In the spirit of Kahneman [1973] we argue that attention is a scarce cognitive resource and therefore measurable attention shocks give information on agents' expectations that can be used for policy identification. To our knowledge search engine data has so far not been used in the context of monetary policy analysis.

2.3 A Preferred Habitat Model of International Policy Transmission

We explain policy transmission with an extension of the preferred habitat model in Vayanos and Vila [2009] as proposed by Altavilla et al. [2015] and Lenza et al. [2015]. This model serves as theoretical workhorse throughout this thesis and we will adapt it to foreign exchange swap markets in Chapter 4. The aim of this section is to adapt an existing model for domestic policy transmission onto fixed income markets to a setting of global policy transmission. For this purpose, we derive bond yields as a function of premia over expected risk-free rates. This has important implications for policy transmission: Policy enters either directly through its effect on expected risk-free rates, or indirectly through its effect on volatility premia. These policy channels are outlined in section 2.3.1 below. The aim is then to investigate

[4]Recent figures suggest Googles market share of all online searches is above 90%, its search engine captures 62% of the search engine market (see: https://www.businessinsider.com/how-google-retains-more-than-90-of-market-share-2018-4?r=US&IR=T)

the existance of derived direct and indirect transmission channels and their implications for global policy transmission empirically. At this point we neither aim to fitting and simulating the model nor to develop a theory of volatility, as this would be beyond the scope of this thesis.

Demand for assets is split between two types of agents, arbitrageurs, ω, and preferred-habitat investors, ξ. Preferred habitat investors have local demand preferences for assets in one specific habitat i, which leads to a segmented market. Arbitrageurs use ω to obtain an optimal portfolio of fixed income assets with portfolio return, R^P. Returns are given as one-period holding returns, where the payout price at the end of the second period (maturity) is subject to credit default probability, ψ. This is sensitive to a vector of macroeconomic factors, X, captured by a sensitivity factor, γ_i. Macroeconomic factors, in turn, follow a vector-autoregressive process with variance-covariance matrix, Ψ, and bond prices are affine in those factors. An arbitrage opportunity exists through the preferences of preferred habitat investors that cause market segmentation, which arbitrageurs can mitigate following their objective function, depending on risk-aversion and sensitivity parameters.

Following the portfolio optimisation outlined in appendix B.1, and given the assets considered, we can describe yields on asset i with maturity in n periods as follows[5]

$$
\begin{aligned}
y_{i,t}^{(n)} = \frac{1}{n+1}\sum_{j=0}^{n} E_t(\overline{r}_{t+j}) + \frac{1}{n+1}\sum_{j=0}^{n} E_t\left(\gamma_i'(\mu+\Phi X_{t+j})\right)\frac{1}{n+1}\sum_{j=0}^{n} E_t\left((\overline{b}_i'+\gamma_i')\Psi\lambda_{t+j}\right) \\
-\frac{1}{2}(\overline{b}_i'+\gamma_i')\Psi(\overline{b}_i+\gamma_i),
\end{aligned}
\tag{2.1}
$$

where

$$\lambda_t \equiv \sigma\sum_{i=1}^{n}(\omega_t^i)(\overline{b}_i+\gamma_i),$$

and

$$\omega_t^i = S_t^i - \xi_t^i.$$

In (2.1), bond yields, $y^(n)_{i,t}$, are determined by the average of expected future short-term risk-free rates, $\overline{r}_t$, a credit premium of a risk-neutral investor arising from the credit risk *at* maturity (second term in 2.1) and a volatility premium to compensate a risk-averse investor for uncertain payoffs *prior to* maturity (last term). $\overline{b_i}$ gives the sensitivity of bond price i w.r.t. X, ω_t^i is arbitrage demand which enters as a portfolio weight and is given by the difference in local bond supply, S_t^i, and preferred habitat demand, ξ_t^i.

[5]2.1 assumes that the pricing coefficients, $\overline{b_i}$, are constant across maturities, to allow for an unordered portfolio of fixed income assets.

The volatility premium rewards an investor for price (or equivalently yield-) fluctuations over the lifetime of a security, i.e. prior to maturity. Risk is priced into the volatility premium as the product of expected quantity of risk, i.e. volatility captured by Ψ, and price of risk, λ_t. λ_t is endogenous and can depend on arbitrage, and equivalently the degree of segmentation in the market, risk aversion, and credit risk parameters. As in Vayanos and Vila [2009], one can easily show that for risk-neutrality of arbitrage ($\sigma = 0$) the premium disappears. The endogeneity of λ_t subject to credit risk parameters governs the intensity of the credit premium channel and marks the main innovation proposed in Altavilla et al. [2014]. Credit risk parameters affect returns in (2.1) both directly and indirectly through its effect on λ_t.

2.3.1 Policy Channels

Domestic Transmission Channels Policy affects returns in the model through direct and indirect channels. Direct effects are through changes in the expected path of short-term policy rates, $\frac{1}{n+1}\sum_{j=0}^{n} E_t(\bar{r}_{t+j})$, (signalling channel). Indirect effects are through the policy impact on credit and volatility premia. Policy affects the volatility premium in particular segments through asset purchases, that imply local supply scarcity. This scarcity leads to a decrease in local arbitrage portfolio weights, ω_i as arbitrageurs are crowded out of the market segments and into other segments. In the absence of any further effects such as a reduction in duration or compression of credit premia, policy affects the composition of arbitrage portfolios but not the market price of risk and therefore the volatility premium. Asset purchases that imply a decrease of the average maturity of bond supply can affect λ, leading to a decrease in the volatility premium, as the pricing sensitivity to macroeconomic factors,$\overline{b_i}$, is higher for long term bonds (duration channel). Similarly, purchases that target lower quality bonds, that carry higher credit default risk, γ_i, can lead to a decrease in λ. Note that the credit effect on the market price of risk is through allowing γ to vary across the portfolio. This is similar to assuming a direct effect of policy on credit default probabilities (credit premium channel), highlighted in Altavilla et al. [2014]. In both cases, duration and credit premium channels, the effect of asset purchases can be understood as freeing up arbitrage capital. Local supply scarcity then induces portfolio rebalancing, subject to arbitrageurs' risk bearing capacity, that transmits policy effects on other market segments.

Policy Transmission and Global Financial Cycles This model features a generalisation of the model proposed in Altavilla et al. [2014]. Arbitrageurs can hold an unspecified portfolio of fixed income assets, where bonds can differ in credit quality not just with respect to duration. In this setting arbitrageurs can also hold foreign assets and therefore feature international transmission of policy through portfolio-rebalancing. Such global arbitrage portfolios are in the spirit of Global Financial Cycles, following Rey [2015] and Miranda-Agrippino and Rey [2015]. Accordingly, there is empirical evidence for a global financial cycle that co-moves with one global factor, identified as implied volatility of the S&P 500 index, VIX. In the context of our model this might indicate dominance of US$ denominated assets in a global arbitrage portfolio and therefore US policy dominating global portfolio rebalancing.

2.3.2 Empirical Implications

The preferred habitat model presented in this section shows how policy can affect mean returns directly through the signalling channel or indirectly through credit and volatility premia. We can thus summarise 2.1 as

$$\Delta y_{i,t}^{(n)} = \Delta \frac{1}{n+1} \sum_{i=0}^{n} \mathbb{E}\bar{r}_{t+i} + \Delta CP(x,\iota) * \Delta VP(\gamma_i, \lambda(\sigma, \omega(S_i, \xi), \bar{b}_i, \gamma_i), \Psi). \tag{2.2}$$

Returns for assets of some maturity n are expressed as changes in yields, $\Delta y_{i,t}^{(n)}$, CP is a credit premium that collects terms, given in the second summation in 2.1. It captures the direct effect of a reduction in credit default probability through parameters γ_i and μ. VP is a volatility premium that collects terms, given in the third summation in 2.1. It is the market expected product of quantity of risk that is driven by volatility, here represented by macroeconomic shocks, Ψ, and the market price of risk, λ. This term thus entertains any effects of policy that are transmitted through volatility.

2.2 implies a mean-variance relationship that provides the starting point for the empirical estimations in the remainder of this chapter. Accordingly, returns are directly affected by expected future policy rates only. Other channels are indirectly affecting yields through amplification or reduction of volatility premia. Volatility should significantly affect asset returns but policy itself can also affect volatility. This is not explicit in our model but can be seen from volatility entering as innovations to macroeconomic factors, such as policy. Following this, policy can affect volatility, which can then affect asset returns through the channels discussed above. We estimate this empirically in a set of conditional volatility models, where we include policy and risk measures in mean and variance processes. We outline our empirical specification further below, following a discussion of the data employed, with a focus on our policy measures in particular.

2.4 Data

We employ data from two main sources: fixed income returns and data on online search engine queries, gathered through Google trends. We use daily data spanning from January 2014 to June 2016. The dataset marks a time where monetary policy between US Fed and ECB diverged, which accommodates the analysis of spill-over effects. We only consider US and Eurozone data, due to the similar size of the currency areas. The choice of daily data allows us to observe volatility clusters and to use the policy attention indices as measures to identify monetary policy shocks. All variables apart from policy attention are assumed to be difference-stationary. Policy attention is stationary in levels. A list of variables is reported in tables 2.1 and 2.2 below. We distinguish the policy indices, the VIX and futures, which enter our models exogenously, and the remaining variables that enter endogenously.

Table 2.1 Variables and Datasources – Endogenous Variables

Label	Variable	Unit	Source
XOIS	European Overnight Index Swap Rate	%	Reuters Datastream
XCORP_HY	IBOXX EUR Liquid Corp. HY Index	% Yield	Reuters Datastream
XCORP_Y	IBOXX EUR Liquid Corp. Index	% Yield	Reuters Datastream
XBUND	10-year German Government Bonds	% Yield	Reuters Datastream
USOIS	US Overnight Index Swap Rate	%	FRED
US_CORP_HY	BoAML US Corp. Master Effective Yield Index	% Yield	FRED
US_CORP	BoAML High Yield Effective Yield Index	% Yield	FRED
US10Y	10-year US Government Bonds	% Yield	FRED

Table 2.2 Variables and Datasources – Exogenous Variables

Label	Variable	Unit	Source
XEONIA	1Month EONIA Futures Rate	%	Quandl
USFF1M	1Month Fed Funds Futures	% Yield	FRED
VIX	Chicago Bond Options Exchange Volatility Index	Index Value	FRED
ECBMPSI	ECB Monetary Policy Search Index	Index Value	Google/ own calculations
FEDMPSI	FED Monetary Policy Search Index	Index Value	Google/ own calculations

2.4.1 Google Data

MPSI Index Construction The Monetary Policy Search Index (MPSI) uses an index based on a number of search queries related to one particular central bank investigated.[6] The index will be constructed following the approach of Da et al. [2015] in that the search topics "European Central Bank" and "Federal Reserve System" are entered into the Google

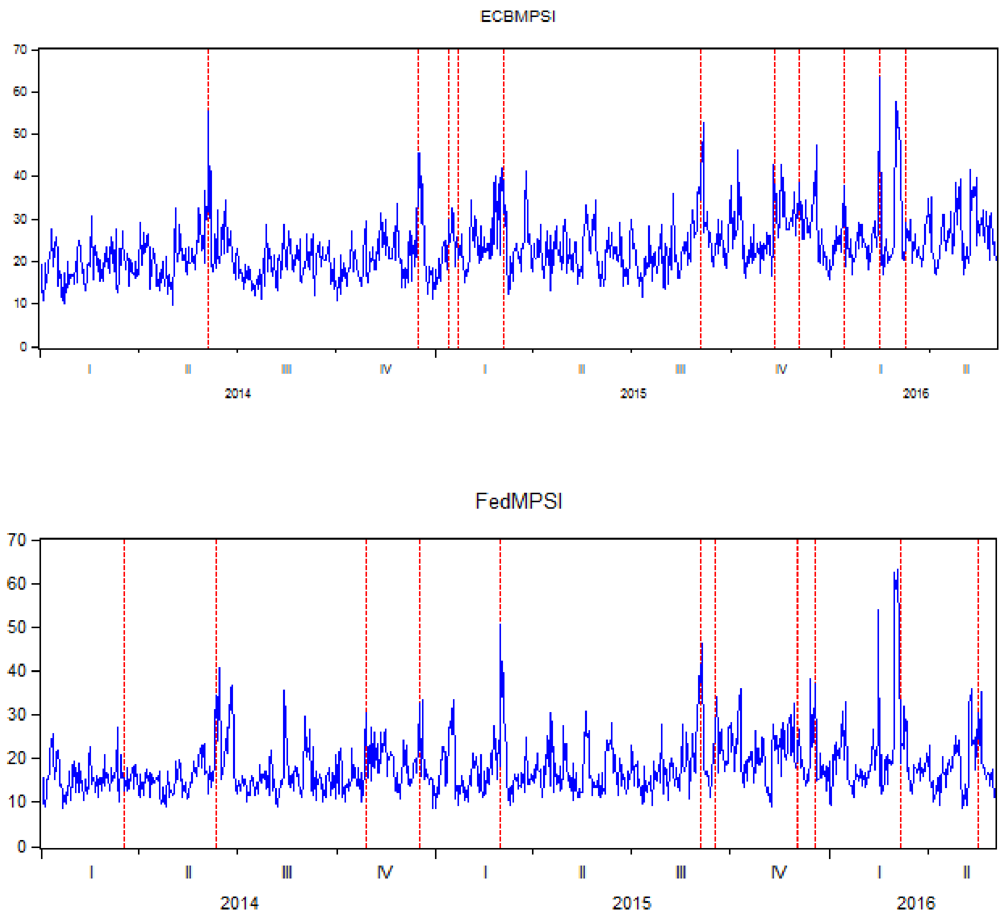
[6]A list of search words, used for the indices is given in table D.1 in appendix D

Trends user interface, which returns a list of related top searches, which will then enter each index, weighted by the impact value assigned by Google. Search terms that are ambiguous or unrelated will be excluded. It is crucial at this stage to stress that weights are not constructed through data-mining approaches such as using uninformed correlation measures, but instead uses Google's measure of *related searches*, which gives correlations based on search terms the same users also entered. Using this measure avoids spurious relationships.

The search indices for ECB and Fed related searches are plotted in figure 2.1. The vertical lines represent identified events, which are given in tabkes D.2 and D.3 of appendix D.1.[7] We can observe that the indices exhibit strong volatility, owing partly to noise, but we can also see that they are clearly heteroskedastic and can even identify several volatility spikes and clusters that coincide with policy events. The most significant events seem to be relating to the launch and extension of asset purchases for the ECB and interest rate hikes for the Fed, which is in line with the patterns we observed for the fixed income series, described in section 2.4.2 below. Identifying certain relevant events using our indices is not a comprehensive exercise, which would compromise the very reason for using such measures, but provides evidence that the MPSI measures can replicate policy events and do not just follow noise.

[7] Events are identified through Google searches of relevant search terms in two-day windows around observed index spikes.

Fig. 2.1 Google Search Indices and Identified Events



Notes: Vertical lines represent individual identified events. Vertical axis gives a search volume index value, which is normalised on a percentage scale, obtained through Google Trends for individual search words (see appendix A.3 for details). Data source: Google Trends (www.google.com/trends)

Working with Google Trends Data Google Trends provides data on web searches through the Google search engine. Through its web-interface,[8] users can download a search volume index that gives the number of searches for a particular search term within a time-frame as a share of the total number of searches over that time. The length of the time frame depends on the frequency of the data used - i.e. one day for daily data etc. The index is then further normalised against the highest observation within the reported time sample, which is by default scaled to 100. Theoretically, data is available in monthly, weekly, daily and

[8]trends.google.com

intra-daily frequency. However, Google limits the size of its reports to 90 observations. To observe daily data for more than 90 days we therefore have to download the reports in steps, which requires re-indexation of the data since the default normalisation would otherwise force cyclical behaviour on the data.[9]

A further complication arises from the sampling underlying publicly reported data on Google Trends. For computational efficiency, Google calculates its indices based on a random sample of the actual search data. These resulting sampling errors are well documented in the literature[10] and concluded to be small and mostly occur if the data is downloaded over long periods of time (see Carrière-Swallow and Labbé [2013] and Choi and Varian [2012]). Li (2016) evaluates the sampling error in the context of nowcasting modelling and observes an effect on significances across different search terms used. This is unsurprising since the size of the sampling error is likely related to the size of the underlying true populations for that search term. They conclude as best practise to download several series from different IP addresses within one day and use an average of the downloaded samples. This problem is, however, relevant when using Google data in the context of real-time models, as the search index gets continuously updated. As real-time data is not applied in our research and described biases are reported to be small, we judge this issue to be negligible.[11]

2.4.2 Fixed Income Data

We use yields on European and US American European fixed income assets that reflect different credit and maturity segments. We use 10y German government bonds for the European and 10y Treasury Notes for the American government bond market, which is a canonical choice for long-term risk-less assets. Overnight index swap (OIS) rates will be used to capture the short end of the money market. Lower risk assets are captured, using corporate bond indices, IBOXX EUR Liquid Corporates BBB and IBOXX EUR Liquid Corporates from Markit for Europe, and Bank of America Meryll Lynch's US Corporate

[9]We follow an algorithm described in http://www.clintonboys.com/google-trends-scraper/ to gain daily data, which uses a similar approach to that described http://erikjohansson.blogspot.co.uk/ used in Li (2016). The Python script described in this blog may be due to changes in the Google Trends web interface, in which case the data may have to be downloaded manually for replication.

[10]see Li (2016) for a review

[11]The sampling algorithm used by Google to report SVIs is subject to changes. One example has been applied on 01/01/2016, which has not affected the data sample obtained for this research. However, we cannot rule our further changes that can affect replicability of indices, based on data publicly available on Google Trends. For the purpose of replication of our results, downloaded data used for the contruction of the indices is available on request.

Master Effective Yield Index and its High Yield Effective Yield index for the US.[12] The choice of the indices is owing to their high market liquidity as they are commonly used as benchmarks on the corporate bond market. We further use an index of implied volatility for the S&P 500 index, VIX, as a proxy for global market risk, and one month Fed Funds and EONIA Futures as proxies for policy rate expectations. All European futures and fixed income series are converted to USD. Futures data is obtained through Quandl and European fixed income data through Reuters Datastream and the US indices and the daily USD/EUR exchange rate through the FRED database.

Figures 2.2 and 2.3 plot the raw series for the non-search data used for this analysis. The vertical axis measures interest in percentage for all series but the VIX in Fig 2.3, where prices are plotted instead. From a quick inspection of the graphs, a few patterns become immediately apparent: The fixed income series follow co-movement and there appears to be a period of heightened volatility on European markets towards the end of 2015 and on US markets in the first half of 2016. This coincides with key monetary policy announcements, regarding the introduction of a quantitative easing programme in Europe and of a rate contraction in the US. The observation of diverging policies between Fed and ECB is further supported by the widening spread of both money market futures and OIS rates between the two currency areas. Descriptive evidence, hence does suggest a divergence of monetary policy cycles and announcements to have had an impact on fixed income markets.

[12]Both, European as well as US bond indices, are each mutually exclusive in the sense that they define clear rating thresholds, currency inclusion criteria and are provided through the same respective sources. This ensures that at every point in time each security can only be captured once, and hence avoids double-counting.

Fig. 2.2 European FI Series

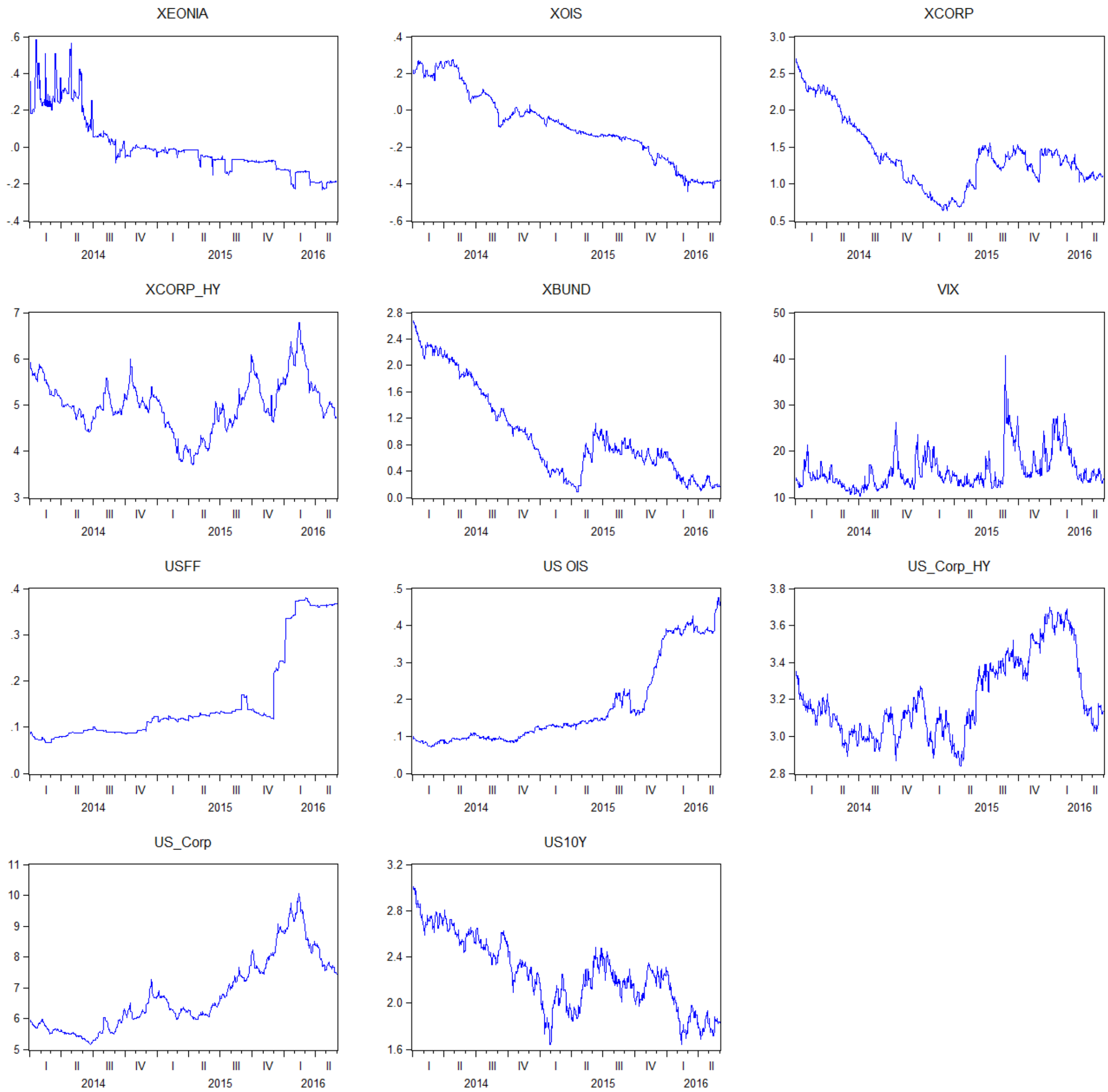
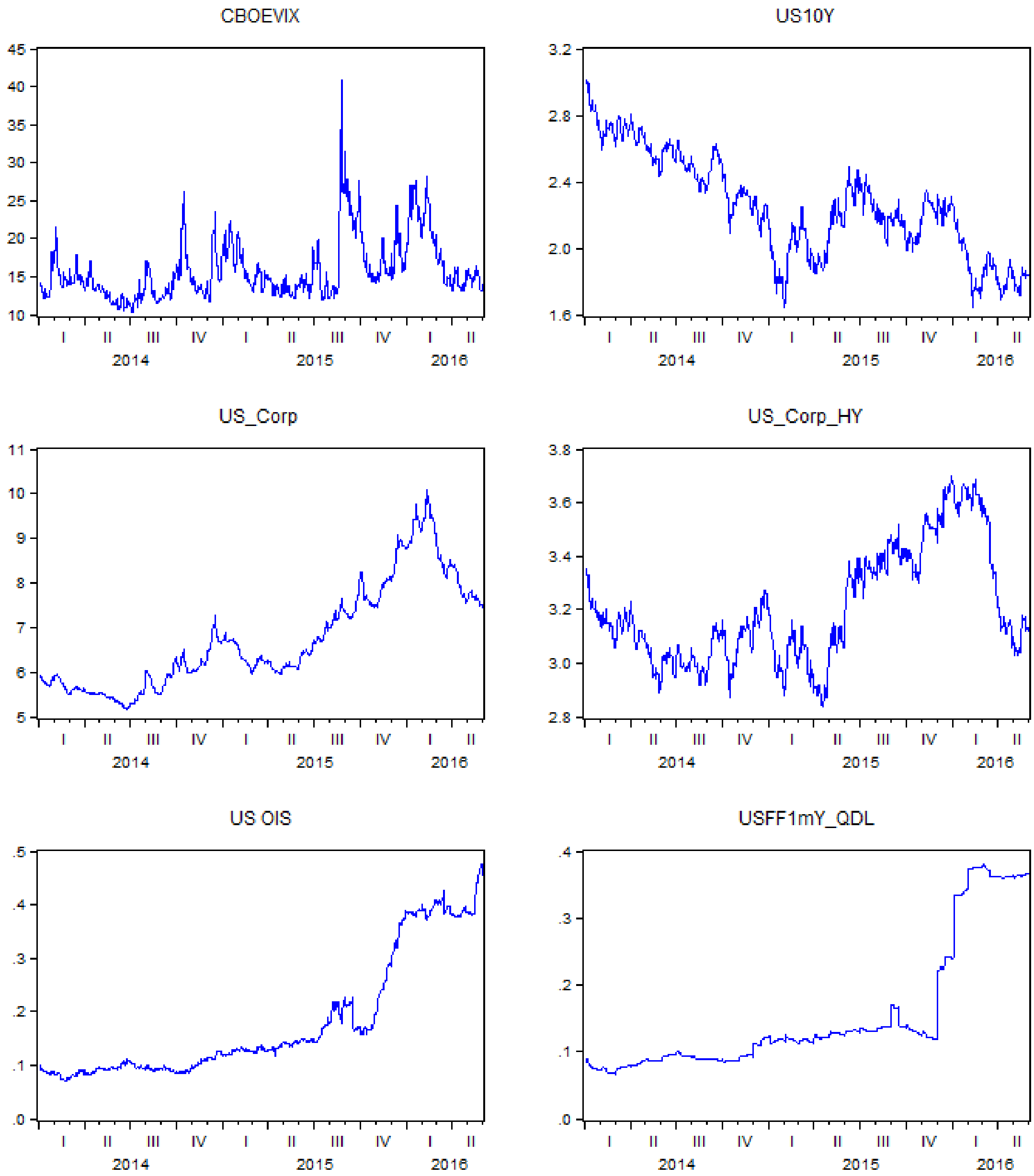


Fig. 2.3 US FI Series and VIX



2.5 Transmission in Conditional Volatility Models of Asset Returns

We follow the strategy in section 2.3.2 and estimate a mean-variance relationship of considered fixed income asset returns. Such financial data is typically subject to autoregressive conditional heteroskedasticity that leads to volatility clustering and therefore biased estimates of standard errors. These autoregressive conditional heteroskedasticity (ARCH) effects are widely known and controlled for in conditional volatility models that specify variance equations explicitly (see Bollerslev [1990] Engle [1982]). We apply a set of exponential (EGARCH) models that further account for the skewness in asset returns, due to disproportionally large impacts of negative news shocks described in Nelson [1991]. Following this framework, we estimate the direct effect of policy measures and volatility on mean asset returns. There are several measures for volatility. In our model it enters as implied volatility, captured by VIX, as well as through allowing feedback of estimated variance onto means (GARCH-in-mean), which gives a measure for predicted volatility. We abstained from considering realised volatility, as this would require intra-day data, which was not available. A more detailed description of the model selection for mean equations is given in section 2.6 below. Equation 2.3 below gives the baseline specification of our empirical estimates. We consider further extensions, including GARCH in mean, in 2.5.4 below.

$$\Delta y_t^i = \beta_0 + \beta_1 \Delta VIX_t + \Psi_t \tag{2.3}$$

where

$$\Psi_t = \varepsilon h_t^{1/2}, \quad \varepsilon \sim t(0,1,\nu)$$

and

$$\log h_t \;=\; c_0 + c_1 h_{t-1} + c_2 \left|\frac{\Psi_{t-1}^2}{h_{t-1}}\right| + c_3 \frac{\Psi_{t-1}^2}{h_{t-1}} + c_4 VIX_t + c_5 ECBMPSI_t + c_6 FEDMPSI_t.$$

h_t follows a EGARCH(1,1)-process, c_0 is a constant, the first three terms in the variance equation represent capturing ARCH, GARCH, and asymmetry effects with their respective coefficients, c_1 - c_3. VIX gives implied volatility on the S&P 500 stock index, FEDMPSI and ECBMPSI are US and European policy attention indices. Asset returns and VIX are entering 2.3 in first differences. This is to achieve covariance stationarity, which is a necessary to achieve well-behaved estimates of standard errors. In this baseline model policy enters variances only through our policy attention measures. Both, European and US monetary policy attention enter variances to capture domestic as well as international tramsmission effects. VIX enters variances to control for global market risk, but as it is a volatility measure, it also captures the volatility premium in mean equations. Mean equations are specified following the model selection exercise in section 2.5.1.

2.5.1 Specification of Mean Returns

We build mean equations, following a general-to-specific strategy. We start with a general ARIMA model, (2.3) of the return on asset i, r_t^i, that includes foreign and domestic policy measures, both policy rate expectations, $FF_{US,t}$ and $FF_{EU,t}$, and policy attention, as well as first order lags of all other assets, considered as dependent variables, $\sum_{j=1}^{k} a_j \Delta y_{t-1}^j$. This last term considers cross-correlation between mean returns, similar to a VAR framework. Whilst theory would suggest cross-correlation to be significant, due to portfolio rebalancing, empirical evidence typically suggests univariate models such as ARIMA processes, that control for serial correlation and avoid unstable processes, arising from unit roots that are typically present in time series data.

$$\begin{aligned} r_t^i = \Delta y_t^i = c + \beta_1 \Delta y_{t-1}^i + \beta_2 \Psi t - 1 + \beta_3 \Delta FF_{US,t} + \beta_4 \Delta FF_{EU,t} + \beta_5 \Delta ECBMPSI \\ + \beta_6 \Delta FEDMPSI + \beta_7 \Delta VIX_t + \sum_{j=1}^{k} a_j \Delta y_{t-1}^j + \Psi_t, \qquad (2.4) \\ \forall i \neq j. \end{aligned}$$

Selection Criterium: We compare the fit of several restricted model that are nested within eq. (2.4) based on the Bayes-Schwarz Information Criterion (BIC).[13] Information criteria capture the trade-off between model fit and consistency of estimates, i.e. the trade-off between type I and II errors of the estimation, through likelihood based measures that penalise model complexity given by the number of parameters in the model. In simple significance tests, the type I error converges to zero as $T \to \infty$ but the type II error remains constant, leading to inconsistency. BIC gives a consistent selection criterium through increasing the penalty term proportionally with the sample size. One can easily see that an information criterium, $IC: -2(l_u - l_r) + A_T(k_u - k_r) \Leftrightarrow -1(l_u - l_r) > A_T(k_u - k_r)$, where the sub-indices indicate some unrestricted and a restricted model and A_T the penalty term, is equivalent to the likelihood ratio test $-2(l_u - l_r) \sim \chi^2(k_u - k_r)$ with critical level $\alpha = A_T$. As information criteria differ with respect to the choice of A_T, the choice of different information criteria

[13] The following definition is used: $BIC = -2l/T + (k \log T)/T$, where l is the log-likelihood, T gives the sample size, and k the number of parameters estimated.

is equivalent to applying log-ratio tests for different significance levels. The choice of BIC for our model selection therefore errs on the side of model parsimony and demands higher confidence in the adequate fit of a model.

We consider the following models: (1) a random walk that only includes a constant term, (2) a regression on a constant term and VIX, (3) an AR(1) process and a constant term, (4) a MA(1) process and a constant term, (4) an ARMA(1,1) process and a constant term, (5) an AR(1) process with constant term and policy rate expectations, (6) an AR(1) process with constant term and both policy measures included, (7) an AR(1) process with constant term, policy rate expectations and VIX included, (8) an AR(1) process with policy rate expectations and first lags of remaining assets that are considered as dependent variables, and (9) gives the general specification given in 2.4.

Results are given in table 2.3 below. The last column reports the sum of all the individual BIC values across models for one particular specification. We select the model that gives the lowest sum of BIC.[14] Following this exercise, a regression on VIX and a constant provides the best fit. This is in line with model predictions whereby VIX captures the effect of the volatility premium. Models that include policy measures are over-fitted, which is not in line with theoretical predictions. According to (2.1) ff_{US} and ff_{EU}, that capture the signalling channel, should have a significant effect on asset returns. However, both measures do not improve the information contained in the model according to BIC. In this sense, policy appears to mostly affect variances rather than means of fixed income returns, and it is likely that feedback of that effect onto means is captured by VIX. The next section discusses the effects of policy alongside risk on return variances.

2.5.2 Estimation and Convergence Issues

We estimate the specification above using a t-distributed maximum likelihood estimation. Following Hamilton [1994], Engle and Ng [1993] and Pagan and Schwert [1990], the sample log likelihood is

[14]This approach implicitly assumes independence of errors. We follow this approach as we will allow for multivariate dynamic covariances in the following chapter, and therefore require the best joint specification of all models considered.

Table 2.3 BIC for Different Mean Specifications

Specifications	XOIS	US10Y	US_CORP	US_CORP_HY	US_OIS	XBUND	XCORP_Y	XCORP_HY	SUM BIC
(1)	-7.42*	-3.79	-3.41	-4.46	-8.77	-3.97	-4.61	-3.43	-39.86
(2)	-7.41	-4*	-3.49*	-4.56*	-8.78*	-4*	-4.61*	-3.46	-40.31*
(3)	-7.42	-3.78	-3.43	-4.45	-8.77	-3.96	-4.607	-3.48*	-39.897
(4)	-7.42	-3.78	-3.43	-4.44	-8.77	-3.96	-4.607	-3.47	-39.877
(5)	-7.4	-3.77	-3.41	-4.44	-8.77	-3.94	-4.59	-3.43	-39.75
(6)	-7.4	-3.75	-3.39	-4.42	-8.76	-3.93	-4.58	-3.42	-39.65
(7)	-7.4	-3.99	-3.5	-4.55	-8.78	-3.98	-4.6	-3.45	-40.25
(8)	-7.36	-3.72	-3.37	-4.39	-8.73	-3.9	-4.54	-3.47	-39.48
(9)	-7.34	-3.7	-3.35	-4.37	-8.71	-3.89	-4.52	-3.45	-39.33

Notes: This table gives the Bayes-Schwarz Information Criterion (BIC), obtained through alternative specifications in the mean equations of a set of considered EGARCH(1,1) models regressed on each of the 8 considered yields for daily data over 2014/01/01-2016/06/30. Values with asterisk indicate the preferred specification choice.

$$
\begin{aligned}
L(\theta) \quad = \quad & T\{\log(\nu/\lambda) - (1+\nu^{-1})\log(2) - \log[\Gamma(\nu^{-1})]\} \\
& -\frac{1}{2}\sum_{t=1}^{T} |(y_t - \boldsymbol{b}'\boldsymbol{x} - \delta h_t/(\lambda\sqrt{h_t})|^{\nu} \\
& -\frac{1}{2}\sum_{t=1}^{T} \log(h_t), \qquad (2.5)
\end{aligned}
$$

where Γ is the Gamma-function and ν are degrees of freedoms, y gives the dependent variable, $\mathbf{x}$ is a vector of covariates with coefficients, $\mathbf{b}$ and h gives conditional variances. The likelihood parameters are estimated as

$$
\hat{\theta} = \max_{\boldsymbol{b},\delta,\nu} L(\theta).
$$

Using t-distributed GARCH models is motivated by the relatively high frequency of the data, which often yields leptokurtic error-processes; and indeed, the describtive statistics of our data report an appreciable degree of excess-kurtosis, especially for our MPSI series. [15]

We generally achieved convergence for all models considered. However, some of the parameters, especially error estimates and estimated degrees of freedom, were at the edge of the parameter space, hence suggesting fatter tails than could be replicated in a t-distribution.

[15] In fact, as the coefficient on the degrees of freedom for the models in all specifications shows, the tails of the t-distribution might not be fat enough to account for the variance in the data; it is close to the minimum defined value of 2. We regard this as a sign of misspecification potentially arising from variance cross-correlations and state-dependent results as we point out in another context below. As obtained estimates are otherwise plausible, particularly, given that t-statistics do not indicate zero standard errors, we proceed with obtained estimates.

We therefore re-estimated the models assuming a generalised error distribution. This again resulted in estimated standard errors close to zero and was therefore disregarded for further analysis. We believe some of these issues might, as above, be due to misspecification of the variance equations or outliers.

2.5.3 Results

This section discusses the impact of risk and policy attention on asset return variances, resulting from estimating eq. 2.3. We focus on international spill-over and portfolio-rebalancing effects in particular, which relates estimates to our theoretical model. Here, policy spill-overs are indicated by foreign policy significantly affecting some asset variance. Portfolio rebalancing is captured by effects on the corporate bond segments as these were not directly targeted by policy.

On the US fixed income market, we find evidence for spill-over effects on both money and capital markets. *ECBMPSI* is significant in US_OIS and US_CORP, the policy instruments are both significant for US_OIS and $XOIS$. US policy does only appear to affect capital markets as $FEDMPSI$ remains insignificant in US_OIS but enters significantly in all other US models. This could be as a result of unconventional policies specifically targeting the longer end of the yield and the lower end of the credit curve. On European markets there is evidence for spill-over effects on money markets only – $FEDMPSI$ significantly enters $XOIS$ only. This is likely due to the dominance of rate-setting measures in the US throughout the sample. As before, there is evidence of domestic policy effects, as *ECBMPSI* enters significantly in $XBUND$ and $XCORP\_Y$, albeit less so than for the US assets. It is interesting to note significant policy effects across almost all assets considered, particularily the investment grade corporate markets, which indicates effectiveness of policy at the time. Furthermore, note that, apart from $XCORP\_Y$[16], none of the coporate bond segments have been directly targeted by central bank asset purchases. Reactions in those indices hence provides evidence for transmission via portfolio-rebalancing. However, this interpretation comes with a note of caution as we only observe contributions to variance processes and can only make limited judgements on the direction of effects based on the descriptive evidence provided in figures 2 and 3 in section 4.1 above. Noting the trends apparent in the data we can assume that the impact should be positive on US and negative on European yields, which is in line with ECB policy expanding further whilst the FED withdrew policy accommodation over

[16]As of 01/06/2016 the ECB engaged in investment grade corporate bond purchases within its Corporate Securities Purchase Programme (CSPP). To a large extend the CSPP has been anticipated. This might be picked up by $XCORP\_Y$, which would then indicate effects of direct policy interventions rather than portfolio-rebalancing.

Table 2.4 EGARCH Models

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	US_OIS	*US10Y*	*US_CORP*	*US_CORP_HY*	*XOIS*	*XBUND*	*XCORP_Y*	*XCORP_HY*
Mean								
C	8.27E-05	-0.000821	-0.000573	-0.000665	-0.000182	**-0.001477***	**-0.001230****	**-0.002101****
	(1.201929)	(-0.979054)	(-0.567386)	(-1.506669)	(-1.359356)	**(-1.758433)**	**(-2.063785)**	**(-1.956880)**
VIX	**-0.000363*****	**-0.015963*****	**0.012238*****	**-0.006992*****	**-0.000157***	**-0.005107*****	**-0.001627*****	**0.007015*****
	(-6.816837)	**-26.69563**	**(15.10092)**	**(-15.61869)**	**(-1.753395)**	**(-8.325512)**	**(-3.621788)**	**(8.236160)**
Variance								
C	-6.960750	-3.662015	3.073327	-4.441654	-2.569310	2.865323	-2.214482	3.577638
	(-0.872901)	(-0.388372)	(0.020390)	(-0.549369)	(-0.042524)	(0.010400)	(-0.041745)	(0.010826)
ARCH	20.44661	5.348404	155.5151	5.951210	51.63544	117.2196	11.11799	134.1159
	(0.290274)	(0.277227)	(0.013698)	(0.349205)	(0.034565)	(0.006978)	(0.039883)	(0.005876)
Leverage	3.885094	0.403395	18.69268	-1.576078	-5.017070	35.75017	0.120822	31.91964
	(0.286310)	(0.257894)	(0.013702)	(-0.345037)	(-0.034562)	(0.006977)	(0.036414)	(0.005876)
GARCH	**-0.140841****	**-0.311574*****	-0.032728	**-0.416927*****	-0.043762	0.039020	-0.057923	0.029076
	(-1.985410)	**(-3.047732)**	(-0.451202)	**(-4.360583)**	(-0.786600)	(0.314563)	(-0.568688)	(0.338143)
VIX	**0.112182*****	0.052028	**0.081371***	-0.049157	0.026983	**0.096461****	-0.005116	0.035915
	(3.099007)	(1.358781)	**(1.957764)**	(-1.338626)	(-0.602928)	**(2.248105)**	(-0.128902)	(0.920422)
ECBMPSI	**0.043695*****	-0.006596	**0.031453****	-0.003569	-0.006118	**0.025148***	**0.030100*****	0.012360
	(3.170908)	(-0.462849)	**(2.246342)**	(-0.275538)	(-0.602646)	**(1.804188)**	**(2.670313)**	(0.888251)
FEDMPSI	0.018162	**0.036729****	**0.042090*****	**0.027850****	**0.046660*****	0.007628	-0.010964	0.018484
	(1.254542)	**(2.428278)**	**(2.714482)**	**1.980296)**	**(4.388056)**	(0.534976)	(-0.860060)	(0.888251)
T-DIST. DOF	2.000418	2.004981	2.000008	2.004470	2.000060	2.000010	2.001112	2.000009
BIC	-8.782046	-4.003451	-3.494414	-4.561140	-7.412446	-3.997059	-4.612905	-3.455146

Significant coefficients (< 10% level) are given in bold-faced letters; significance levels: $^{*} < 10\%, ^{**} < 5\%, ^{***} < 1\%$; z-values in parantheses; mean equations are specified based on the Schwarz criterion; Estimation of all models as ML with EGARCH(1,1) specification assuming t-distributed errors and optimisation using the Eviews legacy algorithm with Marquard steps in all models. BIC gives the Schwarz-Bayes Information Criterion. ECBMPSI was lagged once in model (5) and FEDMPSI lagged once in model (7) to avoid endogeneity problems.

the sample period. It is again interesting to find VIX entering significantly in both, variance and mean processes. For the former, we only find a modest contribution mainly on US money markets. On the latter it is highly significant on almost all market segments considered – surprisingly, VIX affects most yields negatively. Lastly, we find significant GARCH effects in half of the models whilst there is no evidence of ARCH or leverage effects.

In summary, the results of this exercise suggest international effects of policy, as measured by policy attention indices, on both, money and capital markets, for the US and on money markets for the Euroarea. It further suggests domestic effects across different credit segments in both the US and Europe. For the US, there is also evidence of portfolio-rebalancing.

2.5.4 Extensions

We consider two extensions to the estimates presented above: The effect of differences in exchange trading hours, i.e. the effect of absence of market dexterity, and we consider feedback of variance processes onto mean returns through GARCH in mean. The latter gives an indication of volatility premia in addition to volatility effects captured by VIX.

Dexterity Market dexterity is a form of market efficiency, whereby "[...] asset prices adjust completely and instantaneously in response to new information." Engle et al. [1988]. A

Table 2.5 EGARCH Models – Accounting for Differences in Trading Hours

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$US\_OIS(-1)$	$US10Y(-1)$	$US\_CORP(-1)$	$US\_CORP\_HY(-1)$	$XOIS$	$XBUND$	$XCORP\_Y$	$XCORP\_HY$
Mean								
C	9.95E-05	-0.000874	-0.000605	-0.000669	-0.000179	**-0.001416***	**-0.001236****	**-0.002477****
	(1.455980)	(-1.040752)	(-0.595493)	(-1.063829)	(-1.331533)	**(-1.647228)**	**(-2.044889)**	**(-2.383513)**
DVIX(-1)	**-0.000332*****	**-0.015920*****	**0.012285*****	**-0.007003*****	**-0.000168***	-0.000442	0.000607	**0.008739*****
	(-6.284286)	**-26.42407**	**(15.23624)**	**(-15.53776)**	**(-1.781040)**	(-0.610528)	(1.137273)	**(9.744267)**
Variance								
C	-4.478406	-3.770121	3.213564	-4.682761	-0.824474	-1.643582	-2.965814	-2.756257
	(-0.321773)	(-0.388172)	(0.027118)	(-0.583573)	(-0.002737)	(-0.022622)	(-0.191373)	(-0.732182)
ARCH	62.31569	5.416066	168.8871	6.051359	87.02810	10.27594	7.956732	3.217988
	(0.155560)	(0.267755)	(0.017538)	(0.354287)	(0.006704)	(0.029172)	(0.149630)	(0.393729)
Leverage	11.37521	0.407257	16.68910	-1.606020	-9.230848	2.833425	-0.074996	1.103296
	(0.154333)	(0.249835)	(0.017545)	(-0.350091)	(-0.006703)	(0.029179)	(-0.070733)	(0.387391)
GARCH	-0.080243	**-0.305464*****	-0.039642	**-0.427585*****	-0.009543	-0.059911	-0.159400	0.242084
	-1.167349	**(-2.940554)**	(-0.515590)	**(-4.463736)**	(-0.163045)	(-0.459974)	(-1.456054)	(2.3601171)
DVIX(-1)	**0.102685*****	0.052047	**0.086818****	-0.049185	0.052444	0.006995	0.075655	-0.034166
	(2.705928)	(1.357263)	**(2.093145)**	(-1.341107)	(1.193445)	(0.159605)	(1.489734)	(-0.574976)
ECBMPSI	**0.039556*****	0.004709	**0.020304***	0.012512	**0.026978****	0.019507	**0.026252****	**0.027810****
	(3.381643)	(0.415938)	**(1.827304)**	(1.167974)	**(1.978716)**	(1.620891)	**(2.355384)**	**(2.499708)**
FEDMPSI(-1)	**0.028576****	**0.030693****	**0.055420*****	**0.024365****	**-0.040630*****	0.009078	-0.006021	-0.008715
	(2.239208)	**(2.547974)**	**(4.530519)**	**(2.065635)**	**(-2.962897)**	(0.742122)	(-0.466014)	(-0.773531)
T-DIST. DOF	2.000049	2.004872	2.000008	2.004256	2.000024	2.001145	2.001964	2.012588

Significant coefficients ($< 10\%$ level) are given in bold-faced letters; significance levels: $^{*} < 10\%, ^{**} < 5\%, ^{***} < 1\%$; z-values in parantheses; mean equations are specified based on the Schwarz criterion; Estimation of all models as ML with EGARCH(1,1) specification assuming t-distributed errors and optimisation using the Eviews legacy algorithm with Marquard steps in all models.BIC gives the Schwarz-Bayes Information Criterion. ECBMPSI was lagged once in model (5) to avoid endogeneity problems.

lack of dexterity would hence be present if markets adjusted sequentially to news-shocks. Engle et al. [1988] describe this effect as *meteor showers*, which rain down as the earth rotates. Analogously, one particular news shock could be priced into markets at different times as global trading hours vary. For obvious reasons, this effect is most relevant for intra-day data. We do, however, consider it as a robustness exercise as common trading hours between US and European exchanges vary sufficiently enough for some US news-shocks to be potentially digested on European markets on the next trading day. Examples for this are FOMC press conferences that are typically held after European trading hours. Table 2.5 hence lags variables from US exchanges by one day. The exercise confirms previous results and notably leads to improvements in observed significances – most notably on US and European money markets – as well as a reduction of the impact of the intercepts in some models; most notably we find significant coefficients on the domestic policy indices on money markets and *ECBMPSI* entering significantly in $DXCORP_HY$. The latter provides evidence for portfolio-rebalancing on European fixed income markets, as high-yield corporate bonds were not eligible for ECB's CSPP.

GARCH-in-Mean Theory suggests that market volatility directly affects mean holding returns as the volatility premia in eq (2.2) affect yields directly through spreads. To account for this, we estimate a GARCH-M effects following Engle et al. [1987]. We include the

Table 2.6 EGARCH-in-Mean Models

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable	*US_OIS*	*US10Y*	*US_CORP*	*US_CORP_HY*	*XOIS*	*XBUND*	*XCORP_Y*	*XCORP_HY*
Means								
GARCH	0.000120	-6.65E-06	0.000307	0.005895	-0.000219	-0.000908	-0.000620	**0.234844*****
	(0.827619)	(-0.003007)	(0.151924)	(1.470042)	(-0.710579)	(-0.411573)	(-0.374148)	**(2.671077)**
C	0.000421	-0.000837	-0.000844	0.042873	-0.000706	0.001702	-0.002116	-0.304170
	(0.7028)	(-0.16643)	(-0.013633)	(1.441888)	(-0.080515)	(0.001478)	(-0.062982)	(-0.026158)
DVIX	**-0.000355*****	**-0.015963*****	**0.012054*****	**-0.006598*****	**-0.000159***	**-0.005036*****	**-0.001638*****	**-0.026158*****
	(-6.455817)	**-25.97639**	**(14.78074)**	**(-10.57359)**	**(-1.722502)**	**(-8.062438)**	**(-3.648303)**	**(-3.325918)**
Variances								
C	-4.523132	-3.663851	-0.850531	**-7.434103*****	-3.431676	2.470229	-2.135370	0.923531
	(-0.470277)	(-0.388494)	(-0.004143)	**(-5.076441)**	(-0.081480)	(0.002032)	(-0.037228)	(0.414007)
ARCH	58.40339	5.344029	23.47386	**0.309985*****	35.91690	95.65461	11.38814	0.464204
	(0.235978)	(0.277239)	(0.009924)	**(4.081082)**	(0.050201)	(0.001576)	(0.036888)	(0.643240)
Leverage	10.39249	0.403143	3.098492	0.008873	-3.280258	29.52816	0.097681	0.880016
	(0.233214)	(0.257592)	(0.009924)	(0.166719)	(-0.050191)	(0.001576)	(0.032783)	(0.659386)
GARCH	**-0.128392***	**-0.311668*****	-0.018871	0.033566	-0.056461	0.041789	-0.057995	**0.279813*****
	(-1.806820)	**(-3.039642)**	-0.259909	(0.173867)	(-1.030337)	(0.342023)	(-0.571428)	**(4.631262)**
DVIX	**0.106049*****	0.052038	**0.082411****	-0.008071	0.025341	**0.096129****	-0.002742	**0.142818*****
	(2.931549)	(1.359048)	**(1.979101)**	(-0.272490)	(0.567593)	**(2.238030)**	(-0.069165)	**(3.128005)**
ECBMPSI	**0.046357*****	-0.00663	**0.030812****	0.002829	-0.001585	**0.024377***	**0.030208*****	-0.001171
	(3.376351)	(-0.465319)	**(2.200826)**	(0.299583)	(-0.158226)	**(1.767270)**	**(2.694652)**	(-1.355664)
FEDMPSI	0.014643	**0.036765****	**0.042086*****	0.000979	**0.046988*****	0.008736	-0.012506	0.001420
	1.021342	**(2.425968)**	**(2.710903)**	(0.101584)	**(4.424726)**	(0.617517)	(-0.997050)	(1.478612)
T-DIST. DOF	2.000051	2.004988	2.000343	4.984492	2.000122	2.000014	2.001056	2.000288
BIC	-8.775250	-3.995762	-3.486722	-4.470004	-7.405392	-3.989583	-4.605459	-3.498024

Significant coefficients (< 10% level) are given in bold-faced letters; significance levels: $^{*} < 10\%$, $^{**} < 5\%$, $^{***} < 1\%$; z-values in parantheses; mean equations are specified based on the Schwarz criterion; Estimation of all models as ML with EGARCH(1,1) specification assuming t-distributed errors and optimisation using the Eviews legacy algorithm with Marquard steps in all models. BIC gives the Schwarz-Bayes Information Criterion. ECBMPSI was lagged once in model (5) and FEDMPSI lagged once in model (7) to avoid endogeneity problems.

log variance in the mean equations to account for the exponential GARCH models we estimated. Results of the GARCH-M estimations are reported in Table 2.6. There is evidence of GARCH-M effects for the European High-Yield Market only. GARCH is insignificant in the mean processes of all remaining models considered. We obtain the same result based on model selection using BIC.

The lack of evidence for GARCH in mean in most models has repercussions on the theoretical implications outlined above. In particular, it suggests the absence of an effect of asset volatility on the mean process of yields. This is somewhat counter-intuitive as one would expect the existence of a volatility premium; portfolio theory suggests this – literature on the use of mean-variance portfolio optimisation goes back to contributions Sharpe [1966], Markowitz [1952] and Jensen et al. [1972] and is a widely accepted theoretical result. Whilst we believe this result is likely due to volatility effects being captured by VIX in mean equations, it could also be due to the presence of cross-correlation of variances. We investigate this with the analysis of residual correlations and principal components in the following section.

2.6 Multivariate Interactions

The analysis in section 2.5 assumes the absence of cross-correlation between asset variances. This is a strong assumption as portfolio rebalancing implies asset cross-correlation and hence also variance cross-correlation. We have further restricted our analysis to univariate models. Whilst this was justified in the light of the model specification exercise in section 2.5.1, we now consider cross-correlation between residuals. We also obtain further descriptive evidence based on a principal component analysis of variables considered.

2.6.1 Residual Cross-Correlations

We investigate variance cross-correlation in a multivariate frame work using a reduced form VAR in both, levels as well as first differences. Estimating results in levels allows to retain the information that would be lost through differencing. We obtained similar correlations in both cases. It is important to note that this exercise is purely descriptive and we do not draw any causal conclusion and hence to not apply any inference as part of our analysis. This exercise is in the spirit of Sims [1980]. The correlation matrices are reported in table A.3 in appendix A.2.

$$y_t = A_1 y_{t-1} + A2 y_{t-2} + \varepsilon \tag{2.6}$$

$$\Delta y_t = \Delta A_1 y_{t-1} + \Delta A2 y_{t-2} + \vartheta. \tag{2.7}$$

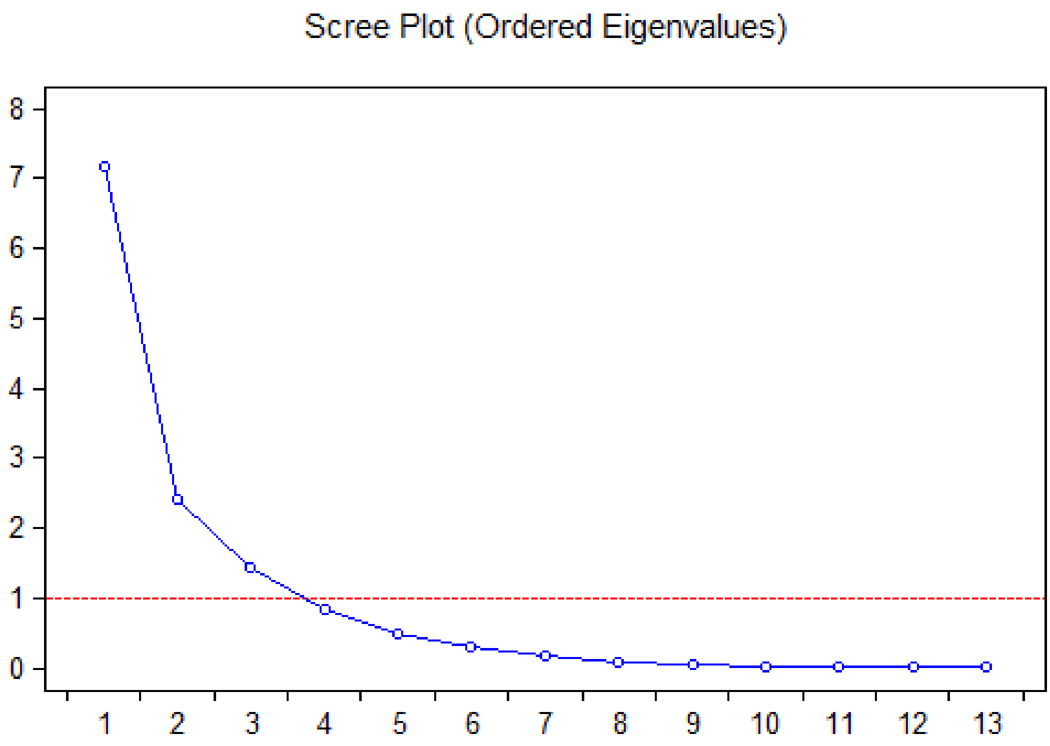
y is a column vector of all N variables A_1 and A_2 are $N \times N$ coefficient matrices, ε and ϑ are $N \times N$ variance-covariance matrices. We assume the covariance matrices non-diagonal and constant over time. The models indicate the presence of cross-correlation, which, given the rejection of multivariate mean processes, raises the necessity to consider cross-correlations in the variance processes, and hence relax the diagonality assumption of the conditional correlation matrix.

We find a strong correlation between the US High-Yield Corporate Bond Index with US Treasuries. In itself this might reflect low-rated corporate bonds following shifts of the yield curve and a certain degree of co-movement one would expect on fixed income markets. It is somewhat surprising though to find such a strong correlation for lower rated corporate bonds, whilst the investment-graded index only exhibits a small and even negative correlation with Treasuries. The negative correlation indicates some degree of portfolio shifts as yield-compression for high quality assets pushed demand further along credit ratings, but yet not enough to cause the same effect for the High-Yield segment. Hence, this provides evidence for both the strong segmentation of the fixed income market and yet some degree of portfolio shifts. We can also find evidence for some co-movement of US and European rates: German 10-year government bonds are positively correlated with Treasuries and US corporate bonds (investment grade), albeit to a lesser extent, and we do find some correlation of the IBOXX EUR corporate bond index with US Treasuries and the US High-Yield market, but strikingly not with US investment-grade bonds. The latter might again be due to market segmentation: Investors on the American investment-graded corporate bond market face a similar burden to invest in European bonds than to invest in the High-Yield market. Lastly, there is some (weak) correlation of VIX with the observed rates, with the strongest correlations, unsurprisingly, for American rates, particularly US_CORP and $US10Y$. The strongest correlation, the American corporate bond index, is positive, which is what we would normally expect – an increase in risk, measured as implied volatility in VIX, leads to a drop in demand for corporate bonds, and hence an increase in yield. Somewhat surprising is thus to find the negative correlation for the High-Yield index, where this risk-off effect should be more pronounced. The correlation for Bunds and Treasuries are expected, given, again the save-haven properties of the assets.

2.6.2 Principal Components

We investigate descriptive evidence of multivariate interactions with a non-parametric analysis of common factors in our 13 yield and policy variables using principal components. This analysis is for robustness purposes not for causal analysis or inference. Results are given in table 2.7. Following a simple cut-off rule, considering Eigenvalues that are greater than one, we can extract three factors. A scree plot is given in figure 2.4 below. Given the unordered nature of our data along several dimensions (US-EUR, term-structure, credit structure) we cannot trivially attribute these three factors to the commonly observed level, curvature and slope factors on fixed income markets.

Fig. 2.4 Principle Components



For the first factor, European and US rates display opposite signs of roughly similar magnitude. This suggests that this factor reflects international transmission effects. For the second factor all rates (but XOIS) load positively, which might suggest some presence of a level factor. The third factor seems largely irrelevant for most variables apart from the policy measures, that both have a strong, similarly sized, positive loading on it. We can also note a fourth factor that is close to the cut-off point with an Eigenvalue of .85. This is particularly interesting, given that this factor has a strong loading on the VIX, which supports Rey [2015]. However, it accounts for less 10% of the variation in the data, where even the second and third factor may be cast in doubt.

Table 2.7 Factor Loadings

Variable	PC 1	PC 2	PC 3	PC 4
XOIS	0.361767	-0.012941	0.07472	0.143942
XEONIA	0.337199	0.111986	0.078032	0.010444
XCORPBBB_Y	0.227791	0.481676	-0.049922	-0.159763
XCORP_Y	0.26346	0.442069	-0.02386	-0.119256
XBUND	0.345987	0.226147	0.038761	-0.05117
USFF1M	-0.301778	0.224564	-0.137151	-0.381261
US_OIS	-0.313711	0.252646	-0.123074	-0.324676
US_CORP_HY	-0.195648	0.440683	-0.07601	0.208642
US_CORP	-0.324477	0.279259	-0.109998	0.083806
US10Y	0.33334	0.178384	0.037879	-0.01409
VIX	-0.170537	0.265373	0.003824	0.790178
ECBMPSI	-0.164871	0.09167	0.65323	-0.097588
FEDMPSI	-0.118255	0.107797	0.709768	-0.037084

2.7 Conclusion and Outlook

This chapter introduced a daily measure for monetary policy attention based on Google Trends data to evaluate international monetary policy transmission. We explain transmission channels adopting a preferred habitat model of global fixed income arbitrage portfolios. Arbitrage is risk averse, which leads to the presence of credit and volatility premia on asset returns. Policy can affect assets through several direct and indirect channels. Effects are then transmitted globally through portfolio rebalancing. We then estimate GARCH models of daily European and US American fixed income returns. There is no sufficient evidence for policy effects on mean returns, which are significantly affected by VIX only. Policy attention significantly affects variance across market segments, providing evidence for international transmission and portfolio-rebalancing. We find significant GARCH in mean effects for European high-yield bonds only, which is likely due to volatility premia being captured by VIX but may also be due to variance cross-correlation that is not captured by our models. Inspecting residuals obtained from a reduced form VAR confirms this: There are considerable residual cross-correlations, particularly for two corporate bonds.

The main contribution of this chapter is to introduce a daily measure for monetary policy attention. Using this measure, we could further show that policy affects assets through variances rather than mean processes, and that mean returns are subject to a volatility premium, captured by VIX, which is in line with preferred-habitat theory. The absense of effidence of policy effects on mean returns has important implications for policymakers: Policy measures aiming at targetting assets directly may be less effective than assumed. Instead policy appears more effective through its effect on volatility, which feeds back onto means. This analysis gives a starting point that allows investigating policy effects on asset variances using high-frequency data, controlling for conditional heteroskedasticity. However, conclusions are limited by the presence of variance cross-correlations. We therefore extend this approach, by investigating policy effects on dynamic asset covariances. We further developed a theoretical model that explains international transmission channels. Whilst this limited empirical analysis did not aim at specifically testing the model we could validate some important implications, such as portfolio rebalancing, the presence of a volatility premium, and of international transmission effects. We return to this model in chapter 4, to explain imbalances on foreign exchange swap markets.

Chapter 3

The Effect of Monetary Policy on Global Fixed Income Covariances

3.1 Introduction

Asset return covariances play a crucial role in global monetary policy transmission. Policy that affects particular market segments leads to changes in optimal portfolio weights that induce portfolio rebalancing behaviour. Dynamic covariances allow for direct observation of this. There is an increasing body of evidence suggesting that policy primarily affects return variances, whereas mean returns follow random walks, which is in line with our findings in chapter 2. But the analysis of asset variances in a univariate set-up does not consider contemporaneous asset cross-correlations. The analysis of dynamic covariances reveals further information about portfolio-rebalancing behaviour as a crucial factor of policy transmission.

In this chapter we relax previous assumptions and evaluate policy effects on dynamic return covariances. Empirically, we employ three methods to obtain covariances that negotiate the trade-off between model sparsity and computational efficiency on one hand and allow for rich multivariate interactions on the other. Dynamic conditional correlations use variance targeting to achieve computational efficiency. This implies dynamic updates through variances only. Multivariate GARCH extensions, such as the BEKK model, allow for dynamic updates of the covariance structure but come at the expense of computational efficiency. We accommodate this by estimating bi-variate covariances. Long-memory exponential smoothers provide a computationally efficient multivariate alternative but are noisy. We obtain estimates of policy effects on dynamic covariances by regressing policy measures, alongside risk measures, on filtered covariances and compare results for robustness purposes.

Our main contribution is to provide evidence for international policy transmission on asset return covariances, which implies portfolio-rebalancing behaviour. Using both, a policy attention measure as well as short-term interest rate futures, we find evidence for an impact of rate-setting expectations on portfolio rebalancing. We further provide evidence on policy transmission onto variance, in line with previous results, that is controlling for multi-variate feedback. Our results therefore add to evidence on the joint importance of portfolio-rebalancing as well as a signalling channels for monetary policy transmission domestically and internationally. Employing a measure of policy attention allows us to get a more detailed understanding of policy transmission effects.

The remainder of this paper is structured as follows: The next section gives an overview of the relevant literature. Section 3.3 introduces our estimation strategy, section 3.4 gives a summary of the data used and section 3.5 presents our results. Section 3.6 offers a conclusion and an outlook.

3.2 Literature on Asset Co-Movement and Dynamic Covariance Estimation

This section gives a brief review of the literature on global asset co-movements and covariance estimation. Given the overlap with other chapters, particularly the introduction, we keep a narrow focus on these two branches of the literature. Whilst there are several contributions, studying dynamic asset co-movement, few explicitly regress factors on filtered co-variances. Policy is largely analysed in the context of global financial cycles, using macro-econometric methods. The estimation of dynamic covariances is difficult and ultimately involves a trade-off between allowing for rich multivariate dynamics and efficiency of the estimation. BEKK and DCC models are typical choices for both ends of the spectrum.

There is a well developed financial literature studying co-movements across asset classes (Shiller and Beltratti [1992]) and countries (Ammer and Mei [1996], dAddona and Kind [2006]). The impact of policy on global asset movements have been discussed primarily within the context of global financial cycles in Rey [2015] and Gourinchas et al. [2019]. Yet there is relatively little empirical research on the impact of policy factors on asset correlations. Dynamic correlations are typically used to analyse the relationships of variables with asset returns jointly, such as Antonakakis et al. [2013], who analyse dynamic conditional correlations between policy uncertainty, VIX, and equity returns. Using dynamic correlations as dependent variables to evaluate the impact of factors on assets linkages is in the same vein as Gomes and Taamouti [2016] who use risk factors based on Google data in regressions on weekly European asset covariances. In particular, they show that covariances between assets are linear functions of such risk factors. We employ the same approach using our policy measures instead of risk factors.

The analysis of dynamic covariances is linked to a large body of literature on multivariate GARCH (M-GARCH) modelling (see Bauwens et al. [2006] for a comprehensive review). Multivariate GARCH models have been developed as extensions to GARCH models (Bollerslev [1986], Engle [1982]) as a tool to model second moment return co-movement, which could be used to estimate time-varying pricing factors in the Capital Asset Pricing Model (Engle et al. [1987], Bollerslev et al.[1988]). Such simple GARCH extensions require a large amount of parameters to be estimated. The literature on M-GARCH models hence evolved around the aim to find models that could capture multivariate second moment dynamics, whilst retaining some degree of computational efficiency to be viable in practise. The M-GARCH extension proposed in (Bollerslev et al.[1988]), VEC-GARCH, is based on vectorisation of the lower-triangular part of variance-covariance matrices. The model proposed by Baba et al. [1990], often referred to as BEKK model, is further applying restrictions to the triangular part of variance-covariance matrices. But both approaches remain computationally expensive. Practical applications therefore rarely use such direct GARCH extensions for more than the bivariate case. The Constant Conditional Correlation model proposed by Bollerslev [1986] simplifies the estimation dramatically by assuming constant off-diagonal elements of variance-covariance matrices, such that dynamic updates are with respect to variances only. This sacrifices dynamics in covariances, which are partly restored in the Dynamic Conditional Correlations (DCC) proposed by Engle [2002]. Here parsimonious estimation of even relatively large correlation matrices is achieved through variance-targetting, i.e. updating covariances by using the information contained in variances. This approach restores the dynamics of the model whilst allowing for efficient estimation and is typically used as a benchmark for dynamic covariance estimation. We follow that approach using a DCC model as a baseline case to obtain our estimates. However, the DCC comes with a series of caveats, that are mentioned in Engle and Sheppard [2001] and further in Aielli [2013], Engle and Kelly [2012] and Hafner and Reznikova [2010], and its variance-targeting technique leads to a number of asymptotic deficiencies, summarised in Caporin and McAleer [2013] and Francq et al. [2011] . This problem of regularisation is most relevant if the number of variables considered relative to the sample size is large. In such a case, where n is greater than T, Bailey et al. [2014] propose a multiple-testing procedure. We consider a small number of variables relative to our sample size ($n < T$). However, we cannot trivially exclude an accuracy loss for daily covariances obtained through a DCC filter. We hence consider BEKK covariances and a long-memory exponential moving average (Zumbach [2007]) as well.

3.3 Estimation Strategy

We are investigating covariation of the US-American and the European fixed income markets in the context of diverging monetary policy reactions between both currency areas. In doing so, we proceed with our estimations in two steps. In the first step we estimate conditional volatilities and covariances, which will then in the second step be regressed against our policy measures alongside a number of further independent variables.

3.3.1 Covariance Filtering

Our baseline models will employ covariances obtained with a dynamic conditional correlation filter following Engle [2002]. We employ two alternative covariance filters, a long-memory exponential smoother (Zumbach [2007]) and a BEKK model (Baba et al. [1990]). This section gives an outline of the different covariance estimators.

Consider a m vector of bond returns $\boldsymbol{y}_t$ on a segmented fixed income market, that are explained by the VIX volatility index and otherwise follow a random walk with drift. $\boldsymbol{b_i}$ is a m coefficient vector and m a residual vector. [1]

$$\boldsymbol{y}_t = \boldsymbol{b}_0 + \boldsymbol{b}_1 VIX_t + \boldsymbol{\upsilon}_t, \tag{3.1}$$

where

$$\boldsymbol{\upsilon}_t = \varepsilon \boldsymbol{H}_t.$$

We are particularily interested in the conditional variance-covariance processes, υ_t. Conditional variances are often explained modelling volatility clusters that are commonly observed in high-frequency financial data using a wide class of ARCH/GARCH models (Engle [1982] Bollerslev [1990]). Such univariate volatility models assume diagonality of $\boldsymbol{H_t}$, and hence no cross-correlations between covariances. When estimating a portfolio[2] of asset returns, this assumption is clearly problematic and estimators might be biased. We relax this assumption and proceed with the estimation of three multivariate volatility models.

[1] Equilibrium returns on a segmented fixed income market can be derived based on a mean-variance optimisation of an arbitrage portfolio in a preferred-habitat model. See Wohlfarth [2018b] for more details.

[2] We do not build sorted portfolios of asset returns but employ bond indices in our empirical models.

DCC Covariances The Dynamic Conditional Correlation model (Engle and Sheppard [2001], Engle [2002]) allows for the estimation of the covariances between assets in (3.1) efficiently through variance-targeting, i.e. the separate estimation of conditional variances and (unconditional) cross-correlations between those variances. Covariances then evolve according to the following decomposition:

$$\mathbf{H_t} = \mathbf{D_t R_t D_t}, \tag{3.2}$$

where

$$\mathbf{D_t} = \begin{pmatrix} \sigma_{1,t} & 0 & \cdots & 0 \\ 0 & \sigma_{2,t} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \sigma_{m,t} \end{pmatrix}, \mathbf{R_t} = \begin{pmatrix} 1 & \rho_{12,t} & \cdots & \rho_{1m,t} \\ \rho_{21,t} & 1 & \cdots & \rho_{2m,t} \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{m1,t} & \rho_{m2,t} & \cdots & 1 \end{pmatrix}$$

and

$$\begin{aligned} \mathbf{R_t} &= \mathbf{Q_t^* Q_t Q_t^*}, \\ \boldsymbol{Q_t} &= (\boldsymbol{R} - \boldsymbol{A}'\boldsymbol{R}\boldsymbol{A} - \boldsymbol{B}'\boldsymbol{R}\boldsymbol{B} - \boldsymbol{G}'\boldsymbol{N}\boldsymbol{G}) + \boldsymbol{A}'\varepsilon_{t-1}\varepsilon_{t-1}'\boldsymbol{A} + \boldsymbol{B}'\boldsymbol{R}\boldsymbol{B} + \boldsymbol{G}'n_{t-1}n_{t-1}'\boldsymbol{G} \\ \boldsymbol{Q}_t^* &= (\boldsymbol{Q}_t \odot \boldsymbol{I}_k)^{-\frac{1}{2}}. \end{aligned} \tag{3.3}$$

$\boldsymbol{D}_t$ is a $m \times m$, diagonal matrix containing the conditional volatilities, $\sigma_{i,t}, i = 1, 2, \cdots, m$, of asset returns estimated in the first stage and $\boldsymbol{R_t}$ contains the pairwise unconditional correlations for the i^{th} and j^{th} assets

$$\rho_{ij,t-1} = \rho_{ji,t-1} = \frac{Cov(r_{it}, r_{jt}|\Omega_{t-1})}{\sigma_{i,t-1}\sigma_{j,t-1}}, \tag{3.4}$$

where $\boldsymbol{A}, \boldsymbol{B}$ and $\boldsymbol{G}$ are diagonal parameter matrices. $n_t = I[\varepsilon_t < 0] \odot \varepsilon_t$ (where $\odot$ denotes the Hadamard product), $\boldsymbol{N} = E[n_t n_t']$, which capture asset specific news impact parameters and asymmetries, derived in Cappiello et al. [2006].

The DCC model above follows a three-step quasi-maximum likelihood estimation: The first step estimates univariate conditional variances and a vector of standardised residuals, $\mathbf{D_{t-1}}$, which we estimated by 3.1, assuming the error process, υ_t, to follow a t-distribution. The second step estimates correlations between the standardised residuals where univariate GARCH models are estimated in the first stage for k residual series, resulting from the mean equations used to estimate constant conditional covariances, $\mathbf{R}$, in the second stage. The dynamic conditional correlations, $\mathbf{R_t}$, are then estimated in the third stage, using $\mathbf{R}$ in the intercepts of $\mathbf{Q_t}$. [34]

Estimation for DCC models uses quasi-maximum likelihood. Parsimony is achieved as the DCC model can be decomposed into two parts, a volatility and a correlation component, which yields the combined likelihood

$$L(\theta,\phi,\boldsymbol{R}) = L(\theta,\phi) = L_v(\theta) + L_c(\theta,\phi,\boldsymbol{R}), \tag{3.5}$$

where

$$L_v(\theta) = -\frac{1}{2}\sum_t (k\log(2\pi) + log|D_t|^2 + r_t' D_t^{-2} r_t),$$

and

$$L_c(\theta,\phi,\boldsymbol{R}) = -\frac{1}{2}\sum_t (\log|R_t| + \varepsilon_t' R_t^{-1}\varepsilon_t - \varepsilon_t'\varepsilon_t),$$

such that the first stage yields the volatility parameters

$$\hat{\theta} = \arg\max L_v(\theta),$$

the second stage uses $\hat{\theta}$ to estimate $\overline{R}$ as $\hat{\overline{R}} = \sum \hat{\varepsilon}_t \hat{\varepsilon}_t'$, where $\hat{\varepsilon}_t = D_t(\hat{\theta})^{-1} r_t$ and then the third stage uses $\hat{\theta}$ and $\hat{\overline{R}}$ to estimate the correlation parameters, $\hat{\phi}$,

$$\max\phi\{L_c(\hat{\theta},\phi,\hat{\overline{R}}).$$

BEKK Covariances To address some of the issues arising from employing DCC covariances, we also opt for a more conservative approach estimating BEKK covariances. It follows from the multivariate extension of GARCH models, where $\boldsymbol{H_t}$ is assumed non-diagonal and is represented by a vectorisation, which in Baba et al. [1990] is given as half-vectorisation, exploiting the symmetry in $\boldsymbol{H_t}$. Hence, in the general case, we have

$$\boldsymbol{H_t} = \boldsymbol{C_0^{*\prime}}\boldsymbol{C_0^*} + \sum_{k=1}^{K} \boldsymbol{C_{1k}^{*\prime}}\boldsymbol{x_t}\boldsymbol{x_t'}\boldsymbol{C_1^*} \sum_{k=1}^{K}\sum_{i=1}^{q} \boldsymbol{A_{ik}^{*\prime}}\boldsymbol{\varepsilon}_{t-i}\boldsymbol{\varepsilon}_{t-i}'\boldsymbol{A_{ik}^*} + \sum_{k=1}^{K}\sum_{i=1}^{q} \boldsymbol{G_{ik}^{*\prime}}\boldsymbol{H}_{t-i}\boldsymbol{G_{ik}^*}, \tag{3.6}$$

[3]Covariances

[4]A derivation of the likelihood function and its properties can be found in Engle [2002] and Engle and Sheppard [2001].

where C_0^* are triangular $n \times n$ parameter matrices, A_{ik}^* and G_{ik}^* are $n \times n$ parameter matrices and C_{1k}^* are $J \times n$ parameter matrices, $\boldsymbol{x_t}$ and $\boldsymbol{\varepsilon}_{t-1}$ are column vectors of covariates and of an ARCH-type error process, respectively.

The BEKK covariances can be estimated by quasi-maximum likelihood. Assuming normality, the likelihood function of the estimator is

$$L_t = \frac{n}{2}\ln(2\pi) + |\Gamma| - \frac{1}{2}\ln|H_t| - \frac{1}{2}\varepsilon_t' H_t^{-1}\varepsilon_t \tag{3.7}$$

and its corresponding derivative

$$\frac{\partial L_t}{\partial \theta} = \frac{1}{2}\left(\frac{\partial h_t}{\partial \theta}\right)'(H_t^{-1} \otimes H_t^{-1})\mathrm{vec}(\varepsilon_t \varepsilon_t') - \left(\frac{\partial \mathrm{vec}(\Gamma)}{\partial \theta}\right)' \mathrm{vec}(\Gamma^{-1\prime}) - \left(\frac{\partial \varepsilon_t}{\partial \theta}\right)' H_t^{-1}\varepsilon_t, \tag{3.8}$$

where

$$\theta = [(\mathrm{vec}\Gamma)', (\mathrm{vec}B)', (\mathrm{vec}\Lambda)', (\mathrm{vec}\Xi)',],$$

and

$$\Xi' = [C_0^{*\prime}, A_{11}^{*\prime}, \cdots, A_{qK}^{*\prime}, G_{11}^{*\prime}, \cdots, G_{pK}^{*\prime}].$$

We can immediately see the difference between (3.6) - (3.8) and the DCC representation in (3.2) and (3.4), given that the BEKK avoids variance-targeting. Whilst this is more in the spirit of a truly multivariate model, it comes with a severe lack of efficiency. The computational demands on BEKK estimations therefore lead to it practically not being applied to more than bi-variate models. We therefore abstain from a simultaneous estimation of all variables and covariances and instead estimate pair-wise covariances. This shuts down potential multivariate feedback channels of a full multivariate specification in H_t and results should hence be regarded as complementary to those obtained with a DCC filter.

RM Exponential Smoother The RiskMetrics methodology outlined in Zumbach [2007] imposes less of a structure than the previous filters. Dynamic covariances are obtained employing a simple moving-average process with an exponential weight factor, ω_i that allows hyperbolical and hence slow decay. We therefore have

$$H_t = \sum_{i=1}^{m} \omega_i H_{i,t} = (1-\lambda_i)\varepsilon_{t-1}\varepsilon_{t-1}' + \lambda_i H_{i,t-1} \tag{3.9}$$

where

$$\omega_i = \frac{1}{C}\left(1 - \frac{\ln(\tau_i)}{\ln(\tau_0)}\right),$$

$$\lambda_i = \exp\left(-\frac{1}{\tau_i}\right),$$

and

$$\tau_i = \tau_1 \rho^{i-1},$$

$$\forall i = 1, 2, \cdots, m.$$

In essence, the RiskMetrics filter obtains covariances recursively through a simple MA-process, that is extended to allow for long-memory decay in the MA components. This is appealing as it avoids restrictions that might have to be imposed in alternative covariance estimation methods but runs the risk of producing noisier outcomes. We parameterised the filter following the standard recommendations for the logarhythmic decay factor, $\tau_0 = 1560$, the lower cut-off, $\tau_1 = 4$, the upper cut-off, $\tau_{max} = 512$, and $\rho = \sqrt{2}$ [5].

3.3.2 Covariance Regressions

Having estimated dynamic covariances, we specify a number of simple ARDL models following Pesaran et al. [2001], regressing these covariances on a number of explanatory variables. For the covariance between the returns of the ith and jth assets, $cov(r^i, r^j)$, we have

$$cov(r^i, r^j)_t = \upsilon + \beta_{ij} cov(r^i, r^j)_{t-1} + \Gamma_{ij}' \boldsymbol{x}_t + \Delta' \boldsymbol{x}_{t-1} + \varepsilon, \tag{3.10}$$

where $\boldsymbol{x}$ is a vector containing the independent variables, i.e. the Google policy attention indices ECBMPSI and FEDMPSI for the ECB and FED respectively, the VIX volatility index that serves as a proxy for risk and front month policy rate futures for the Euro area and the US, EUFF and USFF.

The primary focus of our models is to evaluate monetary transmisssion from Europe to the US and vice versa. To do so, we focus on variances of the assets first, in particular of US bond return dynamics to a change in European policy attention as measured by ECBMPSI and vice versa. Using the MPSI measures does not identify policy itself but policy attention. The identifying assumption here is that important policy events lead to an increase in attention, which we measure as a change in search behaviour. We employ policy rate futures as alternative policy measures, which capture policy guidance and hence the signalling channel proposed in Bauer and Rudebusch [2013]. As obtained coefficients for the MPSI measures do not allow for judgement on the direction of the effect but only on the contribution to variances, we included interaction terms between the MPSI measures

[5] See Zumbach [2007]

and policy rate futures. We draw further conclusions from the covariances between assets: a significant effect of policy on the covariance between two assets implies that policy had an effect on the degree of market segmentation along the two dimensions we consider (domestic and international).[6] Assuming that there were no direct policy interventions across all market segments, this provides evidence for portfolio rebalancing.

3.4 Data

We employ daily fixed income (yield) returns for US and European markets to construct covariances. Explanatory variables use data on money market futures, the CBOE VIX implied volatility index, and web search engine data obtained through GoogleTrends for the MPSI indices, introduced in the previous chapter. Our sample spans from January 2014 until early June 2016, to exploit divergence in monetary policy between FED and the ECB at the time that accommodates the analysis of policy spill-overs. An overview of the data sources used for this paper is given in tables 3.1 and 3.2.

Table 3.1 Variables and Datasources – Endogenous Variables

Label	Variable	Unit	Source
XOIS	European Overnight Index Swap Rate	%	Reuters Datastream
XCORP_HY	IBOXX EUR Liquid Corp. HY Index	% Yield	Reuters Datastream
XCORP_Y	IBOXX EUR Liquid Corp. Index	% Yield	Reuters Datastream
XBUND	10-year German Government Bonds	% Yield	Reuters Datastream
USOIS	US Overnight Index Swap Rate	%	FRED
US_CORP_HY	BoAML US Corp. Master Effective Yield Index	% Yield	FRED
US_CORP	BoAML High Yield Effective Yield Index	% Yield	FRED
US10Y	10-year US Government Bonds	% Yield	FRED

Notes: Prefix ’X’ indicares USD-converted variables.

Table 3.2 Variables and Datasources – Exogenous Variables

Label	Variable	Unit	Source
XEONIA	1Month EONIA Futures Rate	%	Quandl
USFF1M	1Month Fed Funds Futures	% Yield	FRED
VIX	Chicago Bond Options Exchange Volatility Index	Index Value	FRED
ECBMPSI	ECB Monetary Policy Search Index	Index Value	Google/ own calculations
FEDMPSI	FED Monetary Policy Search Index	Index Value	Google/ own calculations

Notes: Prefix ’X’ indicares USD-converted variables.

[6] This is because covariances reflect the strength of association between assets. A strong covariance between two assets therefore indicates portfolio rebalancing behaviour that leads to a less segmented market.

We focus on DCC estimates for covariances as a baseline case, which are plotted in figure 3.1 below. BEKK and RiskMetrics covariances are given in Appendix B. We analyse variances as well as covariances separately and group the latter by market segments. Based on DCC estimates, variances (ie. the diagonals of the variance-covariance matrices) appear to be stronger than covariances between assets, particularly for European high-yield corporate bonds and government bonds. This is reflected in the evolution of covariances, which are particularly volatile between European and US corporate markets. Most covariances tend to become more volatile towards the end of the sample, which coincides with monetary policies in the US and Europe.[7] This is particularly visible for DCC covariance estimates on money markets. Considering the predominantly negative shocks hitting the covariances between US and European Overnight lending rates, indicates divergence in monetary policy between US Fed and ECB, that we aimed to exploit with our sample choice.

We can further see some differences between the filters considered. Overall, the DCC filter tends to produce the least noisy covariances with many being almost at zero. This could indicate some of the accuracy loss associated with variance-targeting in the DCC; in particular for var(US_CORP_HY) and var(XBUND), the DCC seems to be smoothing a lot of the volatility obtained through the other filters. The BEKK and the RiskMetrics filters, both not relying on variance-targetting, show the more nuanced variation in these covariances. The BEKK filter further shows slightly larger differences in the levels of covariances, which might have to do with its pairwise application.

Table 3.3 Sample Asset Return Correlations

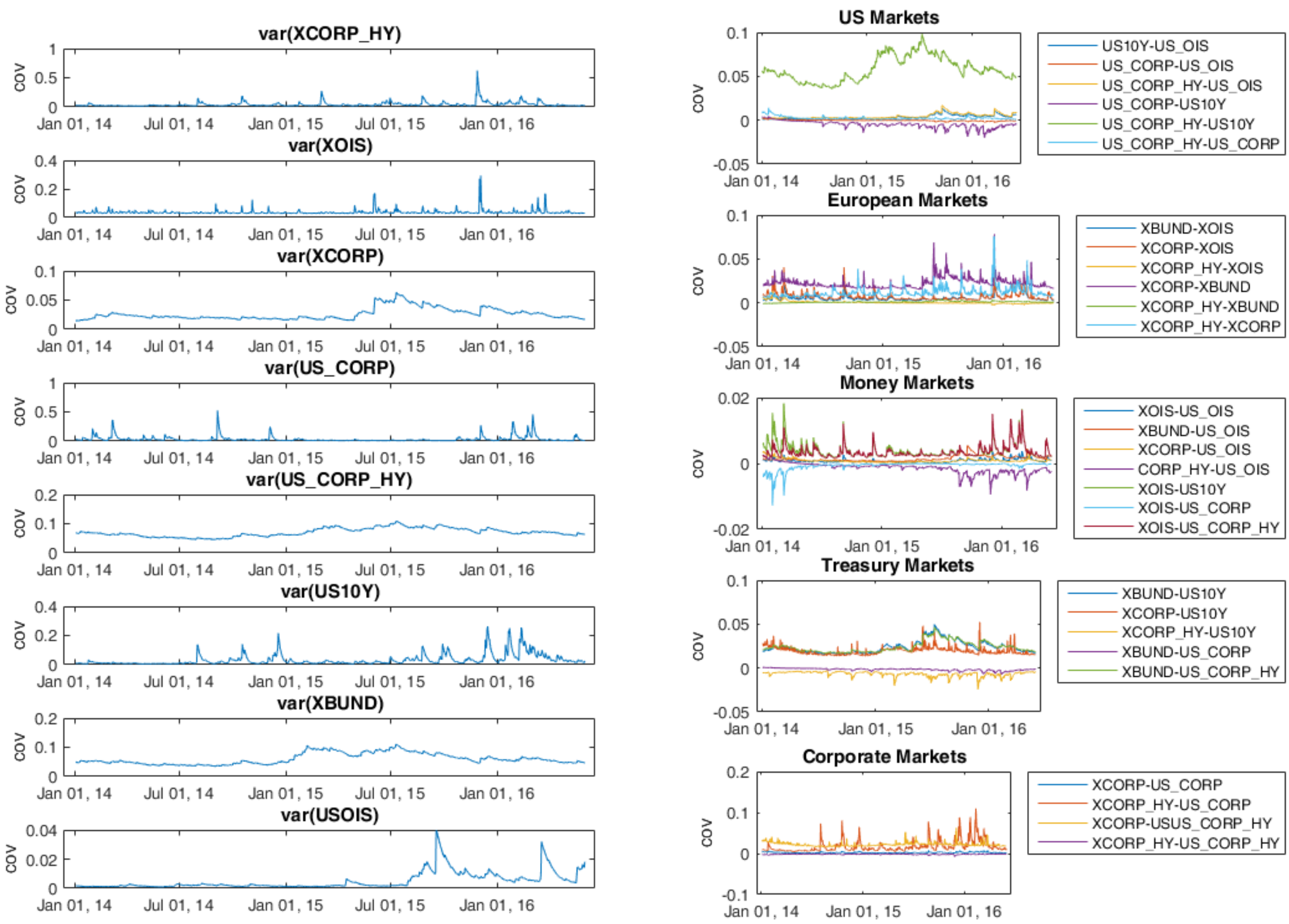
	USOIS	US10Y	US_Corp	US_Corp_HY	XOIS	XBUND	XCORP	XCORPHY
USOIS	1							
US10Y	-0.65255	1						
US_Corp	0.88627	-0.66476	1					
US_Corp_HY	0.63015	-0.17716	0.80752	1				
XOIS	-0.86416	0.82601	-0.84382	-0.52872	1			
XBUND	-0.63232	0.93869	-0.66788	-0.27126	0.88301	1		
XCORP	-0.2907	0.80265	-0.3264	0.053681	0.64088	0.89697	1	
XCORPHY	0.33819	0.031933	0.5038	0.55868	-0.10898	0.15769	0.4316	1

Most covariances are positive throughout the sample. Nevertheless, we do observe instances of negative covariances that evolve almost symmetrical to the remaining covariances. This is unsurprising and reflects the inverse relationship between some assets. The presence of negative covariances between assets does, however, affect the interpretation of coefficients

[7] The ECB considered investment graded corporate bonds in its Extended Asset Purchase Program in early 2016 and the Federal Reserve initiated its first post-crisis increase of the Fed Funds Rate in December 2015.

in covariance regressions: To see this, consider an initially positive correlation between two assets, ρ, and a regression of some variable, x, on the correlation such that $\rho_t = \beta x_t + \varepsilon$. Any significant $\beta > 0$ would indicate x to significantly increase the correlation between the assets and hence strengthen the association between them. Now consider $\rho < 0$. In this case $\beta > 0$ would still indicate x to lead to an increase in ρ but now it would imply a reduction in the association between the variables considered. To cater for this we consider sample correlations reported in table 3.3 above.

Fig. 3.1 DCC Variances and Covariances



3.5 Results

As above, the exposition of our results follows the different market segments considered and distinguishes between variances and covariances. We begin with estimates obtained for variances of the assets. Regarding the covariances, we first consider domestic markets to then investigate covariances between those markets, grouped as (government) treasury, money and corporate markets. We discuss covariances obtained through the DCC filter as baseline case and BEKK and RiskMetrics covariances for robustness. The complete regression output is given in Appendix C.

3.5.1 Variances

Analysing asset variances allows us to investigate the impact of domestic and foreign policy on asset volatility and hence risk inherent in the assets considered. The obtained results have to be understood as a contribution to some variance and hence do not allow for an interpretation of the direction of effects. We therefore included interaction terms between policy rate futures and our attention measures, that allow for the distinction between policy contractions and expansions, by assuming policy contractions to be accompanied by an increase in policy rate futures. Results are given in tables 5, 11 and 17 of appendix A.

Comparing multivariate with the univariate estimates in the previous chapter, observed effects are less prominent and are, in the case of US assets, even reversed. This is as univariate estimates have likely captured some of the dynamic cross-correlations that we considered now. The European index, ECBMPSI, suggests significantly negative effects of European policy on US high-yield corporate bonds as well as Treasuries and significantly positive effects on European investment graded coporate bonds, whilst its lag enters significantly negative in both Bunds and European IG corporates, and (weakly) significantly negative in US coporate bond markets. This gives some evidence for effects of European policy attention accross market segments, albeit somewhat less pronounced. The European interaction term enters significantly positive with a lag for European IG corporate bonds and its American counterpart for European overnight rates. European futures are significantly positive for Bunds and European IG corporates, with these effects being reversed in lags. US futures enter significantly negative in US_OIS and positive in XCORP. We can observe the same significant reversal of effects for the lag of USFF as we could for European futures. VIX is positively significant for US IG and European HY corporates. Again, we see effects reversed in lags.

The above suggests policy to mainly affect volatility, and hence risk, in corporate markets. For the ECB, we find positive effects through both policy rate futures and and policy attention suggesting both policy rate guidance and broader policy measures to have led to increases in volatility. The lagged term in XCORP indicates a reversal of the immediate effect. Futures and the VIX display similar patterns in lags. The significant effect of ECBMPSI and its lag on US assets as well as significant effects of US futures on European assets provide evidence for international transmission of policy through these market segments. It is further unsurprising to find the impact of US policy to be picked up by futures rather than the broader policy attention measure. This reflects the shift in the Fed's focus on traditional rate-setting rather than unconventional policies at the time. The interaction terms, particularly those obtained through alternative covariance filters, provide evidence that policy-contractions lead to increases and expansions to decreases in volatility. VIX's positive impact on both US and European coporate indices is intuitive, as it captures the variance risk-premium, which these market segments are more sensitive towards.

3.5.2 Covariances

In the following we interpret results based on DCC covariance estimates. We compare these results with BEKK and RiskMetrics estimates in section 3.5.3 below. Effects on covariances between the assets considered allow to investigate the impact of policy on market segmentation. For most variables, positive coefficients indicate an increasing strength of the co-movement between assets, hence implying less segmented markets and vice versa. The interaction terms again allow judgement on the direction of the policy effects. Given the presence of a positive correlation between assets [8], a positive coefficient suggests that a policy contraction – an anticipated policy rate rise – would lead to a decrease in market segmentation and vice versa.

Table 3.4 below gives a summary of significant estimates for all 28 covariances considered. It is striking how for European policy measures, the Google attention measure, ECBMPSI, appears to outperform futures, whilst for the US the opposite is the case. This is particularly strong in lagged terms, where ECBMPSI(-1) is significant in almost all models. Considering the joint effects of level and lagged terms shows how most effects are transitory, with ECBMPSI showing persistent effects for most estimates. Offering a more granular point of view, we proceed by discussing individual covariance estimates by market segments.

[8] See section 3.4 for a discussion of the signs of considered covariances.

Table 3.4 Summary of Covariance Estimates

Variable	significant estimates			jointly significant levels and lags		
	Number of Cases					
	Pos. significant	neg. significant	total	same sign	switch	total
ECBMPSI	8	5	13			
FEDMPSI	0	0	0			
VIX	3	6	9			
EUFF	4	0	4			
USFF	7	3	10			
ECBMPSI*EUFF	0	0	0			
FEDMPSI*USFF	6	0	6			
ECBMPSI(-1)	9	15	24	4	9	13
FEDMPSI(-1)	0	0	0	0	0	0
VIX(-1)	6	4	10	0	10	10
EUFF(-1)	0	6	6	0	5	5
USFF(-1)	3	7	10	0	10	10
ECBMPSI*EUFF(-1)	2	0	2			2
FEDMPSI*USFF(-1)	0	0	0			0

European Markets ECBMPSI enters significantly positive in the covariances between XOIS and both corporate indices, the covariances between both corporate indices and the covariance between Bunds and IG corporates. In XBUND-XOIS ECBMPSI is (weakly) negatively significant. The effects are partly reversed in lags; for XCORP_HY-XCORP, XCORP-XBUND and XBUND-XOIS the reversal even exceeds the initial effect in size. FEDMPSI is again insignificant for all models in levels and lags. EUFF enters significintly positive in XCORP-XBUND and XCORP-XCORP_HY. USFF is additionally significantly positive in XCORP-XOIS. Again, most effects of futures (all for USFF) are offset in the lagged terms. The ECB interaction term is insignificant in levels and its Fed counterpart significantly positive in XBUND-XOIS and XCORP-XOIS (both with insignificant lags). Lagged ECB interaction terms enter significantly positive in XCORP-XBUND and XCORP-XCORP_HY. VIX enters significantly positive in XCORP_HY-XBUND and XCORP-XCORP_HY. For the former covariance the effect is again partly offset in the lagged term. Results are given in tables C3, C8 and C14 of appendix C.

The above suggest that ECB policies, as measured through both, the guidance and the attention measure, led to an increase in covariances between the majority of assets considered. This provides evidence for ECB's impact on domestic portfolio rebalancing. For US policy we can observe the same effects, albeit for the futures measure only. This is unsurprising, given the regional focus on rate-setting policies. It is particularly interesting to note that the effects of US Fed Funds Futures are much larger than those of the other measures considered – even larger than the combined effects of ECBMPSI and EUFF. Generally, finding significant effects of futures on covariances suggests signalling effects of portfolio rebalancing that are typically ignored in the literature. The positive coefficients on VIX are somewhat at odds with portfolio theory and might be driven by it being linked to US options markets. Almost all effects observed appear to be transitory.

US Markets The domestic policy attention measure, FEDMPSI, is insignificant in levels and lags for all models. ECBMPSI is significantly positive for US_CORP-US10Y, significantly negative in USCORP_HY-US10Y and it enters weakly significant with a negative coefficient in US_CORP_HY-US_OIS and US10Y-US_OIS. Its lags are significantly positive in US_CORP-US_OIS and USCORP-US10Y and enter significantly negative in USCORP_HY-US10Y and US_CORP_HY-US_CORP. Both interaction terms are largely insignificant in levels and lags. We can only pick up some weakly significant negative effect of the Fed interaction term in levels for US_CORP-US10Y. European policy rate futures are insignificant in levels and lags, whilst USFF enters significantly negative in US10Y-US_OIS and US_CORP_HY-US_OIS in levels, with a reversal of the effects in lags. VIX is significantly negative in US_CORP-US_OIS and US_CORP-US10Y and positive in the covariance between both coporate bond indices, with all three effects being reversed in the lagged term. Results are reported in tables C2, C9 and C15 of appendix C.

The US domestic policy effect appears to be picked up by the rate guidance measure, reflecting the dominance of policy rate expectations in the US. The reversed signs in the lagged terms also follow a familiar pattern, indicating that the covariance effect through rate expectations is transitory. The significant effects of the European policy attention index indicate some degree of policy spillovers. To further qualify these results, we consider the negative sample correlations between Treasuries and all other US assets, indicating that, apart from US10Y-US_OIS European policy as measured by ECBMPSI has tended to increase the association between US assets. Interestingly, the signs of the lagged term indicate persistence in the effect of ECBMPSI, where both, level and lagged terms are significant. US policy, by contrast seems to have the opposite effect on covariances. Here, this might simply reflect a largely isolated effect of USFF on overnight lending rates. VIX appears to have a largely negative effect on US domestic covariances, which is in line with portfolio-arbitrage theory predicting a negative relation between risk and arbitrage. Again, this effect is only transitory.

Money Markets Having discussed domestic covariances above, we now regard global covariances. Hence for money markets we consider covariances between European OIS rates and US assets, US OIS rates and European assets and covariances between US and European OIS rates. Results are given in tables C4, C10 and C16 of appendix C.

ECBMPSI enters significantly positive in the covariance between European IG corporates and US money markets and is negatively significant for the covariance between US HY and European money markets as well as weakly significant negative for XOIS-US10Y. Effects again tend to be transitory. FEDMPSI and EUFF are insignificant in levels an lags. USFF is significantly negative in XBUND-US_OIS and significantly positive in XCORP-US_OIS, with effects again being reversed in the lagged terms. The US interaction term is significantly positive in XOIS-US_OIS, XOIS-US10Y and XOIS-US_CORP_HY and largely insignificant in lags. VIX has significantly negative but transitory effects on XCORP_HY-US_OIS only.

Sample correlations are negative for all covariances considered apart from XOIS-US10Y and US_OIS-XCORPHY. Taking this into account, ECBMPSI indicates a positive effect of ECB policies on the (inverse) co-movement between European money markets and US high-yield markets, whilst market segmentation increased between European IG coporate bonds and US money markets. This might reflect different policy reactions between FED and ECB over the sample period. US policy rate expectations appeared to have led to an increase in market segmentation US money markets and Bunds and to a strengthening association between European IG corporate bond markets and US money markets. There thus appear to be some arbitrage effects between European corporate bond and US money markets linked to policy rate expectations. The increasing segmentation indicated between Bunds and US money markets likely reflects different dynamics, owing to the safe haven properties of Bunds.

Treasury Markets With treasury markets we refer to covariances of assets with a foreign yield curve benchmark (10y government bonds). The results are given in Tables C5, C11 and C17 of appendix C.

ECBMPSI is significant for all models. It enters positively in covariances with both IG corporate bond indices and negatively in the remaining models. Effects are relatively persistent, with only covariances with European corporate bond indices being partly reversed in lags. Rate expectations are only significant for XCORP-US10Y (bar weakly significant positive coefficients on EUFF in XBUND-US10Y and XBUND-US_CORP_HY), with both European and US futures entering positively and being almost exactly offset in lags. Again, USFF carries a relatively large coefficient. Both interaction terms are largely insignificant in levels and lags; only for XCORP-US10Y the US term picks up some weakly significant positive effect. VIX enters significantly negative in XCORP_HY-US10Y and XBUND-US_CORP, with both effects being transitory.

There are negative sample correlations between both Treasury bond markets and US corporate bond markets. Taking this into account, our results suggest ECB policy, as measured through both futures and policy attention, to significantly reduce market segmentation between investment graded corporate bond markets and Treasury markets, whilst it led to an increase in market segmentation for high-yield markets. This implies that whilst ECB policy led to portfolio shifts between government bond and respective foreign investment graded corporate bonds, this did not affect high-yield markets. It is interesting to note the persistence of these effects for ECBMPSI, particularly on US corporate bonds. Effects on the covariance between both government bond markets are ambiguous: The attention measure indicates a negative effect whilst EUFF suggests a positive effect. US forward guidance appears to have led to a reduction in market segmentation as well, and the positive interaction term indicates these effects to be attributable to monetary contractions.

Corporate Markets We consider covariances between European corporate and HY corporate bond markets and their US counterparts. Results are given in tables C6, C12 and C18 of appendix C.

ECBMPSI enters positively significant in the covariances between the two European corporate indices and US investment grade corporates and negatively significant in the covariance between US and European high-yield markets. Effects are reversed (and overcompensated) in lags. FEDMPSI is again insignificant in lags and levels. Futures are positively significant for both European and American markets in XCORP-US_CORP_HY and USFF is further positively significant in XCORP-US_CORP. Effects of EONIA futures are transitory, whilst USFF is insignificant in lags. Again, it is striking to see the strongest effect in all models through USFF. The ECB interaction term is insignificant for all models in levels and lags (bar one weakly positive significant coefficient in XCORP_HY-US_CORP) and the Fed interaction term is positively significant in XCORP-US_CORP and XCORP-US_CORP_HY. Both interaction terms are largely insignificant in lags. VIX enters positively significant in the first two models and negatively significant in the last, with again significantly reversed signs in lags.

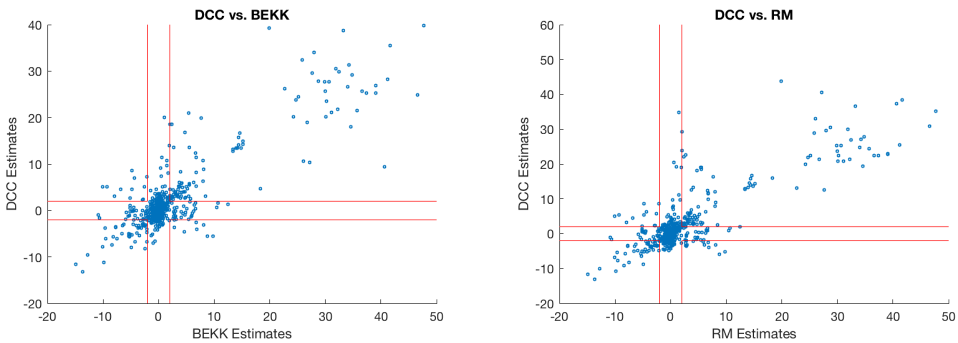
The sample correlations are positive between all corporate bond indices considered, apart from XCORP-US_CORP. But the estimates obtained for ECBMPSI are not robust to applications of different covariance filters. We can hence only conclude that ECBMPSI indicates some degree of impact of European policy on market segmentation. EUFF allows for more specific conclusion, implying European rate guidance to have strengthened the association between each domestic investment graded and foreign HY corporate bond market segment, whilst it has weakened covariances between the remaining segments. This suggests the presence of portfolio rebalancing effects between investment graded and foreign high-yield markets internationally rather than between domestic and foreign IG and HY markets, respectively. The Fed interaction term gives some evidence that effects on portfolio rebalancing between both IG indices is triggered by monetary expansions, whilst portfolio rebalancing between European IG corporates and and US HY corporates likely follows monetary contractions. However, these results are reversed in BEKK and RM covariance filters.

3.5.3 Robustness to BEKK and RM Filters

As a robustness exercise, we consider alternative models introduced in section3.3.1 to filter covariances and draw conclusions from a simple comparison of t-statistics for the estimates.

Figure 3.2 shows scatter plots of the estimates for the whole sample. The red lines indicate critical values of |2| and hence observations outside these bands are significant for both filters considered. Robust estimates would be found either in the upper right or lower left corner of the plots. Estimates within the significance bands and outside the centre of the plot indicate non-robust estimates that are significant in one and insignificant in another model. Estimates in the upper left or lower right corners indicate non-robust estimates that changed signs and remained significant in both models. We will turn most of our attention on the first and the last case.

Fig. 3.2 Comparison of Estimates – Whole Sample



Overall estimates are positively correlated; most estimates appear to be either in the upper right or lower left corners or in the centre of the plot. They are hence either positively or negatively significant or insignificant in both models. Looking at sub-samples, we see a more nuanced picture. Figures 3.3-3.5 compare the estimates of BEKK and RM filters with the DCC estimates for the different market segments considered. We can see a strong positive correlation for variances and domestic covariances, whilst for international covariances, particularly for money and corporate markets, the correlation appeared to have weakened considerably.

Fig. 3.3 Comparison of Estimates – Variances

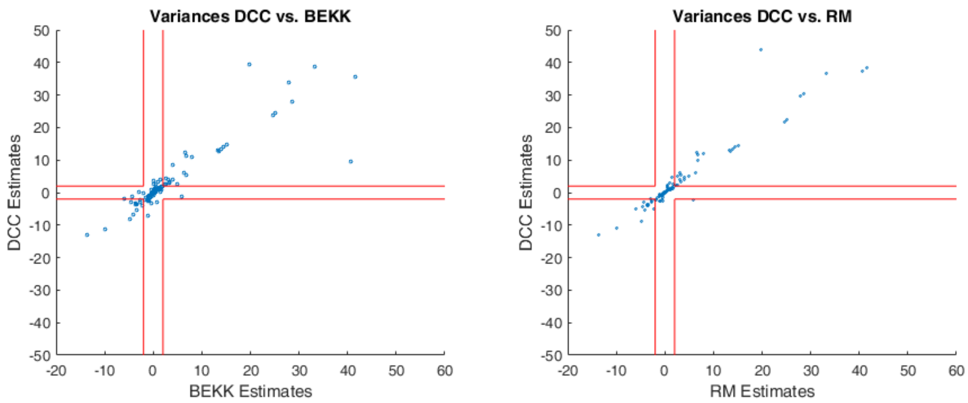
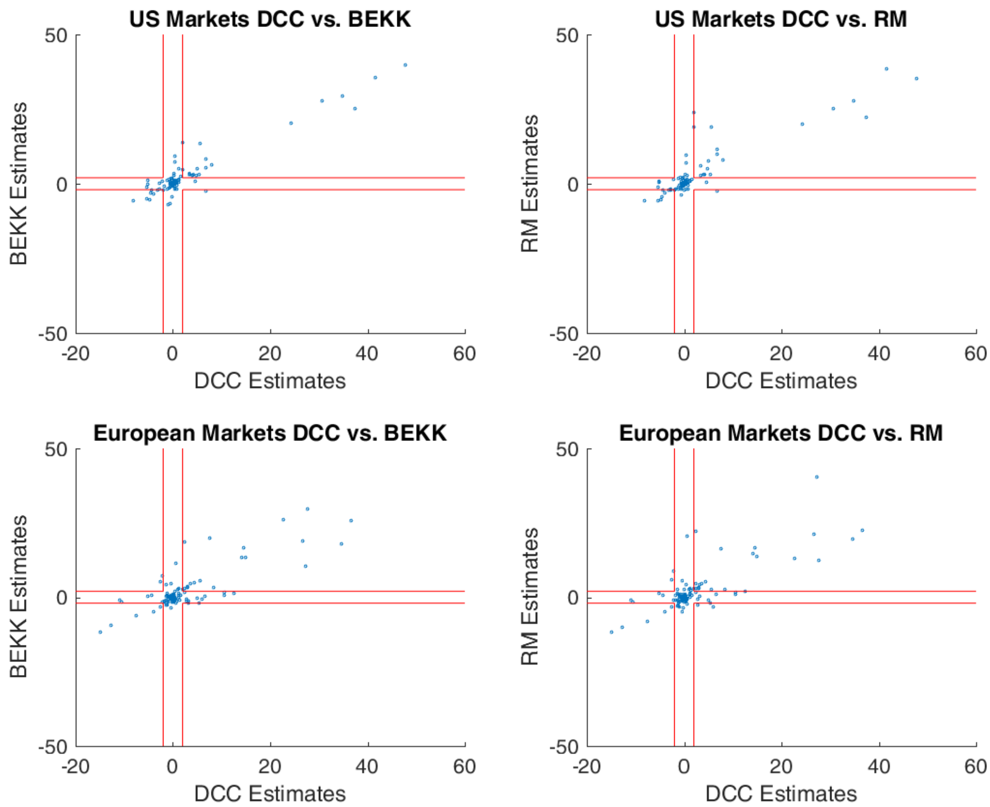
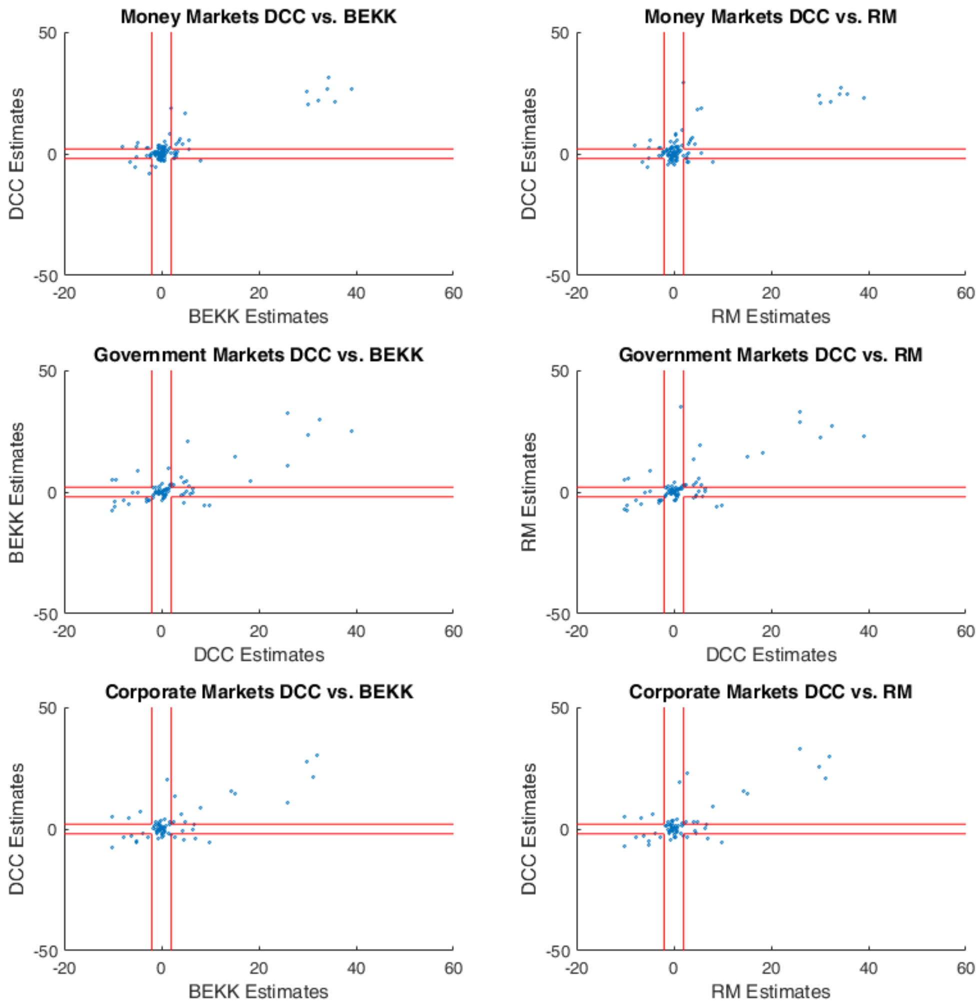


Fig. 3.4 Comparison of Estimates – Domestic Covariances



Specifically, for corporate markets, estimates for ECBMPSI and its lag are neither robust to BEKK nor RM filters; both with respect to significances and estimate signs. For money markets we could only observe a significant change in signs on interaction terms in XOIS-USCORP, and for treasury markets we cannot confirm the sign on ECBMPSI in XCORP_HY-US10Y. Otherwise non-robust estimates reflect significances only.

Fig. 3.5 Comparison of Estimates – Domestic Covariances



3.6 Conclusions

We study international transmission of monetary policy onto European and US American fixed income covariances using policy attention measures based on search data as well as policy rate futures. Dynamic covariances are obtained using a DCC model as well as a BEKK model and a RiskMetrics long-memory exponential smoother for robustness purposes. Obtained covariances are then regressed on policy measures and a factor controlling for market risk in a series of ARDL models.

We find that policy attention measures for ECB policies capture most policy effects on asset return covariances. An increase in attention tends to be followed by absolute increases in correlations, indicating strengthening co-movement between assets. This links policy directly to portfolio rebalancing behaviour and hence arbitrage. Most US policy was captured by the futures measure, indicating a dominance of signalling effects of changes in the fed-funds rate at the time. It is likely that this result reflects policy attention capturing more variation due to unconventional elements of policy, particularly asset purchases, which were dominant in Europe over the sample horizon. Both measures suggest policy to affect domestic as well as international return covariances. For the ECB, policy effects seem to be mainly carried through corporate and treasury markets, whilst US measures indicate particularly strong effects on European domestic covariances.

We further find evidence for transmission of monetary policy between ECB and FED. Our results suggest these policy spillovers to be present in both directions across a broad spectrum of fixed income variances and covariances. Effects of ECB policy on US domestic asset covariances appear to be transmitted by government bonds whilst global covariances are mainly affected by corporate bonds. For the US, policy effects are mainly transmitted by the corporate market segment.

Both, FED and ECB policy had a positive effect on the majority of covariances, indicating a reduction in market segmentation. Where significant, futures tend to have a larger effect than policy attention indicating dominance of the signalling channel of monetary transmission. However, portfolio-rebalancing effects captured by attention indices are more frequent, particularly in cases where policy operates at or close to the zero lower bound. The dominance of particular transmission channels hence likely depends on the policy environment. Furthermore, finding significant signalling effects onto covariances suggests a link between signalling and portfolio rebalancing channels.

Our results are largely robust to application of alternative covariance filters. The majority of non-robust estimates are for covariances on corporate and government bond markets. These are also some of the most volatile covariances, which might be due to problems in the variance-targeting applied in the DCC model, mentioned in the literature on multivariate volatility models.

These results confirm several findings documented in the literature on monetary transmission: Market segmentation does produce different reactions to policy shocks across many of the assets considered, confirming Krishnamurthy and Vissing-Jorgensen [2007] and much of the literature on preferred habitat theory of the fixed income market, following Vayanos and Vila [2009]. The presence of both, signalling and portfolio-rebalancing effects is in line with Bauer and Rudebusch [2013] and Bauer and Neely [2014]. International transmission effects are present, but appear to be relatively small, which caveats some of the findings in Neely [2015]. Furthermore, the vast majority of effects observed are reversed in lags, and are hence transitory. Market risk appears to play a crucial role in policy transmission particularly on corporate markets, which is in line with volatility premiums proposed in the previous chapter and by Altavilla et al. [2015]. It is further an important factor in international transmission, which supports the theory of global financial cycles (Rey [2015]).

Overall, it seems much of the transmission effects observed are not only very sensitive to model specification as highlighted in Bauer and Neely [2014], but also to policy measures themselves and the frequency of the data obtained. Using policy attention as a measure for policy, accounts for a much wider set of policy interactions and hence a more realistic picture of its effects, whilst employing higher-frequency data allows capturing time-varying volatility that is crucial in the analysis of financial time series. This also opens several routes for further research. In terms of model specification, employing realized volatility models such as Corsi [2009] and Buccheri and Corsi [2017] appears particularly promising.

Chapter 4

Preferred Habitat, Policy, and the CIP Puzzle

4.1 Introduction

The foreign-exchange swap market is one of the largest markets in the world, both in size and liquidity. And it fails. Since 2008, its crucial no-arbitrage condition, the covered interest parity (CIP) condition, does not hold. CIP requires that on foreign exchange markets interest rate differentials equal the forward premium between spot and forward exchange rates, closing otherwise existing arbitrage opportunities. CIP held almost exactly before 2008, when substantial cross-currency bases (CCBS), a measure for CIP deviations, emerged. Unlike previous episodes, which only lasted for minutes, or could be explained through small transaction costs, CIP deviations were large and persistent. This reflected a shortage of dollar liquidity, following a sharp decline in collateralised lending on inter-bank markets. Until 2014 a common explanation for this was the emergence of risk following the financial crisis of 2008: Previous trading models, where derivatives, such as cross-currency swaps, could be marketed to market without considering counter-party risk, e.g. the "flow-monster"[1], had to be revisited. CIP recovered and currency bases narrowed again, following large liquidity injections by a number of central banks and reforms to money market funds that alleviated some risk. But since 2014 the *CIP Puzzle* returned as parity failed again in relatively calm markets. Despite several important contributions to solving this conundrum, recent CIP failure could not be explained entirely. At the same time shifts in the global monetary policy environment had repercussions for foreign exchange swap markets: Following the monetary

[1]The term refers to large foreign-currency arbitraging banks, that could, owing to their size, mark FX derivatives to market without considering conter-party default. See: https://ftalphaville.ft.com/2014/05/30/1866432/the-europe-based-flow-monster-is-under-siege/

policy reaction to the global financial crisis (GFC), the US Federal Reserve (FED) initiated a process of policy normalisation both, with respect to its asset purchases and rate-setting. Meanwhile other central banks, notably the European Central Bank, engaged in further policy expansions. This led to severe global policy imbalances, that came with an excess demand for now higher yielding USD denominated liquidity.

This chapter tackles this development and proposes a link between policy and FX swap market imbalances, that are at the core of the CIP Puzzle. For this, we approach the CIP Puzzle from both, theoretical and empirical angles. We first develop a framework of market segmentation as a source of swap market frictions, by combining the preferred-habitat model developed in Chapter 2 with a model of incomplete arbitrage on swap markets. This model allows us to derive international channels of monetary transmission. We further adapt the preferred-habitat model to an open economy setting by considering segmentation along two dimensions: A domestic dimension, driven by term- and credit-structure, and an international dimension, driven by financial intermediation costs on swap markets. Arbitrage, which is subject to limited risk bearing capacity, is crucial in absorbing that segmentation. Our model closely follows Altavilla et al. [2015] for domestic arbitrage, which we adapt for an open economy setting. The inclusion of cross-currency frictions follows the setting of bounded CIP arbitrage, proposed by Sushko et al. [2017]. We employ a measure of policy asymmetry instead of their measure of hedging demand to expose specific policy transmission channels. Monetary policy enters the model by changing rate expectations and local asset supply, which affects arbitrage demand and the market price of risk, and hence pricing through the volatility premium on assets. This corresponds with Gabaix and Maggiori [2015] and Avdjiev et al. [2016] who, among others, highlight the risk-structure as driver to open arbitrage opportunities. Empirically, we investigate two main features of our model. Its implications on market segmentation, which should be time-varying and linked to volatility. We analyse co-movement along the term structure of the currency basis swap market to investigate market segmentation, using a VECM structural framework, with restrictions assuming constant spreads between CCBS tenors. The second feature predicts an impact of policy imbalances and volatility on swap markets. We investigate this in GARCH-in-Mean regressions of CCBS on the two policy measures derived in previous chapters, controlling for risk and transaction costs. We find significant GARCH-in-mean effects on the USD/EUR cross-currency basis, providing evidence for the existence of a volatility premium, as well as significant effects of policy asymmetries on swap markets. Based on our policy attention measures we can attribute the majority of this effect to US policy. Nonetheless, policy attention does indicate significant contribution of European policy on the long and short end of asset maturities, which suggests local effects of ECB policies.

The remainder of this paper is structured as follows: The next section gives a description of CIP failure and links it to the evolution of recent European and US monetary policy, followed by a brief review of the relevant literature. Section 4.3 entertains the theoretical background, using preferred habitat theory, and highlights particular policy transmission channels. Our theoretical model leaves three main questions that we answer empirically: What is the nature of market segmentation? Is there transmission of policy imbalances onto FX swap markets? And is this via means or variances? Section 4.4 answers the first question in an analysis of co-movement between CCBS tenors. We investigate policy transmission with EGARCH-in-Mean models in section 4.5. Section 4.6 offers conclusions and an outlook for further research.

4.2 CIP Failure

4.2.1 The CIP Condition and the Cross Currency Basis

Covered interest parity implies that return differences for otherwise equal domestic and foreign assets should be explained by (hedged) exchange rate differences, hence

$$(1+r_t) = \frac{F_t}{S_t}(1+r_t^*), \tag{4.1}$$

where r_t denotes the yield on a domestic asset at time t, r_t^* the yield of a foreign asset, F_t forward, and S_t spot exchange rates at t. Using a logarithmic approximation, we can re-write 4.1 in terms of the forward spread as

$$f_t - s_t \approx r_t - r_t^*. \tag{4.2}$$

4.2 is a no-arbitrage condition as, in the absence of frictions and exchange rate risk,[2] risk-less profits could be realised through cross-currency swaps. The resulting price of such swaps is closely related to the cross-currency basis, b,[3] which in the no-arbitrage case can be expressed as

$$b_t = r_t - (r_t^* + f_t - s_t) = 0.$$

[2]The cross-currency basis, b, implied by eq. (4.2) does not carry any foreign currency exchange rate risk, as this is hedged through the forward leg of the swap. In section 4.4.1 we will use an augmented CIP condition that introduces counter-party default risk, which is different from the FX exchange rate risk present in uncovered interest parity.

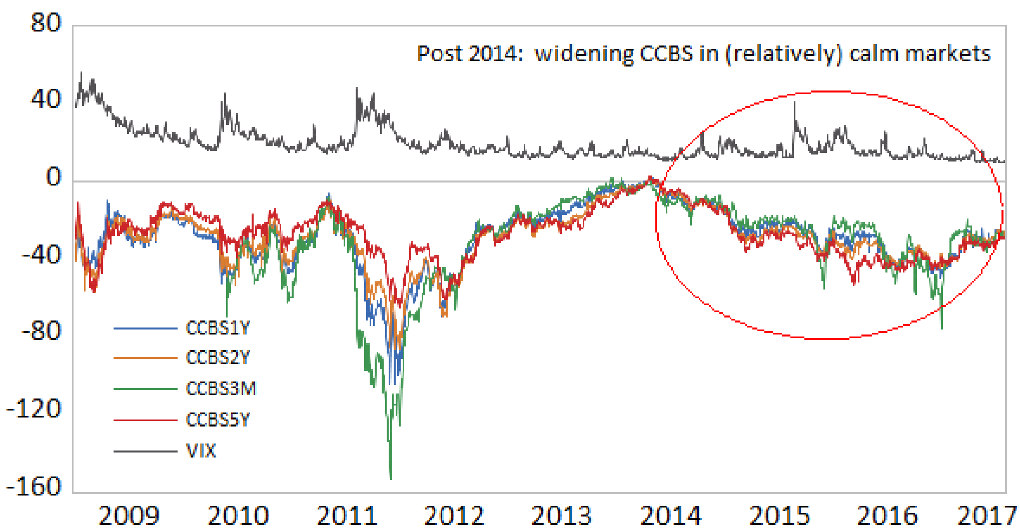
[3]Underlying trades are cross-currency swaps, which are floating/floating swaps with each respective libor rates as benchmarks. In the covered no-arbitrage case, cross currency swaps imply eq. (4.2) and a non-negative cross-currency basis hence implies CIP failure.

From an arbitrageurs' perspective, some non-negative b implies an arbitrage opportunity. Assuming the domestic rates exceed foreign rates, ie. $r_t > r_t^*$ arbitrage is profitable if the forward spread is larger than the interest spread, $f_t^i - s_t > r_t - r_t^* \Rightarrow b_t = r_t - (r_t^* + f_t^i - s_t) < 0$. In other words: An increase in US dollar denominated returns leads to a shortage of US dollar liquidity and a negative USD cross-currency bases. b can in this respect be interpreted as the degree to which the CIP condition is violated. Violations persist because of frictions to arbitrage on swap markets, such as banks facing wholesale refunding costs on repo markets, market liquidity premiums on swap markets, and costs of banks' balance sheet exposure arising from counterparty risk on FX swap hedging demand.

4.2.2 Swap Markets and Monetary Policy Post GFC

The foreign currency swap market is vast. The combined outstanding volume of forward, FX-swap, and currency swap trades, reached more than USD78 trillion as of December 2018, making it the main locus of foreign currency arbitrage.[4] US dollars and euros are the most commonly traded currencies. All the more spectacular is hence the failure of its main no-arbitrage condition, covered interest parity, on the Eurodollar market.

Fig. 4.1 CCBS Rates and Risk.



Notes: Figure plots 3M-5Y Cross-Currency Basis Swap rates (CCBS) (negative) with S&P500 implied stock options volatility (VIX).

[4] See: https://www.bis.org/statistics/d5_1.pdf

In the aftermath of the great financial crisis CIP has been subject to frequent, persistent violations. Figure 4.1 gives the evolution of the 3m-5y USD/EUR CCBS and implied volatility of S&P 500 options (VIX) post 2008. Widening of CCBS, especially for short maturities, was associated with the combination of a widespread USD shortage and emerging counter-party credit risk on Swap markets during the GFC and the Eurozone debt crisis. Bases successively narrowed again, following liquidity provisions through central banks. CIP deviations re-emerged in 2014 (BIS [2015a]), despite relatively low market risk. Spikes in VIX, that could be observed in 2015 seem less clearly correlated with currency bases. Market risk does clearly not offer a sufficient explanation for CIP deviations. At the same time divergence in monetary policies increasingly affected FX swap market clearing (BIS [2015b]). Figure 4.2 plots US and European policy rate futures, fed-funds (FFUS) and Euribor (FFEU) futures, which are used as proxies for rate-setting expectations. Whilst for large parts of crisis periods, both FED and ECB entered an aggressive easing cycle, albeit a short period of early attempts of monetary contraction in Europe, policy expectations diverged from 2014 onwards. This is linked to a FED policy contraction with the tapering of its asset purchase programmes in 2013 and further with first interest rate hikes in 2014, while the ECB eased monetary conditions further at the time, allowing for negative deposit rates and implementing its first large-scale asset purchase programme.

Fig. 4.2 US and Eurozone Policy Rate Expectations.

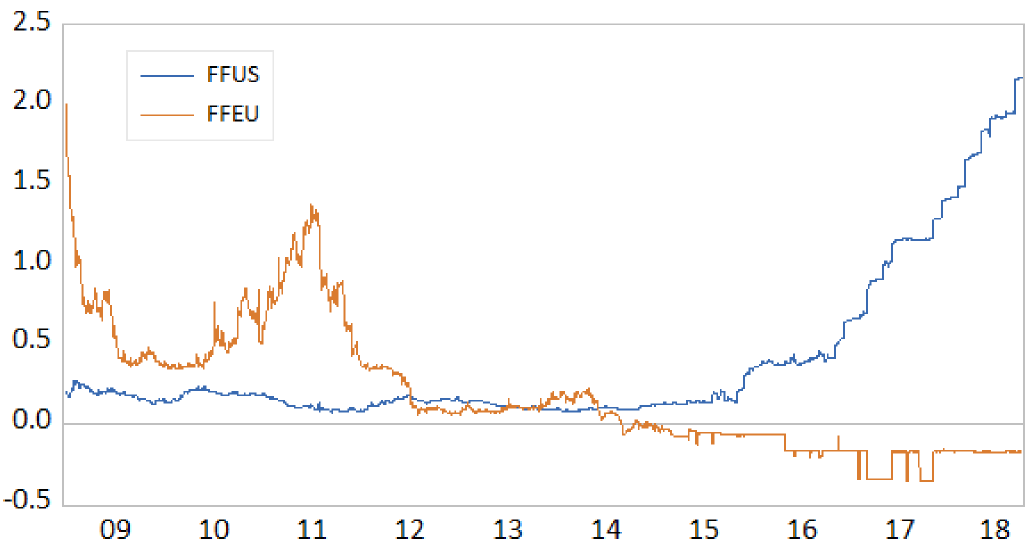


Figure plots 1m ahead FED Funds (FFUS) and 1m EURIBOR (FFEU) futures.

4.3 Literature on Global Policy Imbalances and the CIP Puzzle

The CIP puzzle exists as deviations from parity emerged at a time of relatively calm markets. This suggests the impact of other factors than risk, such as policy and intermediation costs. There is strong evidence on global policy spill-overs as well as ample contributions investigating the impact of policy, risk and intermediation cost as well as other factors on FX swap markets. But there is no unified framework explicitly investigating the role of policy imbalances, volatility and market segmentation on the CIP puzzle.

Early contributions investigating post-crisis CIP failure highlight risk factors, which was plausible given the preceding global financial crisis (GFC). Akram et al. [2008] document the existence of frequent CIP violations pre 2008, but those were generally short-lived and arbitrage opportunities hence quickly closed. Coffey et al. [2009] investigate CIP failure following the GFC, which they link it to a mixture of adverse funding conditions and heightened counterparty risk. They attribute a significant role of a subsequently observed narrowing of CCBS to coordinated monetary policies, such as swap-agreements. Gabaix and Maggiori [2015] propose a theoretical framework, integrating financial frictions in a general equilibrium model of exchange rate determination. Here financial intermediaries' limited risk bearing capacity constitutes a mark-up over marginal costs, resulting in CIP deviations. But Avdjiev et al. [2016] and Du et al. [2017] observe a return of CIP violations post 2014 in a comparatively low-risk environment. This suggests that risk factors alone are insufficient in explaining CIP failure. This widening of cross-currency basis swap rates (CCBS), a common measure for the degree of CIP failure, in a relatively calm risk environment post GFC is often referred to as the CIP puzzle.

There are several attempts to explain re-emerging CIP failure post 2014. Du et al. [2017] highlight the role of financial intermediation costs, such as balance sheet costs and end of quarter effects, which are arising from changes in the regulatory framework post GFC. This is particularly important as it offers an explanation for the persistence of observed CCBS movements and also gives evidence for causes of CIP failure. Avdjiev et al. [2016] investigate the relationship between the external value of the US dollar, CIP violations and cross-border USD denominated bank-lending. They find a positive relationship between USD appreciations and CIP deviations, which, as Du et al., they attribute to banks' costs of USD-denominated balance sheet exposure. Sushko et al. [2017] include these observed frictions in a model of bounded arbitrage on swap markets. Here, CCBS is a function of hedging demand and market-structural factors such as banks' ability to raise funding on repo-markets and market liquidity. In this framework, a cross-currency basis opens due to hedging demand-shocks, most notably monetary policy induced rate-compression, which then persists due to market-structural factors implying intermediation costs on swap markets. Empirically, they find significant impacts of both, a proxy for hedging demand and structural factors, on the short term (2 month) JPY/USD basis and of hedging demand only on the equivalent long-term (2 year) cross-currency basis. Using a panel of several different freely floating currencies largely validates results, albeit less robustly. Rime et al. [2016] investigate money-market CCBS rates, finding that risk-less CIP arbitrage opportunities exist for large international banks only. Money market cross currency bases mainly arise from differences in arbitrageurs' access to funding liquidity, which has been greatly affected by the shift from collateralised (repo) funding to unsecured funding markets post GFC, which only large international banks could access at competitive marginal costs.

The role of the US dollar takes a centre stage in FX imbalances observed over the last decade for several reasons. There is strong evidence suggesting that US monetary policy drives global financial cycles (Rey [2015], Miranda-Agrippino and Rey [2015]), which implies periods of abundance and shortage of USD liquidity that are linked to the US monetary policy cycle. In a recent paper, investigating the relationship between US capital flows and the dollar exchange rate, Lilley et al. [2019] even claim an "exchange rate reconnect", initiated by post-crisis US foreign bond purchases. Arguably a large proportion of US foreign bond purchases is linked to monetary policy, particularly unconventional policy such as large scale asset purchases, causing portfolio rebalancing behaviour. Unconventional policies have taken a crucial role in central banks' policy reaction to the GFC and were hence discussed extensively in the recent literature [5]. It is all the more surprising that there is relatively little research explicitly evaluating the effect of recent policy imbalances on foreign exchange markets. Spill-over effects of such policies have been widely documented (Rey [2015], Miranda-Agrippino and Rey [2015], Wohlfarth [2018b], Wohlfarth [2018a], Gilchrist et al. [2019] among others). Globally, policy reactions to the GFC were relatively coordinated at first. But more recently this has become increasingly asymmetric. Arai et al. [2016] highlights the potential impact of global monetary policy imbalances on swap markets using descriptive evidence. He et al. [2015] find significant adverse USD credit supply effects of FED policy normalisation relative to other central banks, that have the potential to cause severe dislocations on FX swap markets. Papers investigating the relationship between policy and CIP failure are even scarcer: Du et al. [2017] and Borio et al. [2016] obtain evidence of policy effects on CIP using event studies on monetary policy announcements between 2010-15 and after 2014, respectively. Both indicate a widening effect of policy on long-term currency swap bases. This is unsurprising, given that policy, particularly monetary

[5] See Bhattarai and Neely [2018] for a comprehensive review.

policy, arguably had a sizeable impact on bank balance sheets, and hence balance sheet costs. Similarly, one would expect policy to have an effect on banks' refunding operations and hence money market arbitrage. However, the impact of the global policy environment on swap markets is treated largely anecdotally in the literature, and there is no explicit investigation of effects of policy imbalances on FX swap markets. Furthermore, whilst there is agreement on risk having an impact on CIP failure, most recent contributions do not account for time-varying volatility due to the absence of policy measures for higher frequencies. To our knowledge there are no contributions investigating market segmentation and policy imbalances on FX swap markets in an empirical framework that caters for time-varying volatility in the underlying data.

4.4 Model

To investigate how policy affects the failure of covered interest parity we derive a structural framework based on two approaches: A model for arbitrage bounds on swap markets, caused by intermediation frictions, and a preferred habitat model of fixed income pricing, based on a mean-variance optimisation of domestic arbitrage portfolios, derived in chapter 2.

We assume an economy with two types of agents, arbitrageurs and investors. Arbitrageurs specialise in (1) CIP arbitrage on FX swap markets or (2) fixed income (FI) arbitrage.

4.4.1 Pricing on FX Swap Markets

The cornerstone of CIP arbitrage is the cross-currency basis with maturity i, $CIP_{i,t}$, which forms a set of arbitrage bounds, $CIP^-_{i,t} \geq CIP_{i,t} \geq CIP^+_{i,t}$, such that,[6]

$$\begin{aligned}
CIP^-_{i,t} &\equiv r_{i,t} - (r^*_{i,t} + f_{i,t} - s_t) \geq -\theta_t \rho \sigma_s^2 D_t^{XC} - c\left[(r_t^{REPO} - r_t) - (r_t^{*,REPO} - r_t^*)\right] \\
&- \left[(f^B_{i,t} - s^A_t) - (f^A_{i,t} - s^B_t)\right]/2 \\
CIP^+_{i,t} &\equiv r_{i,t} - (r^*_{i,t} + f_{i,t} - s_t) \leq \theta_t \rho \sigma_s^2 D_t^{*,XC} + c\left[(r_t^{REPO} - r_t) - (r_t^{*,REPO} - r_t^*)\right] \\
&+ \left[(f^B_{i,t} - s^A_t) - (f^A_{i,t} - s^B_t)\right]/2, \qquad (4.3)
\end{aligned}$$

where $r_{i,t}$ and $r^*_{i,t}$ are domestic and foreign yields, respectively, $f_{i,t}$ and s_t are forward and spot exchange rates, θ_t is a time-varying parameter governing counter-party credit default risk probability on forward swap markets, ρ gives the coefficient of absolute risk aversion, the exchange rate variance, σ_s^2, D_t^{XC} and $D_t^{*,XC}$ give domestic and foreign hedging demand

[6] See appendix E.1 for details.

shocks, and c gives a fraction of CIP arbitrage funded via REPO markets, with r_t^{REPO} and $r_t^{*,REPO}$ giving respective domestic and foreign wholesale refunding rates. The LHS of the inequality in 4.3 directly follows from the CIP relation. Arbitrage opportunities arise from differences between domestic and (hedged) foreign yields, $r_{i,t}$ and $(r_{i,t}^* + f_{i,t} - s_t)$, respectively. The RHS gives persistent CIP deviations, which are a function of balance sheet costs, which in turn are sensitive to aggregate demand shocks, and intermediation/transaction costs. In other words, this reflects imperfect CIP arbitrage.

θ_t plays a crucial role in introducing arbitrage frictions. Owing to the high degree of collateralisation, swaps are usually considered default-risk free trades. But cross-currency basis swaps carry the residual risk of a counter-party being stuck with foreign-currency denominated collateral (Sushko et al. [2017]). Although this default-risk probability is considered small, given the size of the underlying market and hence the associated balance sheet exposure, it can cause considerable frictions. θ_t therefore introduces costs to (hedged) foreign currency balance sheet exposure. Swap market clearing implies that the demand for FX forward hedges corresponds to arbitrageurs' foreign currency exposure. θ_t then implies that arbitrage opportunities, and corresponding hedging demand shocks, need to be sufficiently large to overcome costs from balance sheet exposure. This effectively introduces bounds around CIP that need to be overcome for arbitrageurs to enter a swap position.

4.4.2 Domestic Fixed Income Pricing

Yields are priced on a segmented fixed income market, where FI arbitrageurs exploit arbitrage opportunities, arising from the price-inelastic asset demand of preferred habitat investors. Accordingly, yields, r_t^i are priced as[7]

$$r_{i,t} = \frac{1}{n}\sum_{j=0}^{n} E_t(r_{t+j}) + \frac{1}{n}\sum_{j=0}^{n} E_t\left(\gamma'(\mu + \Phi X_{t+j})\right)\frac{1}{n}\sum_{j=0}^{n} E_t\left((\overline{b}_i' + \gamma')\Psi\lambda_{t+j}\right) - \frac{1}{2}(\overline{b}_i' + \gamma')\Psi(\overline{b}_i + \gamma),$$

and

$$r_{i,t}^* = \frac{1}{n}\sum_{j=0}^{n} E_t(r_{t+j}^*) + \frac{1}{n}\sum_{j=0}^{n} E_t\left(\gamma^{*\prime}(\mu^* + \Phi^* X_{t+j}^*)\right)\frac{1}{n}\sum_{j=0}^{n} E_t\left((\overline{b}_i^{*\prime} + \gamma^{*\prime})\Psi^*\lambda_{t+j}^*\right) - \frac{1}{2}(\overline{b}_i^{*\prime} + \gamma^{*\prime})\Psi^*(\overline{b}_i^* + \gamma^*), \tag{4.4}$$

[7] See appendix A.2 for the corresponding arbitrage portfolio optimisation.

4.4 describes yield pricing as an expected path of premia over short-term interest rates, r. Such premia arise as credit premia, driven by a set of structural macro-factors, X_t, and volatility premia, driven by the underlying asset variance, Ψ, the market price of risk, λ, and bond pricing and credit-risk coefficients, $\overline{b}_i'$ and γ. The dynamics of fixed income arbitrage enter through the market price of risk,

$$\lambda_t = \rho \sum_{i=1}^{N} (S_t^i - \xi_t^i)(\overline{b}_i + \gamma), \tag{4.5}$$

which is a function of risk aversion, ρ, arbitrage demand, given as difference between local asset supply, S_t^i, preferred habitat demand, ξ_t^i, and the pricing coefficients $\overline{b}_i$ and γ.

4.4.3 Monetary Policy Transmission

Domestic Transmission Channels Monetary policy enters 4.3 through its effects on domestic fixed income pricing or through its effects on CIP arbitrage. For the former, it affects domestic yield pricing in 4.4 through either asset supply, S_t^i, affecting arbitrage demand and the market price of risk, or through its impact on the expected path of policy rates, $\frac{1}{n}\sum_{j=0}^{n} E_t(r_{t+j})$. In terms of transmission channels, we can think of asset purchases entertaining some broad portfolio-rebalancing channel and rate expectations a forward guidance/ signalling channel. As highlighted in previous chapters, asset purchases further affect risk, and hence a volatility premium on mean asset returns. Policy therefore affects market returns through a volatility channel.

Transmission via CIP Arbitrage CIP arbitrage frictions can arise from three sources: Hedging-demand shocks, swap market liquidity, and wholesale refunding liquidity. The significance of policy on hedging demand comes in as policy asymmetries affect relative prices of foreign to domestic assets. This induces portfolio rebalancing behaviour and therefore changes to foreign currency denominated asset exposure, which in turn implies effects on hedging demand. It is important to note that the strength of this effect depends not only on changes in FX exposure but also on changes to any of the risk parameters involved. Swap market liquidity can be estimated as simple bid-ask spread and is affected by both, domestic and foreign market activity as well as policy interventions. Wholesale refunding liquidity captures local wholesale refunding costs on repo markets as premium of repo rates over respective interbank rates. Here, central bank interventions could have asymmetric effects, which could cause spill-overs on FX swap markets. Examples of policy interventions to address liquidity premiums include extended liquidity provisions on local fixed income markets (predominantly used by the ECB) and provision of foreign currency denominated liquidity through swap agreements between 6 major central banks[8].

Policy and the Currency Basis Since policy asymmetries affect relative prices between domestic and foreign assets, yield spreads, given in (4.3) directly transmit onto $CIP_{i,t}$. Were (4.3) a binding no-arbitrage condition, the inequalities would disappear and the yield differential would necessarily sum to zero. However, to the extend that frictions on swap markets imply costs to cross-currency arbitrage, (4.3) is bounded away from zero and hence $CIP_{i,t}$ can be non-zero and return differentials are tolerated on swap markets. The impact of policy on $CIP_{i,t}$ stems from the degree to which policy causes rate differentials and hence opens arbitrage opportunities on swap markets, which causes shocks to swap demand, D_t^{XC}. This implies that any asymmetries of the factors that affect domestic and foreign yields in (4.3) lead to a widening of $CIP_{i,t}$, which, following the argument of (Sushko et al. [2017]), the frictions in (4.3) prevent from closing. In this setting domestic policy has spillover effects, and hence affects foreign assets. Similarly, policy has an impact on asset volatility for both domestic and foreign assets. There is therefore an effect of policy on FX volatility, σ_s^2. The CIP arbitrage channel gives policy also a direct impact on the cross currency basis through its effects on arbitrage liquidity.

To expose aforementioned transmission channels we can write (4.4) in terms of premiums over a risk less benchmark, [9]

$$r_{i,t} = \frac{1}{T}\sum_{i=1}^{T}\mathbb{E}\bar{r}_{t+i} + CP(\boldsymbol{x},\iota) * VP(\gamma,\lambda(\sigma,\omega(S,\xi),\bar{b},\gamma),\Psi), \tag{4.6}$$

where CP denotes a credit premium, collecting the second term in 4.4 and VP represents a volatility premium, capturing the remainder of the equation. Substituting for 4.6 in 4.3 gives

$$\begin{aligned} CIP_{i,t} &= \Big(\frac{1}{T}\sum_{i=1}^{T}\mathbb{E}\bar{r}_{t+i} - \frac{1}{T}\sum_{i=1}^{T}\mathbb{E}\bar{r}^*_{t+i}\Big) + (CP-CP^*)(VP-VP^*) \\ &+ \theta_t\rho\sigma_s^2(\Psi,\Psi^*)D_t^{XC}(r_t,r_t^*) + \Lambda(r_{i,t},r^*_{i,t},r_{REPO},r^*_{REPO},f^A,f^B), \end{aligned} \tag{4.7}$$

where Λ denotes swap market arbitrage frictions and collects terms affecting wholesale refunding and swap market liquidity. Accordingly, policy feeds into (4.3) directly through rate differentials as well as indirectly through its effects on CIP arbitrage.

[8]Participating central banks were: Federal Reserve, ECB, Bank of England, Bank of Japan, Swiss National Bank, Bank of Canada. There were further bilateral swap agreements between central banks.

[9]For the ease of exposition, we omit the respective equation for y^*, which is equivalent.

4.4.4 Empirical Implications

The model derived in this section has a number of empirical implications that we test in the following two subsequent sections. In doing so, we will separately investigate market segmentation on FX swap markets and policy transmission onto CCBS. First, we will address properties of market segmentation on foreign exchange swap markets that are implied by the model. Here, our model has two main predictions.

1. Segmentation is time varying.

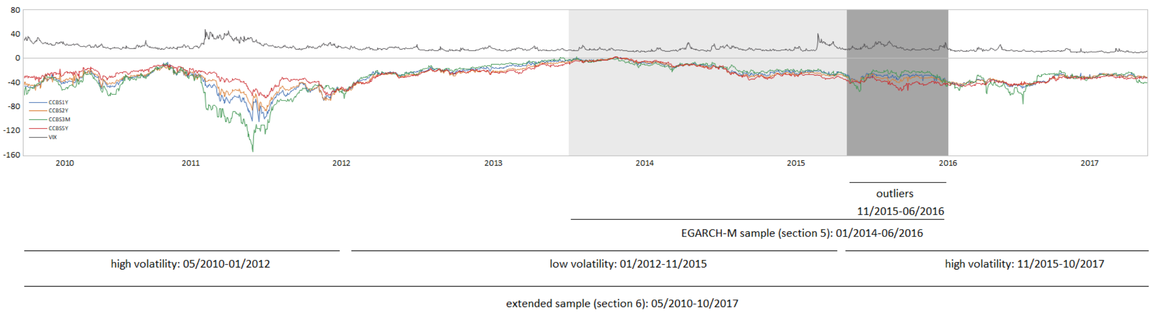
2. Segmentation is linked to volatility.

The first point follows from the relationship between arbitrage and risk, particularly volatility, which is time-varying. As limits to arbitrage is the only channel for market segmentation in the model, time-varying risk should lead to time-varying arbitrage behaviour and therefore time-varying market segmentation. The second point is closely related. It follows directly form the existence of a volatility premium in the model. Again, as limits to arbitrage is the only source of segmentation in the model, and since arbitrage depends on volatility, there should be a link between segmentation and volatility as well.

Model implications on policy transmission, outlined in section 4.4.3 are investigated in section 4.6, where we build conditional volatility models of cross-currency bases.

Samples Throughout the empirical sections of this paper (sections 5 and 6), we employ different samples of the data. An overview of the partitioning is given in Fig. 4.3 below. Section 5 investigates the role of policy in explaining the CIP failure. Following the literature on the CIP Puzzle, we focus on a sample covering the persistent widening of CCBS (01/2014-06/2016), which marks a time when policy asymmetry, measured by spreads between interest rate futures, was particularly strong. We split the sample further, excluding data post 11/2015 that contains several outliers in some regressions. In section 6 we answer questions regarding the co-movement between CCBS, abstaining from the effect of any other exogenous variables. For this purpose we extend the data on CCBS to obtain the longest available continuous series, which is from 05/2010 to 10/2017. We then partition the data into low and high-volatility regimes, based on VIX as indicator for market volatility.

Fig. 4.3 Different Samples Investigated.



Notes: 3m-5y Cross-Currency Basis Swap rates (CCBS) plotted on bottom half, market volatility, measured by VIX on top half. Shaded areas highlight data used for EGARCH-M estimates (section 5), with dark shaded area giving sub-sample containing outliers and light shaded area a sub-sample excl. outliers.

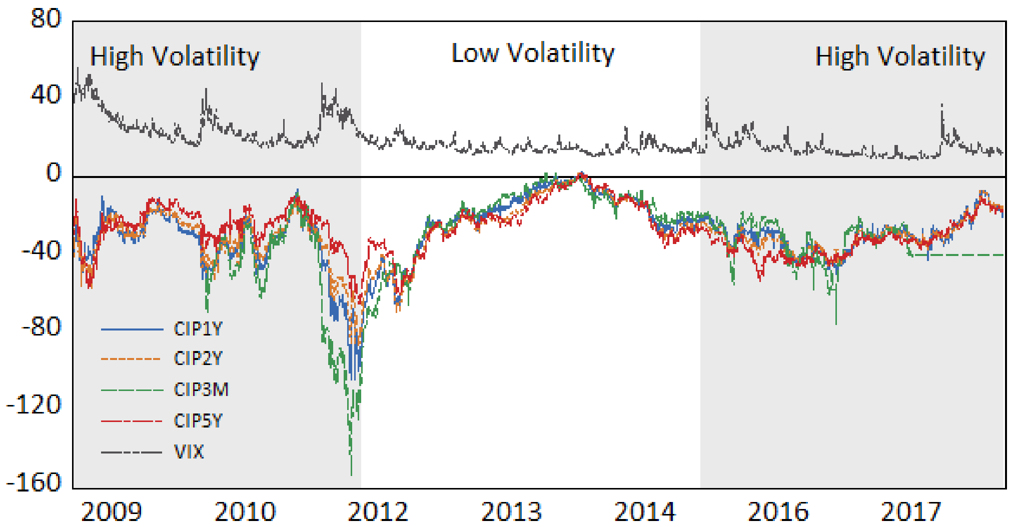
4.5 Volatility and the Term Structure of CCBS Rates

As figure 4.4 below shows, different CCBS rates display patterns of co-movement. Indeed, based on Johansen cointegration tests and depending on assumed deterministic terms and chosen test statistics, there are between 2 and 4 cointegrating relationships between CCBS, for data on the whole available post-crisis period (2008-2018). However, the nature of that relationship appears to be changing over time. Data before 2012 unambiguously suggests 2 cointegrating relationships, there are between 3 and 4 cointegrating relationships for 2012-2015, and almost unambiguously 1 cointegration relationship after 2015.[10] Visual inspection of the data confirms the changing relationship between variables. Following the model in section 3, this could be symptomatic for CIP arbitrage frictions that may have increased due to the presence of a volatility premium. To investigate this, we examine effects of market volatility on the relationship between CCBS rates. For this, we first consider the full sample from 2010 to late 2017, which we then partition into high and low volatility regimes based on global stock options volatility (VIX). We then analyse principal components for the different sub-samples as well as co-movement between CCBS rates in a VECM framework.

Figure 4.4 plots CCBS rates and VIX for the sample considered. The shaded area indicates the high volatility samples.

[10] For the last sub-sample the trace statistic in a model assumning quadratic trends and intercepts indicates two cointegrating vectors. All remaining test statistics indicate one.

Fig. 4.4 Volatility and CCBS.



Notes: The figure plots VIX along with CCBS across maturities. Shaded areas highlight high-volatility regimes.

The dispersion of CCBS appears to be linked to market volatility. This is particularly strong in the second half of 2011, which is likely due to the Eurozone crisis, as well as the last quarter of 2015, that includes the outliers discussed above. The mere existence of changes in dispersion across CCBS tenors is striking and at odds with the common assumption of constant transactions costs. Whilst the existence of some non-negative cross-currency basis could be explained with simple market-structural frictions, such as transaction costs, the spreads between CCBS rates of different maturities indicates the presence of market segmentation. That this dispersion is time-varying and linked to volatility is in line with the presence of a volatility premium.

4.5.1 Principal Components

Since CCBS rates indicate a deviation from no-arbitrage conditions they should, in the absence of frictions, such as market segmentation and intermediation frictions, be zero. Observed bases hence indicate the presence of frictions. In the absence of segmented markets these frictions should be the same along the term structure, CCBS rates should thus be similar and we should not be able to observe more than one principal component. Conversely, the presence of more than one principal component indicates an impact of market segmentation on fx swap market frictions. Following our model, market segmentation is exacerbated through volatility due to the limited risk-bearing capacity of arbitrageurs. To investigate the impact of volatility on frictions through market segmentation, we therefore first compare principal components for the samples considered. The proportion of variances explained through the first three principal components are summarised in table 4.1 below.

Table 4.1 First Three Principal Components

Factors	Variance Proportion		
	Pre 2012	2012-2015	Post 2015
1	0.9497	0.9593	0.7104
2	0.0453	0.0324	0.2629
3	0.0044	0.0063	0.0235

Whilst both, the pre-2012 sample and the 2012-2015 sample yield similar results, there is a striking difference between the post-2015 sample: More than a quarter of the variance is explained by a second factor and more than 2% by a third factor. This is at odds with the absence of market segmentation and strikingly coincides with an increase in volatility, that coincides with diverging policy and is following a period of relatively calm markets.

4.5.2 VECM of the Relationship between CCBS

Following the preferred-habitat theory, frictions should further be time varying: Limits to arbitrage takes a crucial role in explaining frictions and is largely driven by risk, particularly volatility. We investigate both, the time-varying nature of frictions and the relationship between CCBS tenors and volatility with an analysis of the cointegration relationship between CCBS rates. Accordingly, we employ a vector error correction model (VECM) as

$$\Delta y_t = \boldsymbol{A_0} - \boldsymbol{\alpha}(\boldsymbol{\beta}' y_{t-1} + ct) + \sum_{i}^{p-1} \boldsymbol{\Gamma_i} \Delta y_{t-1} + \varepsilon_t,$$

where y_t is a 1×4 column vector of the 4 CCBS rates. $\boldsymbol{\beta}$ is a 3×4 matrix of identifying restrictions

$$\boldsymbol{\beta} = \begin{pmatrix} 1 & -1 & 0 & 0 \\ 0 & -1 & 1 & 0 \\ 0 & -1 & 0 & 1 \end{pmatrix}.$$

The restrictions implicitly treat the system of CCBS-rates analogue to a term structure, so that the it has stationary spreads, $\boldsymbol{\beta}$, which are chosen relative to the 1Y CCBS rate as a benchmark. $\boldsymbol{\alpha}$ gives a 3×4 matrix of adjustment coefficients. We test the restrictions using the LR test for binding restrictions. Note that a non-segmented market implies stationary spreads of zero between CCBS rates, which is contained in the restrictions. Therefore a test of binding restrictions on $\boldsymbol{\beta}$ implies a test for market segmentation.

Table 4.2 Volatility and Cointegrating Vectors

	Cointegrating Vectors								
	2010 - 2012			2012 - 2015			2015 - 2018		
	β_{1Y}	β_{2Y}	β_{5Y}	β_{1Y}	β_{2Y}	β_{5Y}	β_{1Y}	β_{2Y}	β_{5Y}
α_{3M}	-0.054	-0.039	-0.038	-0.051	-0.079	0.030	-0.007	0.020	0.003
	[-2.274]	[-0.330]	[-0.704]	[-3.762]	[-1.340]	[1.318]	[-1.187]	[0.365]	[0.128]
α_{1Y}	0.119	0.180	0.063	0.033	0.224	-0.060	0.015	0.148	-0.011
	[5.476]	[1.632]	[1.258]	[2.093]	[3.229]	[-2.25]	[2.723]	[2.775]	[-0.478]
α_{2Y}	-0.028	-0.631	0.260	-0.049	-0.142	0.042	-0.001	-0.113	0.047
	[-1.43]	[-6.260]	[5.624]	[-3.673]	[-2.422]	[1.861]	[-0.391]	[-2.893]	[3.686]
α_{5Y}	-0.010	-0.100	0.012	-0.023	0.081	-0.053	-0.003	0.059	-0.030
	[-0.663]	[-1.293]	[0.357]	[-1.872]	[1.476]	[-2.495]	[-0.823]	[1.460]	[-1.657]
LR	6.965			37.26			29.87		
p(LR)	0.072			0.000			0.000		
k	59			59			75		

Table 4.2 gives the adjustment coefficients, α_y, on the cointegrating vectors (CV), $\boldsymbol{\beta}$, where the restrictions given above are applied. The restrictions are clearly rejected for the post 2012 and post 2015 samples and cannot be reject at a 5% confidence level for the pre-2012 sample. This indicates that the CCBS market became more segmented after 2012. This is in line with descriptive evidence and the literature, whereby CIP deviations were following risk measures until 2012 followed by a breakdown of that relationship thereafter. The breakdown of this relationship is likely explained by the global policy environment at the time, which had a significant impact on FX swap markets. We will investigate this point further in the following section.

The adjustment coefficients show most significant feedback in the low volatility sample. Between 2012 and 2015 seven out of twelve adjustment coefficients fed back significantly to the CVs, compared to each four in the other samples. This suggests that there is generally more adjustment to cointegrating relationships between CCBS rates in the absence of volatility, which indicates some effect of volatility on the cointegration between CCBS rates. An exception to this is the adjustment of 2Y CCBS to the third CV, which normalises to the spread between 1Y and 5Y CCBS. The same adjustment coefficient turns insignificant in the low volatility sample, where the adjustment of the 2y CCBS with respect to the first (3m/1y) cointegrating vector is feeding back significantly. This suggests that volatility shifts feedback from short to long maturities. The adjustment of the 5Y CCBS to the first CV confirms this (albeit insignificantly): the feedback is largest in the low volatility sample. In the 5y basis we can also observe a change in direction of its feedback to 2y/1y and 5y/1y spreads. This corresponds with narrowing of short tenor CCBS (3m and 1Y) relative to 2y and 5y CCBS pre 2012. In other words: The CCBS curve was inverted pre 2012 and resembled a normal term-structure thereafter. This confirms previous evidence on different dynamics between short and long maturities on FX swap markets, which may be affected by policy as well: At shorter maturities CCBS are mainly driven by risk-factors, which receded between 2012 and 2015. At the long end, CCBS are driven by more fundamental and market structural factors, as well as unconventional monetary policies, which are then exacerbated by market volatility.

4.6 Conditional Volatility, Policy, and the EUR/USD Basis

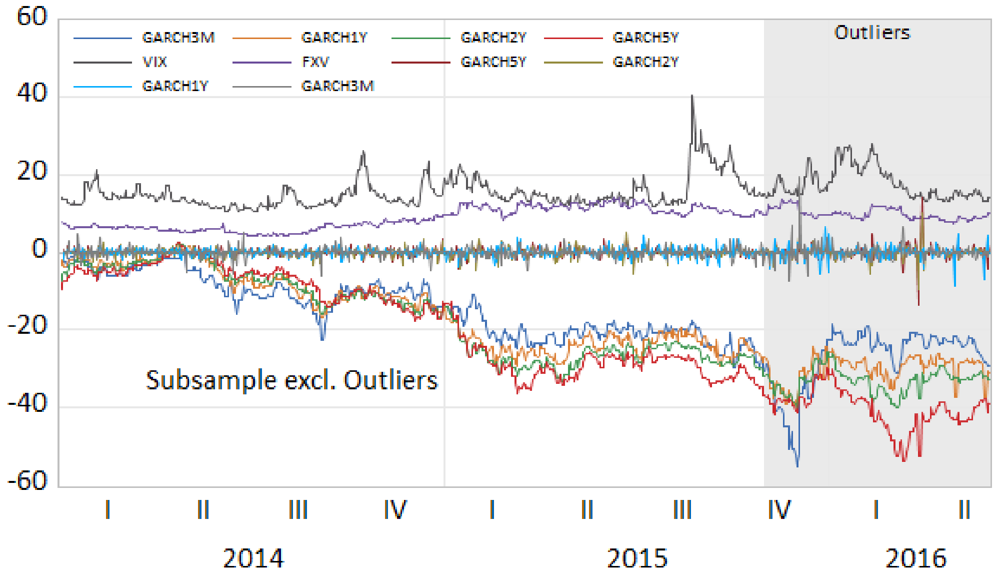
We test for policy channels in 4.3 directly through analysing the effect of asymmetric policy on the EUR/USD cross-currency basis in a GARCH-in-Mean framework.

4.6.1 Data

The data for this analysis is a sample of US and European daily fixed income, foreign exchange and Google search data from January 1st 2014 - June 30 2016. It is chosen in order to capture policy asymmetry between the ECB and the FED, which was particularly strong at the time. We further estimate results for a sub-sample separately due to the presence of outliers after November 2015 [11].

[11] In particular, there is evidence of an outlier on 04/12/2015, which follows a surprise decision of the ECB on 03/12/2015 to extend it's EAPP by less then expected as well as early misreporting of the policy decision by the Financial Times. Both are likely to have contributed to abnormally high volatility on markets.

Fig. 4.5 3m-5y CCBS Rates and Volatility.



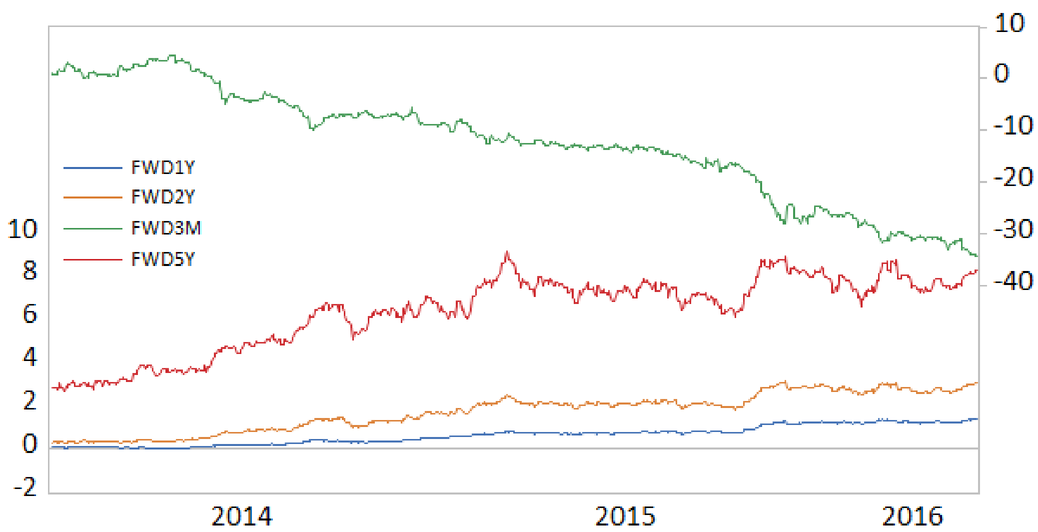
Notes: 3m-5y Cross-Currency Basis Swap rates (CCBS) plotted on bottom half (labels have been omitted for the ease of exposition but can be found in fig 4.1 above), volatility measures VIX and FX volatility (FXV) on top half, and residuals obtained from estimated EGARCH-M models, GARCH3M-GARCH5Y, in centre.

Figure 4.5 plots the evolution of CCBS rates across maturities, together with two volatility measures, VIX and FX volatility (FXV),[12] and residuals obtained from the estimation of EGARCH-M models. Whilst generally a widening of CCBS is observable for all maturities, money and capital markets appear to follow different patterns, particularly towards the end of the sample. This is especially striking when considering the 3m and 5y bases: Initially, 3m CCBS were widening the most, whilst the 5y CCBS was narrowest. This situation is reversed towards the end of the sample. This change in the term-structure of CCBS rates indicates changes to market segmentation over time. There appears to be some link to changes in volatility and GARCH residuals exhibit a series of substantial outliers towards the end of the sample. The latter motivates the estimation of a subsample. It is also interesting to note the difference between the two volatility measures considered: Whilst VIX is relatively volatile but appears to revert to a stable mean, FXV shows relatively little fluctuations but seems to have an increasing mean over the sample. The latter follows a similar pattern to that observed for CCBS rates, giving raise to the existence of volatility premia.

[12]FXV is implied volatility on USD/EUR foreign exchange options as a proxy for FX market risk.

This situation is exacerbated for forward spreads (Figure 4.6), where money market arbitrage, as given by the 3m forward spread, follows a linear, clearly negative trend (in line with the negative CCBS), whilst for other maturities there is no apparent or possibly a small positive trend. The striking difference in arbitrage behaviour suggests fundamentally different market dynamics at play. This is, to some degree, unsurprising, given the importance for market liquidity and wholesale refunding on money markets on one hand, and dominating pricing dynamics on capital markets on the other hand.

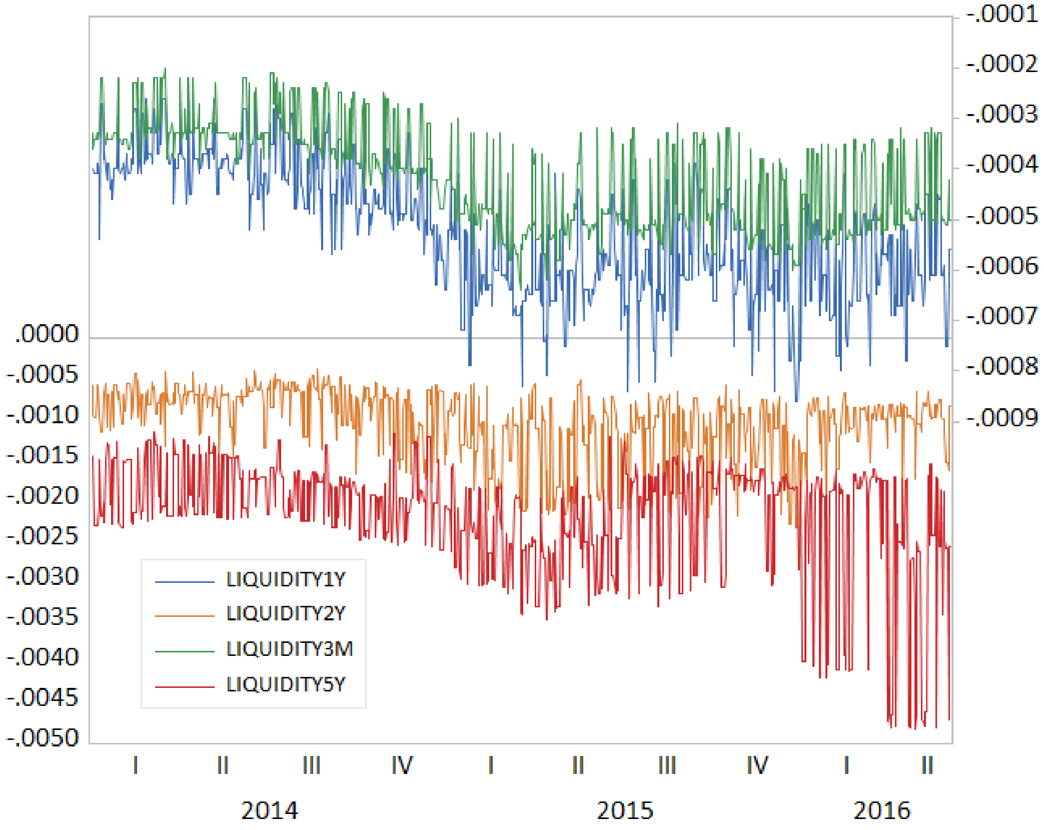
Fig. 4.6 Forward Spreads.



Notes: FWD3M (right), FWD1Y-FWD5Y (left).

Liquidity spreads (Figure 4.7) follow similar patterns across maturities for means and variances, with the 5y swap market liquidity being particularly volatile towards the end of the sample. This corresponds with a relatively sharp drop in the 5Y CCBS rate around the same time and is likely outlier driven, which is reflected in our sample restriction outlined in greater detail in section 4. below.

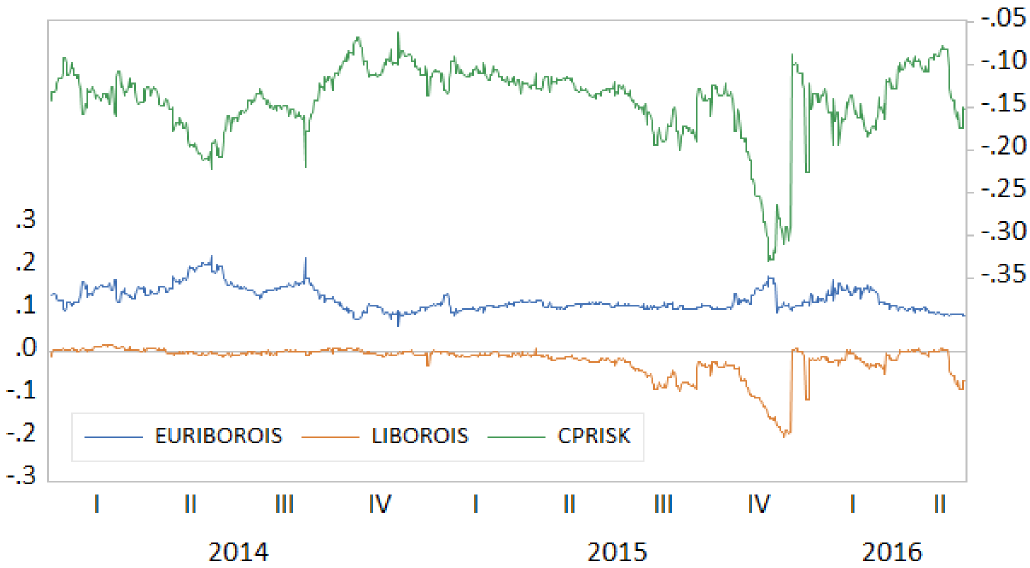
Fig. 4.7 Swap Market Liquidity.



Notes: LIQUIDITY3M and LIQUIDITY1Y (right), LIQUIDITY2Y and LIQUIDITY5Y (left).

Counter-party credit risk measures for US and Eurozone are plotted in Figure 4.8. There are several sharp imbalances in the early half of our sample. CPRISK in this case gives the difference between OIS-Libor and OIS-Eonia spreads, and the spikes reflect spikes in the EONIA-OIS spread at the time, which coincides with decreases in excess liquidity and several ECB policy rate decreases. Drops in CPRISK towards the end of the sample are due to increases in libor, which likely linked to US policy rate increases at the time.

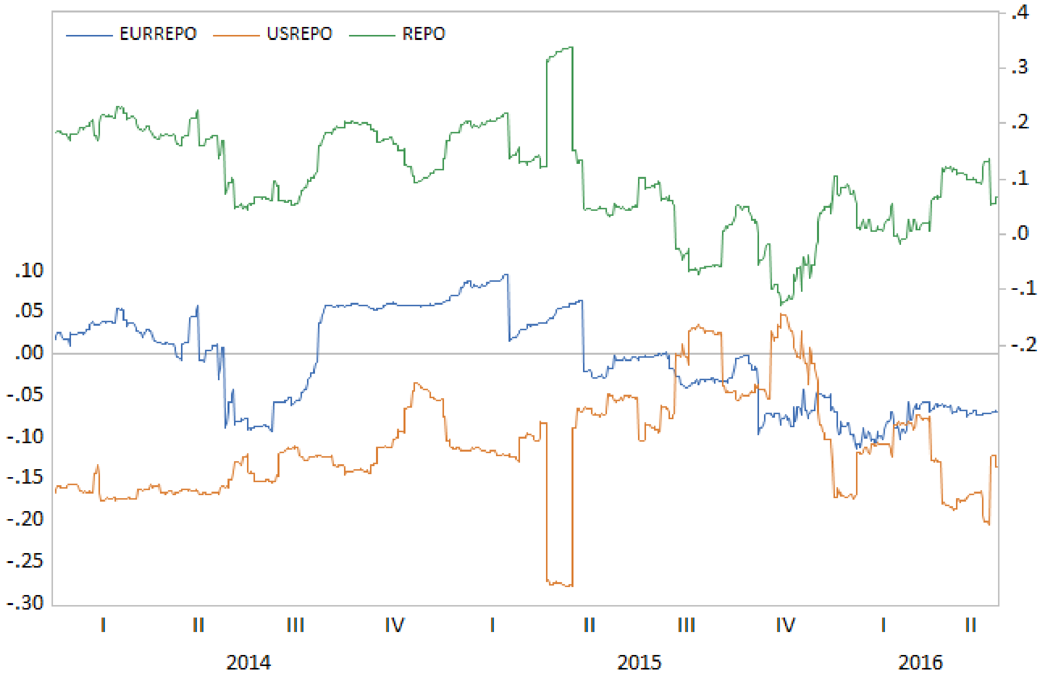
Fig. 4.8 Counter-Party Credit Risk



Note: Figure plots counter-party credit risk, CPRISK and it's constituents, EURIBOR-OIS and LIBOR-OIS spreads

Asymmetry of wholesale refunding liquidity, REPO (fig 4.9), is given as the difference between European and US REPO-liquidity. It drops substantially from the second to the fourth quarter of 2015, with spreads briefly turning negative in the last two quarters of 2015. This drop in REPO coincides with further ECB policy rate decreases and the introduction of negative deposit rates in the Euroarea. The yet relatively small reaction in REPO is due to the fact that its US component was sharply increasing at the time, following policy changes in the US. In other words, policy asymmetries at the time may have overshadowed the severity of adverse policy effects on European money markets.

Fig. 4.9 REPO-Spreads.

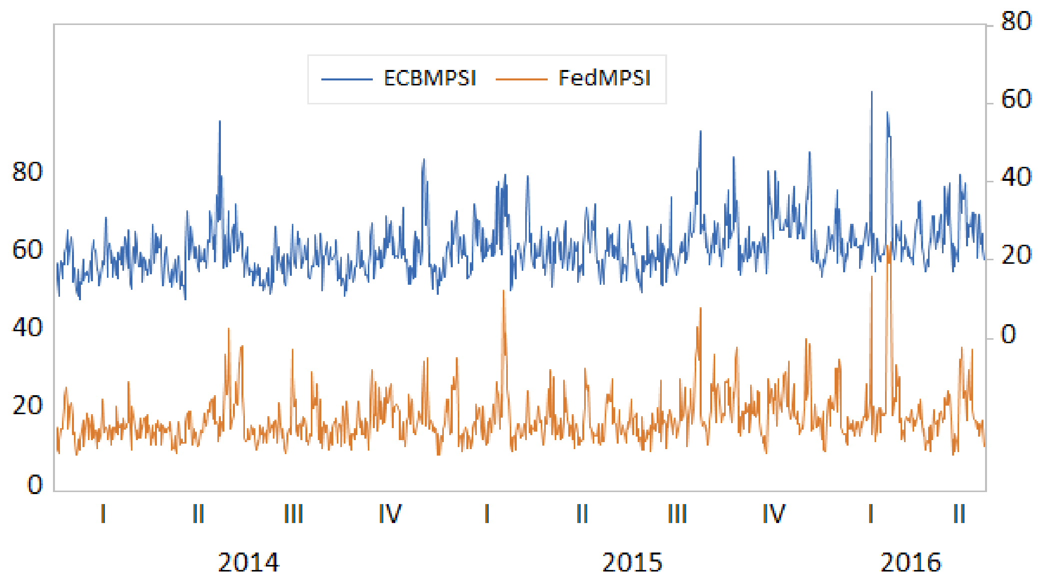


Notes: Figure plots constituents of REPO, 3m EURIBOR-REPO (EURREPO) and LIBOR-REPO (USREPO) spreads.

Figure 4.10 gives the evolution of policy attention, *MPSI* (Wohlfarth [2018b]), decomposed by its US and European constituents. Policy attention is measured based on Google Trends search volume indices for policy related search terms. Both indices spike around a set of identified policy relevant events and display considerable co-movement, which is unsurprising given that both, policy spill-overs and reaction to global shocks affect attention to both central banks. There are, however, differences in timing and magnitude of some of the shocks.[13]

[13] See Appendix C for details on index construction and identified events.

Fig. 4.10 Policy Attention



Notes: Figure plots constituents of our policy attention measure (MPSI), US (FEDMPSI) and European policy attention (ECBMPSI).

4.6.2 EGARCH-in-Mean Models of Cross-Currency Bases

Following eq. (4.7), we estimate a mean-variance relationship for the currency basis swap rates considered as EGARCH-in-Mean models, such that

$$CIP_{i,t} = x'_{i,t}\beta + \nu_{i,t} \tag{4.8}$$

where $x'_{i,t} = \Big(1,\ \log h_{i,t},\ FF_t,\ FWD_{i,t},\ REPO_t,\ Liquidity_{i,t},\ CIP_{i,t-1}\Big),$

$$\begin{aligned} \text{and} \quad \nu_{i,t} &= \varepsilon h_{i,t}^{1/2}, \quad \varepsilon \sim IID(0,\Sigma) \quad \text{and} \\ \log h_{i,t} &= c_{i,0} + c_1 h_{i,t-1} + c_2 \left|\frac{\nu_{i,t-1}^2}{h_{i,t-1}}\right| + c_3 \frac{\nu_{i,t-1}^2}{h_{i,t-1}} + c_4 VIX_{i,t} + c_5 FXV_{s,t} + \\ &\quad c_6 \theta_{i,t} + c_6 MPSI_{i,t}. \end{aligned}$$

β is a 7×1 coefficient vector, $CIP_{i,t}$ denotes the EUR/USD CCBS rate, for swaps with maturity $i = $ 3m, 1y 2y, and 5y. FF_t gives the difference between front-month Fed-Funds and EURIBOR futures for the US and the Eurozone, $FWD_{i,t}$ is the forward spread, given as difference between spot and respective forward exchange rates, and $MPSI_t$ the difference in policy attention indices, using Google search data.We further control for the wholesale refunding liquidity premiums, captured through the LIBOR-REPO spread, $REPO_t$, a swap market liquidity premium, $LIQUIDITY_{i,t}$, given by bid-ask spreads on FX spot and forward markets, and a counter-party risk premium, $\theta_{i,t}$, captured through OIS-LIBOR spreads. VIX_t gives implied volatility of S&P 500 options as a general proxy for market risk and $FXV_{s,t}$ is implied volatility on USD/EUR foreign exchange options as a proxy for FX market risk. Models assume stationarity and all variables enter in first differences, apart from policy attention, which is stationary.

4.6.3 Effects of Policy Asymmetry

In line with the previous section we investigate estimates for the effect of asymmetry, i.e. differentials in interest rate futures. Table 4.3 gives estimates obtained from the full sample and a sub-sample that excludes outliers. Our main findings are based on the latter sample, given the otherwise likely outlier bias. We report both sets of estimates for robustness purposes.

Table 4.3 CCBS Regressions

Mean	3m	1y	2y	5y	3m	1y	2y	5y
	Full Sample 01/2014-06/2016				Excl. Outliers 01/2014-11/2015			
GARCH	-0.077	-0.038	-0.096 *	-0.142 *	-6.751 ***	-0.205 *	-0.134 *	-0.184 *
C	-0.042	-0.013	-0.055	-0.050	-1.692 ***	-0.030	-0.097	-0.104
FF	0.047 *	-0.040	-0.099 ***	-0.054 **	0.079 ***	0.012	-0.084 ***	-0.108 ***
(S-FWD)	0.002 ***	-7.948 ***	-4.482 ***	-1.444 ***	0.007 ***	-10.426 ***	-4.389 ***	-1.267 ***
REPO	-0.001	0.002	-4.921 ***	-4.079 ***	-0.005	-0.023	-0.084 ***	0.642
LIQUIDITY	-10.604 ***	3.552	-67.8547 *	105.917 ***	2.727	3.565	-0.716 *	-0.076 ***
CIP_{t-1}	0.054 **	-0.057 *	0.057 **	0.039	0.683 ***	-0.060	0.068 **	0.042
Variance								
C(8)	-0.328 ***	-0.063	-0.306 ***	-0.232 ***	-0.233 ***	-0.276 ***	-0.333 ***	-0.463 ***
ARCH	0.161 ***	0.402 ***	0.022	0.046	-0.003	0.395 ***	-0.092	0.233 ***
Leverage	-0.028	0.037	0.274 ***	0.271 ***	0.099 ***	0.114	0.224 ***	0.254 ***
GARCH	0.032	-0.707 ***	0.547 ***	0.368 ***	0.063 *	-0.066	0.476 ***	0.360 **
VIX	-0.079 **	0.069 ***	0.106 ***	0.066 *	-0.002	0.077	0.052	0.033
FXV	-0.120	0.091	0.453 ***	0.314 ***	0.002	-0.033	0.272 **	0.227
CPRISK	2.463	1.840	12.483 ***	14.204 ***	0.376	17.601 **	-4.414	-3.322
MPSI	0.045 ***	-0.006	-0.001	-0.021 *	0.001	-0.000	0.006	-0.006
t-DoF	3	3	3	3	3	3	3	3
R2	0.018	0.017	0.081	0.070	0.184	0.035	0.081	0.064
SER	1.207	1.290	0.819	0.998	0.895	0.973	0.726	0.756
BIC	2.650	2.872	2.098	2.385	2.417	2.671	2.013	2.203
DW	2.002	2.214	1.940	2.008	2.125	2.247	2.038	1.953

Notes: Table gives estimates for regressing eq (4.8), where $i = 1m, 1y, 2y, 5y$. The left for columns give results based on a sample including detected outliers (02/01/2014-30/06/2016), the right for columns consider a sub-sample that excludes outliers (02/01/2014-01/11/2015). Dependent variables are 3m-5y CCBS rates. Estimation of all models via maximum likelihood assuming t-distributed errors and optimisation using the Eviews legacy algorithm with Marquard steps. BIC gives the Schwarz-Bayes Information Criterion, DW the Durbon-Watson Statistic and SER the standard error of the regression; Significance levels: $^* < 10\%, ^{**} < 5\%, ^{***} < 1\%$.

Full Sample including Outliers Estimates are given on the left half of table 4.3. Policy asymmetry as measured by futures enters significantly across the whole term structure of CCBS. It is only insignificant for the 1y pocket, which is almost entirely driven by the forward spread.[14] It is negative on capital markets (2Y and 5Y), hence widening the

[14]For all maturities except 1y there is no Granger-causality from dependent to explanatory variables. Granger-causality tests for the one year basis suggests feedback to explanatory variables and coefficients might be biased as a result. See appendix F.2 for details.

(negative) currency basis, whilst we find the opposite effect on money markets (3m). We find significant negative GARCH-in-Mean effects for 2Y and 5Y CCBS. For the former, the coefficient size is similar to FF, whilst for the latter GARCH-in-Mean effects clearly dominate. Policy attention, *MPSI*, enters the variance significantly for 5Y and 3m CCBS. In the case of the 5y CCBS, as it further affects means through GARCH-in-Mean effects, there is evidence for policy transmission via the aforementioned volatility channel. The fact that this evidence appears for longer CCBS maturities may be due to MPSI capturing more unconventional policies, which had a greater impact on capital markets. MPSI enters negatively on capital markets, suggesting a mitigating effect of policy on uncertainty, and positively on money markets, again giving different dynamics for money and capital markets.

Generally, 3mth CCBS appears to be almost entirely driven by market liquidity. Money market dynamics are typically sensitive to traded flow volumes, rendering this result unsurprising. Given the close link to wholesale refunding on money markets, it is somewhat surprising to not find significant effects of REPO liquidity on the short end of the currency basis. This is in line with the shift to unsecured money market funding operations, documented in Rime et al. [2016]. The shift away from wholesale refunding operations could further indicate adverse policy effects on money markets at the time: Beaupain and Durré [2016] investigate ECB's fixed rate full allotment (FRFA) policy introduced in October 2008. Accordingly, following the introduction FRFA, money market liquidity was positively affected by excess reserves, held at central bank deposits. Policy efforts to reduce excess reserves, such as the introduction of negative deposit rates, may have further exacerbated this situation on Repo markets causing arbitrageurs to shift away from wholesale refunding activities. The positive coefficient of FF supports this: It could be indicative of imbalances having offset some of the adverse policy effect on market liquidity and therefore contributed to some narrowing of the basis. In other words: to the degree that domestic expansions helped closing the cross-currency basis on capital markets (and hence international policy imbalances contributing to it widening again), effective contractions on money markets had a widening impact on the cross currency basis and imbalances offset some of this adverse effect. Risk factors enter the variance positively for capital markets, with the effect being dominated by counter-party risk, $CPRISK$. There is a small, significantly negative effect of VIX on 3mth CCBS. There are significant negative effects of changes in the forward spread and REPO liquidity on capital markets, which is in line with Sushko et al. [2017]. On money market CCBS, the forward spread has a small, significantly positive effect on 3m CCBS. FX swap market liquidity is significant in almost all models, with signs switching between maturities, which might indicate local supply scarcity alongside portfolio-rebalancing effects. Coefficient sizes are large and the effect increases dramatically towards longer maturities.

Sub-Sample excluding Outliers Employing a sample that excludes outliers after November 2015 (right half of table 4.3) confirms and further strengthens previous results: Most notably, there is a larger effect of the volatility premium as captured through GARCH-M coefficients. This is especially pronounced for the 3mth basis, where GARCH-M effects turned from insignificance to being the single largest factor, contributing to a widening of the cross currency basis. This further supports the argument in Beaupain and Durré [2016], highlighting the impact of volatility on money markets following ECB's fixed-rate full allotment policy. However, policy attention is now insignificant. Risk is mostly picked up by FXV on capital markets and by *CPRISK* for 1yr CCBS; It is insignificant in 3mth CCBS. In terms of mean effects, we most notably do not observe the strong sign switches of $Liquidity$, but instead observe different signs between money and capital markets, which is in line with the other coefficients. We find a large increase in the explained variation of the restricted sample on money markets, whilst the explained variation for the 5Y basis remained fairly unchanged. This suggests the outlier bias to be particularly strong on money markets.

Robustness We consider two extensions for robustness purposes: The inclusion of Economic Policy Uncertainty, EPU, (Baker et al. [2016]) in all models and of bank credit default swap, CDS, indices for 5y CCBS[15] as an alternative measure for risk. Results are summarised in tables F.5 and F.6, Appendix F.3. Including further control variables confirms findings on direct policy impacts as well as the impact of volatility for 3m CCBS using the restricted sample. For longer maturities and estimates based on the full sample, GARCH-in-Mean coefficients are insignificant. European bank CDS have a significant effect on the widening of the 5y basis, whilst US CDS are significant in the full sample only. EPU enters variances significantly in almost all models. Coefficient sizes are relatively small. Controlling for exchange trading hours validates results for policy measures in regressions using longer maturities. Results on GARCH-in-Mean effects are generally robust.

[15]The choice to control for CDS for 5y CCBS only is based on limited data availability for shorter maturities.

4.6.4 Decomposition of Policy Effects

We decompose policy measures, FF and $MPSI$, into respective constituents to investigate relative contributions of observed policy effects. Results are given in table 4.4 below, with the restricted sample on the left half and the full sample on the right half of the table.

Table 4.4 CCBS Regressions Decomposing US and European Policy Measures

Mean	3m	1y	2y	5y	3m	1y	2y	5y
	Excl. Outliers 01/2014-11/2015				Full Sample 01/2014-06/2016			
FF_{EU}	-0.107 ***	-0.025	0.092 ***	0.105 ***	-0.072 **	0.031	0.109 ***	0.097 ***
FF_{US}	-0.033	-0.036	-0.163 **	-0.192 **	-0.329 ***	-0.062	-0.097 **	0.048
Variance								
$MPSI_{EU}$	-0.001	0.011	0.026 **	0.004	-0.028 **	0.012 ***	0.027 **	0.021 *
$MPSI_{US}$	0.002 **	0.016	0.035 **	-0.010	0.071 ***	0.006	0.011	-0.013
t-DoF	3	3	3	3	3	3	3	3
R2	0.192	0.028	0.062	0.066	0.003	0.014	0.075	0.06
SER	0.891	0.977	0.734	0.756	1.216	1.293	0.821	0.758
BIC	2.424	2.685	2.024	2.222	2.646	2.880	2.108	2.193
DW	2.137	2.26	1.990	1.955	1.989	2.228	1.941	1.951

Notes: The table gives estimates for policy measures, decomposed into US and European constituents. Results are otherwise based on previous specifications (see Table 1), but other variables have been excluded for the ease of exposition. Dependent variables are 3m-5y CCBS rates. Estimation of all models via maximum likelihood assuming t-distributed errors and optimisation using the Eviews legacy algorithm with Marquard steps. BIC gives the Schwarz-Bayes Information Criterion, DW the Durbon-Watson Statistic and SER the standard error of the regression; Significance levels: $^{*} < 10\%$,$^{**} < 5\%$,$^{***} < 1\%$.

In terms of direct effects, widening currency bases appear to be driven by the US for both samples: almost all coefficients on FF_{US} are negative whilst coefficients on FF_{EU} are positive for longer maturities, indicating a narrowing on respective cross currency bases. Effects are generally significant, apart from one year maturities and the coefficient on FF_{US} in the 3m basis in the restricted and the 5y basis in the full sample. Respective coefficients indicate a shift from longer to shorter dated maturities, whilst the opposite effect is observable for the Eurozone. In terms of variances we can observe a shift of policy attention from capital to money markets in the US and to both, the very short and long end of considered tenors in Europe. This is unsurprising, indicating the increasing importance of policy rate-setting following the lift-off and successive increases in the FED Funds rate, whilst with the implementation of negative deposit rates and extensive quantitative and qualitative easing measures ECB interventions appeared to have affected both ends of the term structure.

However, results have to be interpreted with caution owing to detected outliers in the full sample.

4.7 Outlook and Conclusions

We investigate post-crisis failure of covered interest parity. Our theoretical explanation combines two models: The preferred habitat model, derived in chapter two explains pricing on domestic assets. This model allows to derive policy transmission channels onto asset returns. A model of risk averse swap arbitrage explains how intermediation costs lead to arbitrage-free bounds around CIP. In contrast to Chapter two, we hence assume specialised arbitrageurs, that target either domestic markets or FX swap markets. Policy then affects domestic returns, which is in turn transmitted onto FX swaps via CIP. But here arbitrage is costly and therefore incomplete and return differentials between foreign and domestic markets therefore lead to deviations from CIP. Since CIP arbitrage is constrained by risk in a similar way to domestic arbitrage, factors that affect risk, particularly volatility, affect CIP arbitrage directly. This model has implications on market segmentation and policy transmission. On the former, it suggests that segmentation is time-varying and linked to volatility. Policy is transmitted directly through its effect on domestic and foreign returns and indirectly through volatility.

Empirically we tackle three main questions raised by our model. The first two questions relate to the presence of time-varying frictions and a link between volatility and frictions. We answer both in an analysis of co-movement between CCBS rates using principal component analysis and a VECM framework for different volatility regimes with data from 2010-2018. Our findings indicate the presence of a second factor after 2015 as well as an increase in market segmentation after 2012. This marks a time when risk factors became insufficient in explaining observed CIP failures and policy rate expectations drifted apart. Analysing adjustment to an imposed constant term-structure provides further evidence for a relationship between volatility and market segmentation. Again effects differ across maturities: Whilst short dated CCBS continued to be driven by risk factors post 2012, CCBS carrying longer maturities were affected by the increasingly asymmetric policy environment.

We then tackle policy transmission onto CIP, which could be direct via rate expectations or indirect via variance processes. We feature this in models of CCBS of different tenors, that control for various transaction costs in addition to return and forward spreads. The models are estimated with EGARCH in mean, which allows for feedback of variance processes onto mean returns, in line with a volatility premium. As before, policy is captured with short-end interest rate futures and our Google attention measures. The measures enter as spreads, futures in means and attention in variances. This captures policy imbalances, that are presumed to be driving swap market imbalances. We find that both policy and volatility has significantly contributed to the failure of CIP. Swap market volatility is mainly driven by risk, both counterparty and market risk. The evidence suggests different dynamics for short maturities of CCBS, which appear to be mainly driven by volatility premia. Decomposing policy attention measures indicates that frictions are driven by both ECB and FED for short tenors and largely by the FED for longer maturities. There is further evidence indicating a shift of policy attention to the short end of the term structure in the US and both the very short and long ends in Europe, which is in line with respective policy interventions. These results are robust to controling for EPU and bank CDS indices, as well as timing of exchange trading hours. This shows that, when explicitly accounting for conditional volatility, foreign exchange swap markets are significantly affected by policy-imbalances and are subject to volatility premia, resulting from market segmentation. A combination of counter-party credit risk, market volatility and uncertainty, as well as policy affect this volatility channel. The impact of such risk channels is underestimated in models failing to explicitly model conditional variance processes.

Our results have important policy implications on the impact of policy imbalances on foreign exchange market clearing. In particular, our findings shed light on some, potentially unintended, adverse effects following the introduction of negative deposit rates and shows substantial effects of both, US policy rate increases and large scale asset purchases in Europe. More generally our findings highlight the impact of volatility and uncertainty on market returns. In our setting policy can affect uncertainty and improve market efficiency through its effect on arbitrage. On foreign exchange markets this effect is exacerbated as volatility, and therefore uncertainty, enters through both, market returns and its effect on swap market efficiency. This emphasises the need to consider the combination of policy-, risk-, and market-structural factors for the analysis of FX imbalances. Considering high-frequency data in conditional volatility models is crucial here as effects through volatility are otherwise easily overlooked, underestimating the impact of risk in general.

Our findings open several routes for further research. One feature of our analysis is the direct use of futures as policy measures to capture level effects of policy on returns. But policy-rate futures are affected by the zero lower bound, such as with European futures in our case. To mitigate this, policy measures could be extended following the shadow-rate model, proposed in Wu and Xia [2016] and Wu and Xia [2017], for daily frequencies. Since shadow policy rates have been below policy rates during times when the zero lower bound was binding, using this approach would likely further strengthen the effect of policy asymmetries. Policy measures could be further extended to cater for the effects of unconventional policies on the longer end of yield curves. There is further no explicit investigation of volatility effects on the CCBS term-structure, but instead we compare co-movement for different volatility regimes. Whilst this is sufficient for our purposes and provides evidence for the existence of a relation between volatility and segmentation, further research could extend this approach to explicitly evaluate the effect of volatility measures on the CCBS term structure. Lastly, whilst our theoretical structure is sufficient to highlight the transmission channels discussed, it could be extended to a general equilibrium framework, allowing for an analysis of international policy transmission on main macroeconomic aggregates and a discussion of implied welfare effects.

Chapter 5

Conclusion

This dissertation analyses global transmission of monetary policy. Traditional open-economy macroeconomic models assume policy independence, which is achieved by open fixed income (money- and capital-) markets in flexible exchange rate regimes, otherwise known as the impossibility trinity. This narrative informs the benchmark open-economy model, the Mundell-Flemming Model, which goes back to a series of independently published articles from Robert Mundell and Marcus Flemming from the 1960s. Two important parity conditions, covered and uncovered interest parity, follow from this model. Empirically, they both fail. Furthermore, there is mounting empirical evidence that policy is not independent and that, instead there is the presence of co-movement between financial cycles, the global financial cycle, which is linked to US monetary policy. The empirical link to policy is unsurprising, given the unprecedented global monetary expansion over the last two decades. The gradual withdrawal of this policy accommodation by the US Federal Reserve, at a time when other central banks continue their policy accommodation has led to sizeable imbalances on the global monetary policy landscape.

Observed imbalances with respect to policy and on global money and capital markets motivate this study of policy spill-overs, which we approach both theoretically and empirically. To explain international policy transmission, we modify a preferred habitat model of risk-averse arbitrage, that allows for a credit channel of policy, to global arbitrage portfolios. For this, we further assume that credit default risk can vary across assets. We use this model to derive policy transmission channels. Policy can affect fixed income markets directly via its effect on expected interest rates. This is in the spirit of signalling channels of policy transmission, such as forward guidance policies. Policy can further be transmitted indirectly through its effects on arbitrage and credit premia. This is in line with with portfolio-rebalancing and risk-taking channels of transmission, which explain the effectiveness of quantitative and qualitative easing type asset purchases. Policy effects can be amplified by volatility or have a direct effect on volatility and enter the model as volatility shocks. In both cases it affects a volatility premium that in turn affects arbitrage and therefore induces portfolio rebalancing behaviour. These channels are particularly important in terms of international transmission effects due to portfolio-rebalancing as the main driver of policy spill-overs. We further argue that there are signalling effects of portfolio rebalancing and, signalling and portfolio rebalancing channels are therefore not as clearly cut, as often discussed in the literature.

We investigate policy transmission empirically, using a case study of transmission between US and European (ECB) policy. The focus on Fed and ECB is to create a level playing field, as both central banks are similarly sized and operate in broadly similar market structures. We depart from standard macroeconomic low frequency data and analyse policy spill-overs with high-frequency (daily) data, which enables us to observe and control for time-varying volatility. For this, we propose a new high-frequency measure of policy attention using Google Trends data. This can be understood as revealed attention, where policy events are identified by agents' changing Google search behaviour. Using this approach as well as short term interest rate futures, Chapter 1 investigates policy transmission in univariate models of US and European fixed income returns. We find that policy effects transmit onto variances rather than mean processes. Mean returns are best explained by a regression on a proxy for global market risk, implied S&P500 volatility (VIX), only, which underlines theoretical predictions on volatility premia. Policy effects and spill-overs are significant for variance processes, but results are likely biased due to the presence of cross-correlations. We accommodate this in chapter 3 with an analysis of dynamic covariances between the asset returns considered. The estimation of dynamic covariances is difficult and led by a trade-off between computational efficiency and multivariate richness. We therefore use three estimation methods to negotiate this trade-off. We also use a novel approach and regress policy factors directly on estimated covariances. A side-effect of this approach is a dynamic view of portfolio correlations that provide a measure of portfolio rebalancing effects. Results indicate significant policy spill-overs that move both ways. Signalling, captured by interest futures is dominant for US policy, whereas other unconventional measures, captured by policy attention, dominate in Europe. Generally, policy attention allows capturing a larger amount of policy interactions. There is also clear evidence of portfolio rebalancing through both policy measures. For futures this indicates portfolio rebalancing effects through signalling as argued before. Our last chapter addresses policy transmission from a foreign exchange point of view. For this, we address the Covered Interest Parity (CIP) Puzzle as focal point. The puzzle arises from post-crisis failure of CIP, which used to hold almost exactly before 2008, in relatively calm markets. We approach this first by extending our theoretical model:

Instead of one global portfolio we now consider specialised arbitrage on domestic fixed income markets and foreign exchange swap markets. For this, we combine our previous model with a model of limits to arbitrage on swap markets. The model implies time-varying segmentation that is linked to volatility and the existence of direct and indirect transission of policy imbalances onto swap markets, in line with chapter 2. Empirically, we test both separately. We investigate market segmentation with an analysis of co-movement between different tenors of cross-currency bases, a common measure for CIP failure. Our results provide evidence for time-varying segmentation that is linked to volatility. We then analyse policy transmission by building models of CCBS using spreads between our policy measures and controlling for several market structural factors. Estimating with GARCH in mean further allows to test for feedback of volatility onto mean swap bases, which gives a measure for the volatility premium. We find a significant impact of policy rate imbalances, as well as significant feedback of variances onto CIP across tenors. Attention measures indicate that this effect is mostly carried by US policy, but ECB policies were significant for very short and long tenors.

Our results may have some policy implications: Whilst spill-overs are observed for variances rather than means, particularly effects on covariances provide evidence for portfolio rebalancing effects that question policy independence. Crucially, as spill overs are bi-directional, i.e. caused by both FED and ECB policy, large open economies are not immune to policy spill-overs, which challenges the common assumption of policy independence for large central banks. Policy imbalances create global market imbalances, which can be observed on FX swap markets. As arbitrage is limited, these imbalances cannot be completely absorbed and therefore persist. This effect is the stronger the more volatile markets are or the more sensitive pricing (i.e. arbitrage) is to volatility. Our results indicate that the latter is particularly relevant for money markets, where we find evidence for large volatility premiums. Whilst this is primarily driven by US policy, ECB's negative deposit rate policy has likely contributed to it, as it led to stronger link between money market conditions and volatility. This likely affected US money markets, but our results do not provide conclusive evidence. We therefore repeat an old prescription of the need for global policy-coordination, and, in the absence of this echo the claim of Rey among others to consider the use of money and capital market restrictions to contain adverse transmission effects. This is not in itself new, but we believe the severity of the problem is underestimated. Policy coordination is particularly important with respect to money markets, where the combined effect of negative deposit rates in Europe and increases in the fed funds rate in the US caused severe dislocations, that may be affect market stability. In this respect, policy mandates of globally significant central banks should consider the external effects of domestic policy.

Our findings are subject to important limitations. First, our investigation of policy transmission focusses on causal effects and not on forecasting of market returns. Therefore we do not employ sorted portfolios and the two-step estimators suggested by Fama and MacBeth [1973]. Secondly, whilst our models in Chapter 4 generally have good explanatory power in light of similar investigations using high-frequency data, we can only explain a small share of the variation in the data for most models. This hence leaves scope for alternative explanations for the CIP puzzle and a large share of observed imbalances remain unexplained. Lastly, we focus on policy transmission onto fixed income markets only. General equilibrium effects, both theoretically and empirically, are not subject of our investigation as this would go beyond the scope of this thesis and is therefore left for further research.

In addition to these limitations, this dissertation provides several routes for further research. First, we demonstrate that Google data can be used to obtain policy attention indices which are non-directional. Such indices are particularly useful to analyse contributions to second moments and could be replicated in several similar settings to analyse monetary policy in high-frequency settings. Secondly, we employ conditional volatility models to analyse policy transmission, which captures policy effects on risk-premia more accurately as it controls for the heteroskedasticity in the data. Both uni- and multivariate conditional volatility models could be used in several further settings where the relationship between policy and volatility are of interest. In this sense, estimating GARCH in mean is particularly interesting as a measure of volatility premia. Lastly, we analyse market segmentation on FX swap markets using vector-error correction models. This approach could be replicated in several different settings were an analysis of arbitrage and market segmentation is of interest. Our extension of existing preferred habitat models furthermore links domestic policy transmission to an open economy setting, which could also be replicated in different contexts to explain the link between domestic policies and global financial imbalances.

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Appendix A

Data Appendix

A.1 Tables for Section 3

A.1.1 Exogeneity of MPSI

We consider weak exogeneity of ECB and FED through orthogonality between residuals, obtained from a first-stage regression on the policy indices, and mean yields of the assets considered, hence

$$MPSI\_RESID_i \perp y_i$$

in

$$y_i = c + VIX_t + MPSI\_RESID_i$$

where

$$MPSI_t = MPSI_{t-1} + MPSI_{t-2} + MPSI_{t-3} + \sum_{j=1}^{7} y_j + MPSI\_RESID_i$$

$\forall i \neq j$.

MPSI considers either of both indices, i.e. ECBMPSI or FEDMPSI. The condition is violated for significance of $MPSI\_RESID_i$. Table 8 below gives the resulting t-statistics. We find endogeneity in model (5) for the ECB index only and a borderline case for the FED indices in (7) and (8). In these cases we lag the indices (the dependent variables in the first stage) once to satisfy exogeneity with t-statistics of -0.36, 0.5 and 0.8, respectively.

Table A.1 Endogeneity Tests

Dep Variables	(1)	(2)	(3)	(4)
Residuals	DUS_OIS	DUS_10Y	DUS_CORP	DUS_CORP_HY
$ECBMPSI\_RES_i$	0.778665	1.397571	-0.143735	-0.313435
$FEDMPSI\_RES_i$	0.736807	0.571022	0.043745	-0.303685

	(5)	(6)	(7)	(8)
	DXOIS	DXBUND	DXCORP_Y	DXCORP_HY
$ECBMPSI\_RES_i$	2.246291	0.915615	1.568577	0.115936
$FEDMPSI\_RES_i$	-1.196761	0.071963	1.755469	1.830374

We further consider exogeneity in a multivariate framework, based on a VAR(2) of asset means in first differences and a VAR(2) of asset variances obtained through a Dynamic Conditional Correlation filter. P-values of pairwise Granger causality tests are reported in Table 1 below.

Table A.2 Granger Causality Tests

	p-values			p-values	
Assets	DECBMPSI	DFEDMPSI	Asset Variances	ECBMPSI	FEDMPSI
DUS10Y	0.0973 *	0.9956	VAR(US10Y)	0.6707	0.4845
DUS_CORP	0.6302	0.5812	VAR(US_CORP)	0.2256	0.0627 *
DUS_CORP_HY	0.5036	0.9437	VAR(US_CORP_HY)	0.8207	0.6506
DUS_OIS	0.2463	0.4826	VAR(US_OIS)	0.6551	0.2283
DXBUND	0.1466	0.6887	VAR(XBUND)	0.6488	0.9170
DXCORP	0.4234	0.7204	VAR(XCORP)	0.6935	0.8903
DXCORP_HY	0.9252	0.1602	VAR(XCORP_HY)	0.4907	0.5012
DXOIS	0.6821	0.4501	VAR(XOIS)	0.8786	0.5725

Notes: * significant at 10% level.

Accordingly, there is no evidence for significant Granger-Causality on the policy attention measures for both, asset means and asset variances considered at the standard 5% significance level. [1] We therefore conclude that both asset means and variances cannot predict the attention measures proposed.

[1] In addition we considered impulse responses of asset variances to policy attention shocks, which are insignificant for all variances considered and hence not reported further.

A.2 Tables for Section 1.7

Table A.3 Residual Correlation Using Var in Levels and Differences

VAR in Differences

	DUS10Y	DUS_CORP	DUS_CORP_HY	DUS_OIS	DUSFF1M	DVIX	DXBUND	DXCORP_Y	DXCORP_HY	DXEONIA	DXOIS	DECBMPSI	DFEDMPSI
DUS10Y	1.000000												
DUS_CORP	−0.232478	1.000000											
DUS_CORP_HY	0.886253	−0.054648	1.000000										
DUS_OIS	0.281811	−0.128790	0.323901	1.000000									
DUSFF1M	0.049903	−0.033797	0.062790	0.103343	1.000000								
DVIX	−0.365259	0.472402	−0.250892	−0.171167	−0.003060	1.000000							
DXBUND	0.600881	−0.169905	0.561055	0.157824	−0.007553	−0.172810	1.000000						
DXCORP_Y	0.387913	0.033009	0.409418	0.045596	−0.004035	−0.035781	0.744097	1.000000					
DXCORP_HY	−0.156602	0.486512	−0.037626	−0.107220	0.005745	0.292500	−0.064417	0.207665	1.000000				
DXEONIA	−0.006196	−0.023278	−0.036791	0.046866	−0.021744	0.015948	−0.013243	0.005066	0.014710	1.000000			
DXOIS	0.097789	−0.040051	0.092341	0.067059	−0.079669	−0.040488	0.189747	0.208013	−0.042474	0.101069	1.000000		
DECBMPSI	0.043056	0.014718	0.026756	0.012488	0.042375	0.038764	0.053454	0.056064	0.019245	−0.025664	−0.077922	1.000000	
DFEDMPSI	0.002753	0.026137	−0.003602	0.010886	0.028832	0.002272	0.017999	0.071593	0.084173	0.019326	−0.032082	0.606408	1.000000

Notes: Results are estimated based on an unrestricted VAR in first differences including one lag, selected based on Schwarz and Hannan-Quinn LM-lag length criteria. Estimating a VAR with all variables in first differences is following the results of the ADF test, where depending on the assumptions on deterministic terms, we cannot reject unit roots on a 5% level for any of the variables. "X" indicates dollarised variables, i.e. variables variables multiplied by the USD/EUR exchange rate. "US" indicates american indices and VIX is the CBOE VIX volatility index.

VAR in Levels

	US10Y	US_CORP	US_CORP_HY	US_OIS	USFF1M	VIX	XBUND	XCORP_Y	XCORP_HY	XEONIA	XOIS	ECBMPSI	FEDMPSI
US10Y	1.000000												
US_CORP	−0.200647	1.000000											
US_CORP_HY	0.885822	−0.022961	1.000000										
US_OIS	0.287327	−0.139349	0.322199	1.000000									
USFF1M	0.063364	−0.057283	0.064930	0.080555	1.000000								
VIX	−0.357156	0.461250	−0.235641	−0.173438	−0.001904	1.000000							
XBUND	0.585517	−0.147100	0.558193	0.173238	0.024410	−0.161052	1.000000						
XCORP_Y	0.388363	0.049781	0.416621	0.052315	−0.003437	−0.026480	0.751066	1.000000					
XCORP_HY	−0.156304	0.516550	−0.055120	−0.206407	−0.012941	0.348234	0.016248	0.315695	1.000000				
XEONIA	0.003673	−0.023355	−0.026714	0.046255	−0.020108	0.006463	0.009991	0.030619	0.012226	1.000000			
XOIS	0.103285	−0.047595	0.101966	0.076745	−0.044042	−0.028859	0.217593	0.224228	−0.027293	0.106082	1.000000		
ECBMPSI	0.061014	−0.041082	0.019017	0.037513	0.030313	0.001654	0.022449	0.011043	−0.043013	$-4.25E-05$	−0.074524	1.000000	
FEDMPSI	0.013865	−0.009285	0.004131	0.026597	0.023886	−0.010217	0.018102	0.056480	0.065940	0.039998	−0.046479	0.609028	1.000000

Notes: Results are based on estimated an unrestricted VAR in levels including one lag, selected based on Schwarz and Hannan-Quinn LM-lag length criteria. "X" indicates dollarised variables, i.e. variables variables multiplied by the USD/EUR exchange rate. "US" indicates american indices and VIX is the CBOE VIX volatility index.

Appendix B

Technical Appendix

B.1 Arbitrage Portfolio Optimization

Assume an economy with two types of agents – arbitrageurs and investors. Arbitrage arises as holding return $R^P_{(t,t+1)}$ of a security between two respective periods. Eq. (B.1) describes arbitrageurs' preferences based on a mean-variance objective function:

$$E_t R^P_{(t,t+1)} - \frac{1}{2}\sigma Var_t R^P_{(t,t+1)} \tag{B.1}$$

$$R^P_{(t,t+1)} = \sum_{i=1}^{N} \omega^i_t R^i_{(t,t+1)} = \sum_{i=1}^{N} \omega^i_t [exp(\overline{p}^i_{t+1} - \overline{p}^i_t) - 1]$$

where ω^i_t represents the share arbitrageurs' holdings of bonds in habitat i relative to their net wealth W_t, and $\overline{p}^i_t$ is the price of a bond in habitat i at time t. These bonds are subject to credit risk, measured as risk intensity parameter ψ_t, such that

$$\overline{P}^{i,(0)}_{t+1} = \begin{cases} 1, & \text{with probability } exp(-\psi_{i,t+1}). \\ 0, & \text{with probability } 1 - exp(-\psi_{i,t+1}) \end{cases},$$

which is affine in a set of macroeconomic factors

$$\psi_{i,t+1} = \gamma_i' X_{t+1} \tag{B.2}$$

which follow the VAR process

$$X_t = \mu + \Phi X_{t-1} + \varepsilon_t \qquad \varepsilon_t \sim N(0, \Psi) \tag{B.3}$$

with log-bond prices of a pure-discount habitat i, default-risk-less bond given as

$$\overline{p_t^i} = -\overline{a}_i - \overline{b}_i' X_t, \tag{B.4}$$

its corresponding risk-free one-period rate as

$$\overline{r_t^i} = a_i + b_i' X_t,$$

and the continuously compounded yield y_t^i on a n-period bond in habitat i as $-p_t^i/n$. Arbitrageurs' portfolio holding return can be expressed as

$$\begin{aligned} R^P_{(t,t+1)} &= \sum_{i=1}^{N} \omega_t^i [exp(-\overline{a}_i - \overline{b}_i' X_{t+1} + \overline{a}_i + \overline{b}_i' X_t) - 1] \\ &= \sum_{i=1}^{N} \omega_t^i [exp(\overline{b}_i'(X_t - X_{t+1})) - 1], \end{aligned} \tag{B.5}$$

where an arbitrageur chooses ω_t^i such that[1]

$$\begin{aligned} &\max \ E_t[R^P_{(t,t+1)}] - \frac{1}{2}\sigma Var_t[R^P_{(t,t+1)}] \\ &s.t. \ : \ \sum_{i=1}^{N} \omega_t^i = 1 \end{aligned} \tag{B.6}$$

[1]The mean-variance objective function in (B.6) can be seen as no-arbitrage condition, where any positive difference, must be the result of an arbitrage opportunity, realised through the choice of ω_t^i.

where for small time increments we can approximate the conditional variance, $Var_t[R^P_{(t,t+1)}]$, and the conditional expected mean return, $E_t[R^P_{(t,t+1)}]$, such that[2]

$$
\begin{aligned}
E_t[R^P_{(t,t+1)}] &\approx \sum_{i=1}^{N} \omega_t^{(i)}[(-(\overline{b}_i' + \gamma_i')(\mu + \Phi X_t) \\
&\quad + \frac{1}{2}(\overline{b}_i' + \gamma_i)\Psi(\overline{b}_i' + \gamma_i) + \overline{b}_i' X_t]) \\
Var_t[R^P_{(t,t+1)}] &\approx d_t'\Psi d_t,
\end{aligned}
\tag{B.7}
$$

where

$$d = \sum_{i=1}^{N}(\omega_t^i(\overline{b}_i + \gamma_i))$$

represents a factor of exposure to macroeconomic risk.

The FOCs of the Lagrangean, L_t, corresponding with (B.7) are

$$
\begin{aligned}
\frac{\partial L_t}{\partial \omega_t^i} &= -(\overline{b}_i' + \gamma_i')(\mu + \Phi X_t) + \frac{1}{2}(\overline{b}_i' + \gamma_i)\Psi(\overline{b}_i' + \gamma_i) + \overline{b}_i' X_t) \\
&\quad -(\overline{b}_i' + \gamma_i')\Psi\sigma\sum_{i=1}^{N}[\omega_t^i(\overline{b}_i + \gamma_i)] - \chi_t = 0,
\end{aligned}
\tag{B.8}
$$

where χ_t is the Lagrange multiplier of the constraints.

Expressing the FOCs in terms of excess holding returns then yields

---

[2]Hamilton and Wu (2012) Hamilton and Wu [2012] show that for $q_{n,t+1} \equiv \frac{P_{(i,t+1)} - P_{it}}{P_{it}} = \exp\left(\mu_i h + \sqrt{h}\varepsilon_{i,t+1}\right) - 1$, $(\varepsilon_{1,t+1},\ldots,\varepsilon_{N,t+1})' \sim N(0,\Omega)$, the continuous time representation of a discrete time process,

$$
\begin{aligned}
E_t\left(\sum_{i=1}^{N} z_{it} R^P_{(t,t+1)}\right) &= \sum_{i=1}^{N} z_{it}[\mu_i h + \Omega_{ii} h/2 + o(h)] \\
Var_t\left(\sum_{i=1}^{N} z_{it}\right) &= z_t'\Omega z_t h + o(h),
\end{aligned}
$$

for $h = 1$ and $o(h) = 0$ leads to

$$
\begin{aligned}
\frac{P_{(i,t+1)}}{P_{it}} &= \exp[\overline{b}_i'(X_{t+1} - X_t)] \\
\mu_n &= \overline{b}_i'(c + \gamma X_t) - \overline{b}_i' X_t \\
\Omega_{ii} &= \overline{b}_i'\Psi\overline{b}_i,
\end{aligned}
$$

which implies (B.7).

$$\begin{aligned}
\text{where} \qquad R^i_{(t,t+1)} - \bar{r}_t &= \bar{b}_i' \Psi \lambda_t \\
R^i_{(t,t+1)} &\equiv -\bar{b}_i'(\mu + \Phi X_t) + \frac{1}{2}(\bar{b}_i' + \gamma_i')\Psi(\bar{b}_i + \gamma_i) \\
&\quad -\frac{1}{2}\gamma_i'\Psi\gamma_i + \bar{b}_i' X_t \\
\bar{r}_t &= \bar{a}_i + \bar{b}_i' X_t \\
\lambda_t &\equiv \sigma \sum_{i=1}^{N} (\omega_t^i(\bar{b}_i + \gamma_i))
\end{aligned} \tag{B.9}$$

Investors follow their preferred-habitat motifs over specific maturities in their demand as

$$\xi_t^i = \varphi(\bar{y}_t^i - \beta^i) \tag{B.10}$$

where ξ_t^i is the demand relative to the arbitrageurs' net wealth W_t, and β^i its intercept. In equilibrium the combined demand from arbitrageurs and investors then needs to equal the supply of bonds S_t^i

$$\omega_t^i + \xi_t^i = S_t^i \tag{B.11}$$

which combined with (B.9) gives the market price of risk as

$$\lambda_t = \sigma \sum_{i=1}^{N} (S_t^i - \xi_t^i)(\bar{b}_i + \gamma_i) \tag{B.12}$$

Using B.10 in B.12 and rearranging the FOCs in terms of bond yields, r_t^i, gives (2.1). □

Appendix C

Covariance Regressions

C.1 Overview

This section outlines results of the covariance regressions given in 4.8. The regressions use the same specification for dependent variables obtained through three different covariance filters. A.1 gives results using a DCC model, A.2 employs a BEKK model and A.3 uses the RiskMetrics exponential smoother.

The output tables are grouped as follows

- Variances, i.e. covariances of assets with themselves: Tables C.1, C.7 and C.13
- Domestic Covariances
  - US: Tables C.2, C.9 and C.15
  - Europe: Tables C.3, C.8 and C.14
- International Covariances
  - Money markets: Tables C.4, C.10 and C.16
  - Government bond markets Tables C.5, C.11 and C.17
  - Corporate markets: Tables C.6, C.12 and C.18

C.2 DCC Estimates

Table C.1 Variances

	var(US_OIS)	var(DUS10Y)	var(US_CORP_HY)	var(XOIS)	var(XBUND)	var(XCORP)	var(XCORP_HY)
c	0.000468489	0.008447661	0.007103555	-0.032071361	0.005485702	0.044242466	-0.017798717
	(0.16139)	(3.07773)	(3.32301)	(-0.41855)	(3.99261)	(2.60438)	(-0.43157)
AR(1)	1.040369113	0.993572114	1.008202785	0.871918285	1.099609736	0.425370459	0.78648002
	(41.63810)	(25.13671)	(24.65123)	(33.18703)	(40.61949)	(19.84667)	(28.69438)
AR(2)	-0.08583525	-0.008642492	-0.028261322	-0.102724862	-0.116788089	0.138777384	0.042993032
	(-2.85229)	(-0.21806)	(-0.69582)	(-2.73888)	(-4.27837)	(5.89787)	(1.58751)
ECBMPSI	2.36E-05	-0.000145277	-0.000136867	-0.001237764	5.71E-06	0.001055114	0.002060865
	(0.49412)	(-4.22828)	(-5.94272)	(-0.50229)	(0.27832)	(2.59076)	(1.40355)
FEDMPSI)	6.31E-06	-1.14E-05	8.23E-06	-0.000826294	-7.48E-06	-3.54E-05	0.000714214
	(0.12676)	(-0.35158)	(0.32397)	(-0.83587)	(-0.24476)	(-0.11900)	(1.33474)
VIX	1.76E-05	0.000106992	-2.41E-06	0.000213513	-1.94E-05	-0.000512269	0.002805902
	(0.32652)	(-1.90496)	(-0.04555)	(0.10588)	(-0.44105)	(-1.04749)	(3.88507)
EUFF	0.000196941	-0.000209386	-0.000218955	-0.001127157	0.000332593	0.00331551	0.001500602
	(1.11496)	(-1.529)	(-2.03460)	(-0.31646)	(3.30299)	(3.28582)	(0.77328)
USFF	-0.02996761	-0.000188102	0.000820379	-0.017920047	0.009464944	1.136934038	-0.015902417
	(-4.55983)	(-0.01362)	(-0.07247)	(-0.04006)	(1.13708)	(13.39725)	(-0.08751)
ECBMPSIxEUFF	-1.51E-07	1.18E-06	1.09E-06	1.23E-05	-8.22E-08	-9.36E-06	-1.75E-05
	(-0.02398)	(0.50751)	(0.55996)	(0.56136)	(-0.05305)	(-1.79551)	(-1.11892)
FedMPSIxUSFF	-5.70E-05	0.000179347	7.11E-05	0.006431949	5.15E-05	0.001142491	-0.002425673
	(-0.27989)	(1.40358)	(0.61544)	(2.26498)	(0.34739)	(1.12266)	(-0.91966)
ECBMPSI(-1)	-4.29E-05	-0.000116087	-1.29E-05	0.001526819	-0.000177208	-0.001976129	-0.001238149
	(-1.03005)	(-3.46201)	(-0.55750)	(0.53413)	(-9.85195)	(-4.86978)	(-0.87003)
FEDMPSI(-1)	2.09E-05	-1.05E-05	-1.10E-05	0.000499814	-1.42E-05	-6.95E-05	-0.000222464
	(0.42760)	(-0.26915)	(-0.36501)	(0.49163)	(-0.43709)	(-0.19706)	(-0.39572)
VIX(-1)	-4.59E-06	-4.87E-05	3.94E-05	-9.64E-05	4.56E-05	0.000531703	-0.002148158
	(-0.07370)	(-0.84424)	(0.76627)	(-0.05034)	(1.03263)	(1.07131)	(-2.81129)
EUFF(-1)	-0.000204463	0.000145143	0.00017057	0.001428721	-0.000371995	-0.003521009	-0.001446678
	(-1.17361)	(-1.05527)	(1.56330)	(0.40591)	(-3.69799)	(-3.48062)	(-0.74499)
USFF(-1)	0.032611359	-0.003957478	-0.003325993	-0.022405076	-0.012516172	-1.154166816	0.032844411
	(4.84575)	(-0.28628)	(-0.29225)	(-0.05015)	(-1.48496)	(-13.67908)	(0.18014)
ECBMPSI x EUFF(-1)	2.55E-07	9.83E-07	1.00E-07	-1.34E-05	1.46E-06	1.63E-05	1.10E-05
	(0.05089)	(-0.43862)	(0.05438)	(-0.50808)	(1.05952)	(3.06764)	(0.69464)
FedMPSI x USFF(-1)	-2.98E-05	-5.15E-05	-1.81E-05	-0.002874525	5.82E-05	-0.000255466	0.000985379
	(-0.14939)	(-0.30317)	(-0.12588)	(-0.90672)	(0.39316)	(-0.19890)	(0.39398)
Variance	1.90E-06	4.20E-06	2.56E-06	0.000864531	1.75E-06	0.000215674	0.000520988
	(6.70605)	(7.99365)	(6.73946)	(13.94684)	(6.63259)	(14.43589)	(13.37289)
DoF	10	10	10	10	10	10	10
	(3.68259)	(256707.6582)	(93693.45622)	(14.27696)	(525842.93680)	(11.53369)	(13.82676)
R-sq	0.945432876	0.987702928	0.849336144	0.729549957	0.729788014	0.725738142	0.725889641
DW	1.987915747	2.000101102	1.979428625	2.01187849	1.993326176	1.915531708	1.991755

Notes: Dependent variables are obtained through 3-stage DCC filter as outlined in section 2.1; model specification follows conditional auto-regressive dynamic lag representation with error-correction terms as presented in section 2.2; t-statistics are in paranthesis R-sq: adjusted R-squared; DW: Durbin-Watson statistic.

Table C.2 Covariances –US Markets

	US10Y - US_OIS	US_CORP - US_OIS	US_CORP_HY - US_OIS	US_CORP - US10Y	USCORP_HY - US10Y	US_CORP_HY - US_CORP
c	0.000768141	-0.000365668	0.000766923	-0.004519843	0.007045136	-0.000987557
	(2.68290)	(-5.42857)	(1.55504)	(-4.47326)	(3.44102)	(-3.25481)
AR(1)	1.083910427	0.938433666	1.10134014	0.931359661	1.003685909	0.938087887
	(46.52817)	(34.84536)	(47.71786)	(30.68554)	(24.29745)	(37.39530)
AR(2)	-0.114979848	-0.000571507	-0.128466539	-0.034961891	-0.021245422	0.005550305
	(-4.54889)	(-0.02118)	(-5.11669)	(-1.18716)	(-0.51445)	(0.22116)
ECBMPSI	-1.52E-05	1.39E-06	-1.85E-05	4.81E-05	-0.000125234	-6.00E-06
	(-2.15486)	(0.42380)	(-2.15766)	(3.99753)	(-5.37209)	(-0.85747)
FEDMPSI)	-7.54E-07	8.80E-07	1.45E-07	9.00E-06	-2.93E-06	-1.95E-06
	(-0.07878)	(0.25446)	(0.01140)	(0.46513)	(-0.12213)	(-0.21483)
VIX	1.04E-05	-2.24E-05	9.84E-06	-0.000225881	5.02E-05	8.65E-05
	(0.85948)	(-4.79104)	(0.63710)	(-8.17181)	(1.13218)	(6.73920)
EUFF	3.10E-05	-1.18E-05	3.69E-05	4.92E-05	-0.000182243	-1.21E-05
	(0.55718)	(-0.30820)	(0.59613)	(0.63267)	(-1.74975)	(-0.17869)
USFF	-0.00659191	-0.000103952	-0.008368264	-0.005167359	0.000368891	0.000886674
	(-4.04780)	(-0.09982)	(-3.98064)	(-0.63050)	(0.03607)	(0.19949)
ECBMPSIxEUFF	1.28E-07	-1.40E-08	1.54E-07	-3.94E-07	1.01E-06	4.73E-08
	(0.01756)	(-0.00072)	(0.02812)	(-0.21108)	(0.51599)	(0.00879)
FedMPSIxUSFF	6.32E-06	-9.06E-06	2.54E-06	-0.000126105	0.00011841	2.74E-05
	(0.18352)	(-1.15286)	(0.04931)	(-2.07588)	(1.20167)	(0.86519)
ECBMPSI(-1)	-7.45E-06	1.37E-05	-5.43E-06	0.000106434	-6.17E-05	2.96E-05
	(-1.06767)	(4.54279)	(-0.62394)	(7.98999)	(-2.73237)	(4.96905)
FEDMPSI(-1)	5.57E-06	-1.30E-06	6.50E-06	6.72E-06	-9.25E-06	-6.47E-06
	(0.52753)	(-0.36044)	(0.48009)	(0.32701)	(-0.31434)	(-0.65154)
VIX(-1)	-5.39E-06	1.71E-05	-4.79E-06	0.000165363	-8.29E-06	-7.44E-05
	(-0.40696)	(-3.47790)	(-0.28999)	(5.40399)	(-0.18733)	(-5.16045)
EUFF(-1)	-3.76E-05	1.57E-05	-4.35E-05	-7.80E-06	0.000131179	2.07E-05
	(-0.67850)	(-0.41120)	(-0.71032)	(-0.09973)	(1.24834)	(0.30417)
USFF(-1)	0.006965428	-4.96E-05	0.008895031	0.00596206	-0.003456632	-0.001358719
	(4.08317)	(-0.04734)	(4.08728)	(0.71879)	(-0.33625)	(-0.30191)
ECBMPSI x EUFF(-1)	4.08E-08	-1.17E-07	2.03E-08	-9.72E-07	5.20E-07	-2.29E-07
	(0.00655)	(-0.00911)	(0.00437)	(-0.50512)	(0.27656)	(-0.07214)
FedMPSI x USFF(-1)	-1.59E-05	1.02E-05	-1.72E-05	4.81E-05	-3.37E-05	-5.21E-06
	(-0.39654)	(1.19793)	(-0.31325)	(0.72875)	(-0.24784)	(-0.13645)
Variance	1.30E-07	1.95E-08	2.08E-07	1.01E-06	2.42E-06	1.86E-07
	(1.49414)	(0.35655)	(2.06686)	(5.52884)	(6.74279)	(1.96915)
DoF	10	10	10	10	10	10
	(197524.76900)	(513390.23560)	(194778.07590)	(4.43591)	(77687.73504)	(418283.83540)
R-sq	0.946026472	0.946029621	0.947421027	0.987603475	0.98769089	0.847235691
DW	1.987052472	1.968462334	1.986431834	1.983659716	1.994926438	2.001740745

Notes: Dependent variables are obtained through 3-stage DCC filter as outlined in section 2.1; model specification follows conditional auto-regressive dynamic lag representation with error-correction terms as presented in section 2.2; t-statistics are reported in paranthesis R-sq: adjusted R-squared; DW: Durbin-Watson statistic.

Table C.3 Covariances –European Markets

	XBUND - XOIS	XCORP - XOIS	XCORP_HY - XOIS	XCORP - XBUND	XCORP_HY - XBUND	XCORP - XCORP_HY
c	-0.000657621	-0.003916925	-0.000605798	0.018453569	0.00095572	0.006919935
	(-0.34472)	(-0.96714)	(-1.37281)	(5.55699)	(12.47096)	(2.08180)
AR(1)	0.914118233	0.669484607	0.976798545	0.641454493	0.9512559	0.593371156
	(27.60738)	(22.73669)	(34.52856)	(27.20085)	(36.56115)	(26.71644)
AR(2)	-0.065585145	0.084028699	-0.05932907	0.143415782	-0.021200219	0.170978333
	(-1.74930)	(3.09984)	(-2.20175)	(6.03493)	(-0.80297)	(6.60205)
ECBMPSI	-4.50E-05	0.00013963	5.21E-06	0.000182807	-1.59E-06	0.000365081
	(-2.10734)	(3.18710)	(0.72261)	(4.27960)	(-0.42291)	(8.42247)
FEDMPSI)	-3.52E-05	-6.62E-05	-2.70E-06	-2.74E-05	5.21E-06	6.71E-05
	(-1.01600)	(-0.96375)	(-0.22338)	(-0.43656)	(1.14358)	(1.20117)
VIX	1.03E-05	-1.30E-05	6.81E-07	-5.69E-05	3.43E-05	0.000241451
	(0.14160)	(-0.08101)	(0.03063)	(-0.51959)	(5.41654)	(2.43277)
EUFF	4.81E-05	0.000402318	-1.05E-05	0.000819562	2.69E-05	0.000536658
	(0.33129)	(1.37575)	(-0.17317)	(3.48844)	(0.94125)	(2.35323)
USFF	0.005506711	0.07165747	0.000355213	0.192607334	0.0014199	0.241647261
	(0.45463)	(4.87978)	(0.06979)	(10.47287)	(1.21483)	(10.63378)
ECBMPSIxEUFF	5.45E-07	-9.44E-07	-4.23E-08	-1.76E-06	3.56E-09	-3.14E-06
	(0.33322)	(-0.44056)	(-0.01050)	(-0.95817)	(0.00030)	(1.85585)
FedMPSIxUSFF	0.000286833	0.000575812	-8.28E-06	0.000370711	-1.23E-05	-8.82E-05
	(2.80129)	(2.73308)	(-0.21316)	(1.64452)	(-0.60313)	(-0.39290)
ECBMPSI(-1)	6.50E-05	-0.000119164	-1.23E-05	-0.000656265	-2.63E-05	-0.000509233
	(2.46242)	(-2.56922)	(-1.42198)	(-14.94477)	(-7.46668)	(-12.78064)
FEDMPSI(-1)	1.65E-05	3.52E-05	1.78E-06	-1.30E-05	-3.47E-06	-3.33E-05
	(0.45189)	(0.48425)	(0.15496)	(-0.18066)	(-0.73826)	(-0.53195)
VIX(-1)	5.59E-06	3.93E-05	-8.31E-08	0.000137802	-2.98E-05	-0.000119414
	(0.08146)	(0.26015)	(-0.00361)	(1.24410)	(-4.45664)	(-1.17956)
EUFF(-1)	-3.95E-05	-0.000361946	1.59E-05	-0.000928577	-3.49E-05	-0.000589474
	(-0.27191)	(-1.23226)	(0.26421)	(-3.95185)	(-1.21461)	(-2.59194)
USFF(-1)	-0.007107315	-0.074431779	-0.000431685	-0.200066581	-0.001548989	-0.243004125
	(-0.58812)	(-5.13289)	(-0.08428)	(-10.86729)	(-1.31951)	(-10.63177)
ECBMPSI x EUFF(-1)	-5.75E-07	1.01E-06	1.05E-07	5.46E-06	2.27E-07	4.28E-06
	(-0.36047)	(0.52222)	(0.02310)	(3.01153)	(0.02397)	(2.88869)
FedMPSI x USFF(-1)	-0.000143783	-0.000330885	4.70E-06	-9.68E-05	1.17E-05	7.63E-05
	(-1.26410)	(-1.45785)	(0.11846)	(-0.37508)	(0.60582)	(0.28856)
Variance	2.22E-06	9.94E-06	2.15E-07	1.43E-05	4.22E-08	1.22E-05
	(7.66161)	(14.18139)	(2.35340)	(14.83376)	(0.63592)	(14.55750)
DoF	10	10	10	10	10	10
	(343859.85540)	(9.64485)	(28804.52221)	(7.54119)	(204639.64920)	(8.34004)
R-sq	0.729550608	0.729543313	0.729543461	0.729774483	0.729774491	0.725731104
DW	2.014175018	2.005264769	1.971828769	1.982703888	2.011438778	1.945360686

Notes: Dependent variables are obtained through 3-stage DCC filter as outlined in section 2.1; model specification follows conditional auto-regressive dynamic lag representation with error-correction terms as presented in section 2.2; t-statistics are reported in paranthesis R-sq: adjusted R-squared; DW: Durbin-Watson statistic.

Table C.4 Covariances –Money Markets

	XOIS - US_OIS	XBUND - US_OIS	XCORP - US_OIS	XCORP_HY - US_OIS	XOIS - US10Y	XOIS -US_CORP	XOIS - US_CORP_HY
c	-0.000627671	0.000212342	-1.82E-05	-0.000649857	-0.001309534	0.001167994	-0.000516556
	(-6.47048)	(2.82728)	(-0.30640)	(-2.29252)	(-0.99546)	(3.00644)	(-0.46525)
AR(1)	0.952419504	1.129626538	0.809308964	0.900605069	0.941930936	1.022600719	0.924879147
	(32.19506)	(39.07546)	(34.25832)	(34.02278)	(30.06314)	(35.73032)	(29.94782)
AR(2)	-0.101088805	-0.156247461	0.127489865	0.026019742	-0.082233622	-0.127576846	-0.083216611
	(-3.11016)	(-5.18485)	(5.58794)	(1.00027)	(-2.35439)	(-4.83867)	(-2.32150)
ECBMPSI	6.40E-06	-2.55E-06	1.55E-05	6.37E-06	-2.91E-05	1.00E-05	-3.02E-05
	(1.67635)	(-0.60777)	(3.77805)	(0.92012)	(-2.07773)	(1.35977)	(-2.42440)
FEDMPSI)	-3.65E-06	2.05E-07	5.17E-07	-8.39E-06	-2.56E-05	7.86E-06	-2.07E-05
	(-0.69245)	(0.04679)	(0.18523)	(-1.11600)	(-1.06158)	(0.61357)	(-0.99390)
VIX	3.69E-06	4.01E-06	3.97E-06	-6.71E-05	4.38E-06	-1.42E-05	5.31E-06
	(0.37838)	(0.78733)	(0.67830)	(-5.34317)	(0.08404)	(-0.49323)	(0.12229)
EUFF	1.42E-05	2.17E-05	1.96E-05	-5.77E-05	1.95E-05	7.06E-06	4.33E-06
	(0.38299)	(0.55873)	(0.57134)	(-1.05495)	(0.18189)	(0.07820)	(0.04671)
USFF	0.000159052	-0.001983356	0.005404083	0.001057288	0.001921297	0.001037697	0.0026175
	(0.08799)	(-2.78499)	(8.13350)	(0.44691)	(0.17550)	(0.08699)	(0.32250)
ECBMPSIxEUFF	-3.28E-08	2.22E-08	-1.41E-07	-4.70E-08	3.54E-07	-9.89E-08	3.56E-07
	(-0.00297)	(0.00110)	(-0.00614)	(-0.00575)	(0.21449)	(-0.02462)	(0.16324)
FedMPSIxUSFF	3.74E-05	-4.74E-07	8.84E-06	2.96E-05	0.00019568	-3.26E-05	0.000180758
	(2.59411)	(-0.03239)	(1.04810)	(0.93089)	(2.71617)	(-0.66775)	(2.93619)
ECBMPSI(-1)	1.39E-05	-4.81E-06	-2.27E-05	1.38E-05	5.83E-05	-2.91E-05	5.63E-05
	(2.98512)	(-1.27414)	(-5.25248)	(1.94806)	(3.26438)	(-2.92573)	(3.64357)
FEDMPSI(-1)	4.12E-06	1.33E-06	1.85E-07	9.33E-07	1.32E-05	-5.56E-06	1.13E-05
	(0.77344)	(0.27799)	(0.06063)	(0.10566)	(0.52484)	(-0.46147)	(0.51575)
VIX(-1)	-3.75E-07	-1.82E-06	-1.97E-06	5.35E-05	7.41E-06	8.44E-06	3.37E-06
	(-0.03989)	(-0.35617)	(-0.33934)	(4.22630)	(0.14984)	(0.30040)	(0.08220)
EUFF(-1)	-9.28E-06	-2.36E-05	-1.93E-05	6.53E-05	-6.24E-06	-1.69E-05	1.99E-06
	(-0.25168)	(-0.60538)	(-0.56182)	(1.20355)	(-0.05870)	(-0.18799)	(0.02136)
USFF(-1)	8.26E-05	0.002110448	-0.005317289	-0.001649478	-0.0030102	-0.000869209	-0.003391622
	(0.04582)	(2.86063)	(-7.90068)	(-0.69096)	(-0.27502)	(-0.07278)	(-0.41850)
ECBMPSI x EUFF(-1)	-1.22E-07	3.35E-08	1.97E-07	-1.25E-07	-5.15E-07	2.57E-07	-4.95E-07
	(-0.01112)	(0.00188)	(0.00814)	(-0.01511)	(-0.28087)	(0.05831)	(-0.23015)
FedMPSI x USFF(-1)	-3.08E-05	-3.06E-06	-1.02E-05	-3.67E-06	-0.000109628	2.36E-05	-9.78E-05
	(-2.10287)	(-0.19546)	(-1.06121)	(-0.11284)	(-1.40700)	(-0.47867)	(-1.44211)
Variance	4.86E-08	2.06E-08	2.51E-08	1.54E-07	1.09E-06	1.74E-07	7.95E-07
	(0.69871)	(0.37210)	(0.44208)	(1.70377)	(5.55598)	(1.99742)	(4.78355)
DoF	10	10	10	10	10	10	10
	(1031891.57800)	(135230.55400)	(801945.51910)	(881795.69720)	(230614.80020)	(15650.63121)	(316821.87820)
R-sq	0.947413471	0.947425519	0.947423413	0.947385557	0.98765755	0.847235724	0.849335814
DW	2.00435263	1.980608479	1.992795905	1.9833508	2.008928414	1.954893551	2.016968519

Notes: Dependent variables are obtained through 3-stage DCC filter as outlined in section 2.1; model specification follows conditional auto-regressive dynamic lag representation with error-correction terms as presented in section 2.2; t-statistics are reported in paranthesis R-sq: adjusted R-squared; DW: Durbin-Watson statistic.

Table C.5 Covariances –Treasury Markets

	XBUND - US10Y	XCORP - US10Y	XCORP_HY - US10Y	XBUND - US_CORP	XBUND - US_CORP_HY
c	0.004313972	0.014621807	-0.001842215	-0.001098783	0.003397608
	(5.13469)	(5.72282)	(-1.61606)	(-5.79471)	(4.54298)
AR(1)	1.120558958	0.649011927	0.895293679	0.933221011	1.109417558
	(39.04295)	(25.84603)	(30.22465)	(32.48929)	(41.19630)
AR(2)	-0.138273388	0.114143503	-0.038794629	-0.03380182	-0.125515245
	(-4.76280)	(-4.73646)	(-1.24083)	(-1.24382)	(-4.59012)
ECBMPSI	-3.32E-05	0.000180037	-7.03E-05	9.37E-06	-1.95E-05
	(-3.06107)	(4.11775)	(-4.77108)	(2.05895)	(-1.89459)
FEDMPSI)	-7.35E-06	-3.08E-05	-3.62E-05	1.95E-06	-2.41E-06
	(-0.49783)	(-0.72505)	(-1.58722)	(-0.27904)	(-0.15695)
VIX	1.76E-05	-2.97E-05	-0.000210539	-7.84E-05	-2.50E-06
	(0.74694)	(-0.36569)	(-6.60250)	(-7.72907)	(-0.10420)
EUFF	0.000119383	0.000430394	-3.68E-05	4.40E-06	0.000118238
	(1.93522)	(2.51542)	(-0.49160)	(0.08806)	(1.90025)
USFF	0.003717829	0.134431494	-0.005867865	-0.002903621	0.00418179
	(0.41390)	(8.80888)	(-0.37981)	(-1.40621)	(0.64906)
ECBMPSIxEUFF	2.51E-07	-1.71E-06	6.32E-07	-7.60E-08	1.38E-07
	(0.14797)	(-0.64530)	(0.32289)	(-0.01549)	(0.07587)
FedMPSIxUSFF	6.53E-05	0.000342532	0.00010376	-3.78E-05	3.61E-05
	(1.08342)	(2.22798)	(0.98870)	(-1.79085)	(0.49630)
ECBMPSI(-1)	-9.96E-05	-0.000468843	8.21E-05	3.33E-05	-8.28E-05
	(-9.54133)	(-9.60036)	(5.91843)	(6.46898)	(-8.43223)
FEDMPSI(-1)	-7.26E-06	-1.49E-05	2.10E-05	3.72E-06	-7.93E-06
	(-0.44863)	(-0.29674)	(0.94269)	(0.50934)	(-0.49013)
VIX(-1)	4.66E-06	7.79E-05	0.000161001	5.56E-05	2.07E-05
	(0.18956)	(0.95223)	(4.71376)	(5.11463)	(0.86225)
EUFF(-1)	-0.000150549	-0.000504925	5.22E-05	6.30E-06	-0.000142432
	(-2.43615)	(-2.94429)	(0.69237)	(0.12676)	(-2.28637)
USFF(-1)	-0.005939704	-0.142494959	0.006230705	0.003159029	-0.00589847
	(-0.65694)	(-9.31402)	(0.40136)	(1.50310)	(-0.90721)
ECBMPSI x EUFF(-1)	8.20E-07	3.94E-06	-7.52E-07	-3.02E-07	6.82E-07
	(0.47330)	(1.37423)	(-0.40532)	(-0.05224)	(-0.37376)
FedMPSI x USFF(-1)	1.22E-05	-9.50E-05	-7.08E-05	9.17E-06	2.15E-05
	(0.18044)	(-0.52206)	(-0.72620)	(0.41038)	(0.29193)
Variance	6.81E-07	8.16E-06	1.28E-06	1.23E-07	5.66E-07
	(4.08433)	(18.32096)	(5.40640)	(1.43724)	(3.70888)
DoF	10	10	10	10	10
	(107537.80790)	(5.84415)	(3.85919)	(954928.89250)	(92037.79342)
R-sq	0.987632877	0.986664545	0.986611318	0.847235842	0.849419406
DW	1.996789996	1.972946085	1.999190156	1.990483854	1.995315597

Notes: Dependent variables are obtained through 3-stage DCC filter as outlined in section 2.1; model specification follows conditional auto-regressive dynamic lag representation with error-correction terms as presented in section 2.2; t-statistics are reported in paranthesis R-sq: adjusted R-squared; DW: Durbin-Watson statistic.

Table C.6 Covariances –Corporate Markets

	XCORP - US_CORP	XCORP_HY - US_CORP	XCORP - US_CORP_HY	XCORP_HY - US_CORP_HY
c	-0.000263348	0.001749919	0.011681195	0.000203754
	(-0.61540)	(0.26797)	(4.11970)	(1.55240)
AR(1)	0.818893652	0.877922544	0.629556721	0.893825385
	(29.90728)	(31.87892)	(26.00783)	(31.08987)
AR(2)	-0.031011319	-0.04437925	0.1139117	-0.012990073
	(-1.14372)	(-1.68264)	(4.65685)	(-0.44746)
ECBMPSI	3.08E-05	1.48E-05	0.000266342	-1.97E-05
	(4.44201)	(0.21985)	(6.35862)	(-4.36567)
FEDMPSI)	-6.83E-06	7.56E-05	-2.26E-05	-6.08E-06
	(-0.74377)	(0.75764)	(-0.44281)	(-1.07587)
VIX	9.38E-05	0.001398944	-4.29E-05	-5.94E-05
	(6.66738)	(8.13176)	(-0.46557)	(-6.25378)
EUFF	3.25E-05	0.000400686	0.000507711	-6.27E-06
	(0.69120)	(0.87922)	(2.53535)	(-0.10849)
USFF	0.015362299	0.02482042	0.173900899	-0.000593722
	(6.84683)	(0.32938)	(9.76539)	(-0.16415)
ECBMPSIxEUFF	-2.90E-07	-3.44E-07	-2.45E-06	1.76E-07
	(-0.09118)	(-0.19183)	(-1.05708)	(0.02214)
FedMPSIxUSFF	8.66E-05	-3.20E-05	0.000332286	1.80E-05
	(2.84027)	(-0.08582)	(1.82616)	(0.66502)
ECBMPSI(-1)	-5.36E-05	-0.000375511	-0.000467767	7.99E-06
	(-7.74957)	(-5.23155)	(-10.02546)	(1.93397)
FEDMPSI(-1)	-1.58E-06	-0.000100264	-9.14E-06	3.77E-06
	(-0.16174)	(-0.85981)	(-0.15438)	(0.65058)
VIX(-1)	-5.60E-05	-0.00095752	9.28E-05	4.63E-05
	(-3.78097)	(-5.12364)	(0.99835)	(4.78812)
EUFF(-1)	-3.05E-05	-0.000457353	-0.000552466	4.75E-06
	(-0.65011)	(-0.99536)	(-2.75950)	(0.08226)
USFF(-1)	-0.015619818	-0.023840023	-0.180005148	0.000732231
	(-6.80690)	(-0.31272)	(-10.09385)	(0.20101)
ECBMPSI x EUFF(-1)	4.83E-07	3.66E-06	3.93E-06	-8.64E-08
	(0.16066)	(2.07579)	(1.62605)	(-0.01146)
FedMPSI x USFF(-1)	-4.79E-05	0.000179872	-0.000134054	-9.80E-06
	(-1.42809)	(0.42984)	(-0.63069)	(-0.37757)
Variance	3.10E-07	3.53E-05	1.05E-05	8.38E-08
	(2.74807)	(14.36299)	(15.17342)	(1.05710)
DoF	10	10	10	10
	(73571.14925)	(8.25280)	(7.04979)	(1167204.99800)
R-sq	0.84723578	0.846973395	0.849353153	0.849353151
DW	1.992185135	1.985955872	1.963098056	2.005529005

Notes: Dependent variables are obtained through 3-stage DCC filter as outlined in section 2.1; model specification follows conditional auto-regressive dynamic lag representation with error-correction terms as presented in section 2.2; t-statistics are reported in paranthesis R-sq: adjusted R-squared; DW: Durbin-Watson statistic.

C.3 BEKK Estimates

Table C.7 BEKK Variances

	var(US_OIS)	var(US10Y)	var(US_CORP)	var(US_CORP_HY)	var(XOIS)	var(XBUND)	var(XCORP)	var(XCORP_HY)
	0.002691512	0.020047169	0.001797281	0.037326389	-0.004825673	0.047160451	0.025693297	-0.006158931
	(2.61317)	(4.00935)	(0.44942)	(3.09485)	(-0.25572)	(8.33750)	(2.46367)	(-0.40900)
AR(1)	0.977922466	0.967755187	1.029272264	0.908235982	0.9617041	0.264986543	0.86963249	0.769803274
	(35.47620)	(24.50336)	(33.98007)	(23.72682)	(38.71276)	(9.45158)	(39.24702)	(27.81545)
AR(2)	0.000911666	-0.004275126	-0.073432554	-0.031365046	-0.069966432	-0.060767871	-0.030708159	0.048102699
	(0.03224)	(-0.10745)	(-2.47431)	(-0.80876)	(-2.09527)	(-1.05164)	(-1.32274)	(1.79335)
ECBMPSI	6.31E-06	-0.000320991	-6.69E-05	-0.000562914	-0.000648047	-1.17E-05	0.000774275	0.001073397
	(0.35308)	(-6.79197)	(-1.59540)	(-1.89375)	(-3.42497)	(-0.14154)	(4.35601)	(3.92037)
FEDMPSI)	-2.39E-06	-2.43E-05	-1.15E-05	9.99E-05	-0.000338509	-3.35E-05	-1.72E-05	0.00037352
	(-0.11956)	(-0.34028)	(-0.16703)	(0.36971)	(-1.03365)	(-0.24042)	(-0.08311)	(1.33727)
VIX	3.15E-05	0.000236798	0.000555763	0.001204994	0.000135856	-8.93E-05	-0.000372352	0.00146776
	(1.05777)	(1.87617)	(6.04053)	(3.53579)	(0.18171)	(-0.44586)	(-1.12510)	(3.89819)
EUFF	0.000110329	-0.000455858	1.06E-05	-0.000296519	-0.001396457	0.001466634	0.002343367	0.000789771
	(1.49556)	(-1.52631)	(0.03773)	(-0.34392)	(-1.33976)	(3.32498)	(3.40130)	(0.78287)
USFF	-0.012112298	-0.000782331	0.00278135	-0.058546586	-0.010426808	0.040136878	0.752342623	-0.009019223
	(-2.92306)	(-0.02542)	(0.06745)	(-0.78463)	(-0.06907)	(1.07259)	(12.81086)	(-0.09596)
ECBMPSIxEUFF	-4.82E-08	2.60E-06	5.11E-07	3.74E-06	6.62E-06	-1.01E-07	-6.82E-06	-9.13E-06
	(-0.01135)	(1.69133)	(0.32700)	(0.98807)	(2.58521)	(-0.05040)	(-2.17192)	(-2.25492)
FedMPSIxUSFF	2.11E-05	0.000396088	0.000295815	0.000150962	0.002390772	0.000245788	0.000723542	-0.001267002
	(0.29354)	(1.45684)	(1.41471)	(0.12151)	(2.58042)	(0.36131)	(1.00779)	(-0.93083)
ECBMPSI(-1)	-0.000120901	-0.000254759	-0.000188396	-0.000304566	0.000424627	-0.000844281	-0.001393376	-0.00065162
	(-6.97635)	(-5.40850)	(-4.07109)	(-1.03081)	(1.62285)	(-11.18001)	(-7.98817)	(-2.61799)
FEDMPSI(-1)	2.46E-06	-2.28E-05	-2.31E-05	-2.84E-05	0.000298265	-6.92E-05	-5.03E-05	-0.000118473
	(0.10856)	(-0.26440)	(-0.30797)	(-0.10424)	(0.92576)	(-0.46847)	(-0.20948)	(-0.40414)
VIX(-1)	-1.24E-05	-0.00010929	-0.000333253	-0.001062684	-0.000107048	0.000223352	0.000380604	-0.001125178
	(-0.43684)	(-0.84700)	(-3.30895)	(-2.84871)	(-0.14683)	(1.10198)	(1.12291)	(-2.82600)
EUFF(-1)	-0.000133367	0.000306018	-4.93E-05	5.54E-05	0.001442871	-0.001674635	-0.002481261	-0.000762751
	(-1.80733)	(1.02760)	(-0.17438)	(0.06363)	(1.40224)	(-3.78481)	(-3.59510)	(-0.74930)
USFF(-1)	0.0118173	-0.008685932	-0.002361781	0.057518812	0.003761624	-0.055371338	-0.765134704	0.017806104
	(2.76406)	(-0.28136)	(-0.05660)	(0.78924)	(0.02482)	(-1.46680)	(-13.18506)	(0.18888)
ECBMPSI x EUFF(-1)	9.48E-07	2.15E-06	1.85E-06	2.96E-06	-4.35E-06	6.96E-06	1.15E-05	5.78E-06
	(0.23825)	(1.47646)	(0.98002)	(0.77277)	(-1.29756)	(3.43008)	(3.85075)	(1.35225)
FedMPSI x USFF(-1)	1.38E-05	-0.00011721	-0.000114817	-0.000295782	-0.00157139	0.00028995	-7.19E-05	0.000521431
	(0.16515)	(-0.31826)	(-0.49188)	(-0.23454)	(-1.55465)	(0.42908)	(-0.08237)	(0.40744)
Variance	8.07E-07	2.08E-05	9.42E-06	0.000146757	0.000106206	3.54E-05	9.74E-05	0.000142029
	(5.25810)	(10.78528)	(14.87546)	(11.40254)	(13.36425)	(12.35883)	(14.10915)	(13.12692)
DoF	10	10	10	10	10	10	10	10
	(875920.71850)	(5.54710)	(6.49353)	(8.74254)	(14.13219)	(11.71834)	(11.66134)	(13.63243)
R-sq	0.976451109	0.972724364	0.973018663	0.912192976	0.897556295	0.895370445	0.885938135	0.870126249
DW	2.005425923	2.000469896	1.985494164	1.994577502	2.023835458	2.003781717	1.97397469	1.990637006

Notes: Dependent variables are obtained through 3-stage BEKK filter as outlined in section 2.1; model specification follows conditional auto-regressive dynamic lag representation with error-correction terms as presented in section 2.2;t-statistics are reported in paranthesis R-sq: adjusted R-squared; DW: Durbin-Watson statistic.

Table C.8 BEKK Covariances – European Markets

	XBUND - XOIS	XCORP - XOIS	XCORP_HY - XOIS	XCORP - XBUND	XCORP_HY - XBUND	XCORP - XCORP_HY
	-0.011516177	-0.01196904	-0.006385203	0.033002325	0.002371111	0.014597066
	(-3.73859)	(-1.61676)	(-0.87230)	(5.51647)	(1.36535)	(2.58238)
AR(1)	0.946023795	0.907616384	0.788968434	0.269565549	0.917919392	0.721446712
	(29.60183)	(26.21580)	(17.98327)	(10.30468)	(25.66968)	(19.01189)
AR(2)	-0.052456544	-0.060358017	-0.072335308	-0.029245238	0.017470515	0.014535951
	(-1.50228)	(-1.28576)	(-1.74402)	(-0.58389)	(0.48055)	(0.32948)
ECBMPSI	0.000294468	-0.000120673	-8.65E-05	0.000423196	0.000134979	0.00021527
	(7.20885)	(-1.84186)	(-1.24398)	(4.99760)	(4.59502)	(3.10373)
FEDMPSI	3.52E-06	2.79E-05	-5.35E-05	-5.46E-05	-2.80E-06	7.30E-05
	(0.06283)	(0.24265)	(-0.38236)	(-0.40711)	(-0.09516)	(0.75934)
VIX	7.67E-05	0.000161864	-3.39E-05	-0.000199283	-8.25E-05	0.000255213
	(0.79549)	(0.66412)	(-0.17746)	(-0.78116)	(-1.85123)	(1.59292)
EUFF	0.000397683	-0.000514203	-0.0001431	0.001991294	0.000283386	0.001037525
	(2.04645)	(-1.12976)	(-0.33111)	(4.54266)	(2.61889)	(2.94567)
USFF	-0.005575301	-0.026609991	-0.010812215	0.026933246	0.023731738	0.068945031
	(-0.21593)	(-0.38612)	(-0.22815)	(0.70523)	(2.93491)	(1.62453)
ECBMPSIxEUFF	-2.21E-06	1.70E-06	1.53E-06	-3.68E-06	-1.10E-06	-1.98E-06
	(-0.95349)	(0.81279)	(0.85829)	(-1.68647)	(-0.60571)	(-1.24179)
FedMPSIxUSFF	-9.88E-05	-0.000446058	-1.25E-05	0.000411379	6.72E-06	-0.000262391
	(-0.55889)	(-1.24045)	(-0.03046)	(0.72967)	(0.05155)	(-0.69619)
ECBMPSI(-1)	0.000120882	0.000391189	0.000305197	-0.000874601	-0.000145992	-0.000590928
	(2.89884)	(5.08464)	(4.24492)	(-11.59150)	(-6.05641)	(-9.59280)
FEDMPSI(-1)	-1.27E-05	7.39E-06	0.000129184	-1.97E-05	5.46E-06	-8.57E-05
	(-0.21822)	(0.06065)	(0.94229)	(-0.13079)	(0.15202)	(-0.77380)
VIX(-1)	-3.95E-05	-0.000141534	-6.19E-05	0.000277421	3.12E-05	-0.000203381
	(-0.39761)	(-0.59155)	(-0.31009)	(1.16774)	(0.64194)	(-1.19162)
EUFF(-1)	-0.000305389	0.00060471	0.000187329	-0.002112416	-0.000299167	-0.001139663
	(-1.57379)	(1.30972)	(0.42936)	(-4.80160)	(-2.75256)	(-3.26005)
USFF(-1)	0.005225197	0.031399887	0.020805823	-0.037668514	-0.022580238	-0.067979935
	(0.19947)	(0.45417)	(0.43443)	(-0.98335)	(-2.74455)	(-1.59137)
ECBMPSI x EUFF(-1)	-1.04E-06	-3.44E-06	-2.81E-06	7.38E-06	1.35E-06	5.22E-06
	(-0.51051)	(-1.81371)	(-1.62687)	(3.50984)	(0.70505)	(3.10463)
FedMPSI x USFF(-1)	0.00012148	0.000169814	-0.000644675	-3.01E-05	-8.65E-05	0.000291362
	(0.61981)	(0.42059)	(-1.49744)	(-0.04775)	(-0.59887)	(0.68572)
Variance	7.21E-06	2.49E-05	3.55E-05	3.79E-05	2.90E-06	2.91E-05
	(19.95120)	(13.42788)	(18.53728)	(13.44867)	(11.36295)	(16.63105)
DoF	10	10	10	10	10	10
	(8.33166)	(12.72133)	(12.47562)	(12.28413)	(11.57835)	(11.39472)
R-sq	0.897504953	0.896868108	0.895904909	0.894761162	0.894762894	0.885361066
DW	1.995295531	2.002905044	1.98920745	2.008806361	2.003366729	2.007478435

Notes: Dependent variables are obtained through 3-stage BEKK filter as outlined in section 2.1; model specification follows conditional auto-regressive dynamic lag representation with error-correction terms as presented in section 2.2;t-statistics are reported in paranthesis R-sq: adjusted R-squared; DW: Durbin-Watson statistic.

Table C.9 BEKK Covariances – US Markets

	US10Y - US_OIS	US_CORP - US_OIS	US_CORP_HY - US_OIS	US_CORP - US10Y	USCORP_HY - US10Y	US_CORP_HY - US_CORP
	0.015886268	-0.002014771	0.002247976	-0.004640489	0.00952666	-0.00484698
	(3.45042)	(-1.23168)	(2.29934)	(-2.07855)	(3.29786)	(-2.19541)
AR(1)	0.982553693	0.948549159	0.995535003	0.90838442	0.966637646	0.835009205
	(24.92600)	(29.23612)	(39.76321)	(27.62362)	(20.15033)	(25.31832)
AR(2)	-0.005664597	-0.027308297	-0.007600152	0.03734672	0.007030558	0.107498848
	(-0.14308)	(-0.88525)	(-0.29607)	(1.13761)	(0.14928)	(3.30497)
ECBMPSI	-0.000272209	0.000165491	1.26E-05	8.46E-05	-0.000191389	6.65E-05
	(-6.70520)	(7.35315)	(0.82043)	(2.69065)	(-5.00857)	(1.55681)
FEDMPSI	-2.07E-05	3.31E-05	-1.26E-06	5.85E-05	7.40E-06	5.27E-05
	(-0.34783)	(1.09629)	(-0.06267)	(1.26132)	(0.16953)	(1.15965)
VIX	0.000203103	-0.000237451	4.66E-06	-0.000341083	0.000306526	-0.000185846
	(1.88731)	(-5.23760)	(0.15448)	(-5.70901)	(5.15801)	(-2.52605)
EUFF	-0.000391332	0.000233523	9.11E-05	0.000184545	-0.000127177	0.000294573
	(-1.53739)	(-1.90504)	(1.18069)	(1.27204)	(-0.82086)	(1.91370)
USFF	-0.000175243	0.005251524	-0.012424119	0.016828805	-0.006453955	0.01463178
	(-0.00671)	(0.40164)	(-3.31067)	(0.69832)	(-0.50662)	(0.82651)
ECBMPSIxEUFF	2.21E-06	-1.29E-06	-9.47E-08	-7.21E-07	1.39E-06	-5.21E-07
	(1.45587)	(-0.59764)	(-0.02276)	(-0.41119)	(0.61642)	(-0.19805)
FedMPSIxUSFF	0.000337049	-0.000187028	1.25E-05	-0.000292386	0.000100798	-0.000259528
	(1.49185)	(-1.92588)	(0.16658)	(-2.04617)	(0.54774)	(-1.78676)
ECBMPSI(-1)	-0.000215973	2.22E-05	-9.98E-05	0.000221204	-7.09E-05	0.00021725
	(-5.10829)	(0.89211)	(-6.66142)	(6.36473)	(-1.82220)	(5.06087)
FEDMPSI(-1)	-1.92E-05	-1.79E-05	3.84E-06	-3.74E-06	-1.86E-06	-5.16E-06
	(-0.26404)	(-0.49182)	(0.17602)	(-0.07485)	(-0.03823)	(-0.10141)
VIX(-1)	-9.33E-05	0.000142552	7.19E-06	0.000192112	-0.000272383	7.13E-05
	(-0.84970)	(2.95672)	(0.25237)	(3.10911)	(-4.22156)	(1.02508)
EUFF(-1)	0.000268874	-0.000205751	-0.000109756	-0.000132497	6.11E-05	-0.000245045
	(1.05803)	(-1.67547)	(-1.42354)	(-0.90778)	(0.39133)	(-1.58055)
USFF(-1)	-0.007615657	-0.004879736	0.011920813	-0.014273449	0.004641127	-0.011361229
	(-0.29113)	(-0.36937)	(3.09870)	(-0.58774)	(0.36574)	(-0.63493)
ECBMPSI x EUFF(-1)	1.83E-06	-3.06E-07	7.66E-07	-1.98E-06	6.28E-07	-1.88E-06
	(1.13066)	(-0.14512)	(0.21414)	(-1.02667)	(0.27795)	(-0.69708)
FedMPSI x USFF(-1)	-0.000101204	0.000123741	1.83E-05	6.63E-05	-7.07E-05	6.61E-05
	(-0.32528)	(-1.04866)	(0.21853)	(0.41313)	(-0.30387)	(0.37311)
Variance	1.51E-05	2.09E-06	6.70E-07	5.23E-06	5.10E-06	5.29E-06
	(10.75213)	(9.13802)	(4.57245)	(13.51817)	(8.13262)	(13.93847)
DoF	10	10	10	10	10	10
	(141311.01520)	(12.61676)	(291088.84750)	(9.82178)	(5.48255)	(9.35707)
R-sq	0.978828008	0.978744045	0.978774187	0.972453658	0.972397992	0.972801853
DW	2.000312059	1.961193807	2.004178353	1.996098827	1.996775964	2.011117025

Notes: Dependent variables are obtained through 3-stage BEKK filter as outlined in section 2.1; model specification follows conditional auto-regressive dynamic lag representation with error-correction terms as presented in section 2.2;t-statistics are reported in paranthesis R-sq: adjusted R-squared; DW: Durbin-Watson statistic.

Table C.10 BEKK Covariances – Money Markets

	XOIS - US_OIS	XBUND - US_OIS	XCORP - US_OIS	XCORP_HY - US_OIS	XOIS - US10Y	XOIS -US_CORP	XOIS - US_CORP_HY
	-0.002764308	0.000185797	-0.001060272	-0.000934894	0.000454058	-0.000930201	-0.000120536
	(-3.28817)	(0.54821)	(-2.39508)	(-0.66541)	(0.31759)	(-0.10787)	(-0.04093)
AR(1)	0.920686606	0.875435351	0.846694529	0.942861674	0.980986313	0.604032614	0.924322469
	(21.74211)	(26.81710)	(31.37604)	(26.61731)	(20.21512)	(21.49241)	(25.70333)
AR(2)	-0.040251857	0.089946446	0.051669652	0.015238504	-0.011458864	0.146954915	-0.044237255
	(-0.96243)	(2.68785)	(1.83661)	(0.45328)	(-0.23582)	(4.51644)	(-1.07203)
ECBMPSI	3.01E-05	2.63E-05	4.73E-05	7.12E-05	-9.34E-05	0.000157547	-0.00031833
	(2.49223)	(3.56898)	(6.08584)	(3.31610)	(-4.77401)	(1.59323)	(-8.19301)
FEDMPSI	5.71E-06	5.60E-06	-8.76E-07	1.89E-05	4.04E-06	-0.000171618	4.66E-05
	(0.34729)	(0.64227)	(-0.09345)	(0.91056)	(0.13299)	(-1.02369)	(0.77621)
VIX	1.57E-05	-2.01E-05	-5.03E-05	-0.000193748	0.000133289	-0.000438076	8.53E-05
	(0.60856)	(-1.62305)	(-3.12903)	(-5.53884)	(3.01150)	(-2.02488)	(0.79149)
EUFF	0.000223289	0.000103555	8.58E-05	-5.75E-05	-5.76E-05	0.001203593	0.000505526
	(3.10488)	(2.23700)	(1.85883)	(-0.54740)	(-0.48308)	(2.46256)	(2.33803)
USFF	0.003072209	0.005623331	-0.006387519	0.00311226	0.008411919	0.107440746	0.028117177
	(0.58988)	(2.38085)	(-3.12092)	(-0.45986)	(1.32166)	(2.42222)	(1.79223)
ECBMPSIxEUFF	-2.43E-07	-2.05E-07	-3.92E-07	-6.52E-07	7.82E-07	-8.25E-07	2.74E-06
	(-0.08025)	(-0.03772)	(-0.08295)	(-0.21398)	(0.36376)	(-0.46596)	(1.87014)
FedMPSIxUSFF	-9.63E-05	-2.78E-05	3.73E-05	2.00E-05	-2.88E-05	0.001160992	-0.000293967
	(-1.77145)	(-0.79377)	(1.14690)	(0.24962)	(-0.24763)	(2.18241)	(-1.56680)
ECBMPSI(-1)	5.35E-05	-4.00E-05	-9.49E-06	3.45E-06	1.56E-05	0.000230142	0.000218458
	(3.98840)	(-5.41973)	(-1.08294)	(0.15950)	(0.69460)	(2.21924)	(5.17335)
FEDMPSI(-1)	-8.19E-07	-5.66E-06	-3.06E-06	3.52E-06	8.03E-06	0.000195885	-3.09E-05
	(-0.04413)	(-0.51667)	(-0.25741)	(0.12686)	(0.28379)	(1.07688)	(-0.52737)
VIX(-1)	3.56E-06	3.22E-05	4.97E-05	0.000139973	-0.000111592	0.000199274	-6.14E-05
	(0.13218)	(2.46992)	(3.15836)	(3.83443)	(-2.17829)	(0.89384)	(-0.55529)
EUFF(-1)	-0.000203953	-0.000106532	-7.64E-05	7.12E-05	4.96E-05	-0.001165355	-0.000511439
	(-2.85422)	(-2.32942)	(-1.66563)	(0.67868)	(0.41542)	(-2.37354)	(-2.37210)
USFF(-1)	-0.000420002	-0.005084438	0.006585324	-0.003239765	-0.006847794	-0.106790857	-0.024349675
	(-0.07957)	(-2.09995)	(3.07186)	(-0.46514)	(-1.07167)	(-2.44764)	(-1.54150)
ECBMPSI x EUFF(-1)	-4.43E-07	3.17E-07	7.77E-08	-8.27E-08	-1.33E-07	-2.45E-06	-1.70E-06
	(-0.14013)	(0.06170)	(0.01758)	(-0.02807)	(-0.06270)	(-1.25213)	(-1.17165)
FedMPSI x USFF(-1)	6.83E-07	2.01E-05	-1.45E-05	-3.70E-05	-1.20E-05	-0.001390005	0.000174165
	(0.01148)	(0.48846)	(-0.35764)	(-0.36936)	-(0.11127)	(-2.67783)	(0.88186)
Variance	6.58E-07	1.77E-07	2.47E-07	1.46E-06	1.49E-06	4.54E-05	8.97E-06
	(5.04532)	(1.96970)	(2.65895)	(7.99161)	(5.76769)	(18.58274)	(16.73192)
DoF	10	10	10	10	10	10	10
	(6.10587)	(112753.43060)	(10.82185)	(8.79537)	(105865.02940)	(10.25965)	(264243.52900)
R-sq	0.978769724	0.978769088	0.978768422	0.978721926	0.972376486	0.968661546	0.912068527
DW	1.995548935	1.997409633	2.007431566	1.973126531	1.995138167	2.01767618	1.995921016

Notes: Dependent variables are obtained through 3-stage BEKK filter as outlined in section 2.1; model specification follows conditional auto-regressive dynamic lag representation with error-correction terms as presented in section 2.2;t-statistics are reported in paranthesis R-sq: adjusted R-squared; DW: Durbin-Watson statistic.

Table C.11 BEKK Covariances – Treasury Markets

	XBUND - US10Y	XCORP - US10Y	XCORP_HY - US10Y	XBUND - US_CORP	XBUND - US_CORP_HY
	0.00534923	0.002023929	-0.007063823	-0.000532045	0.004298916
	(4.64527)	(2.52728)	(-2.19129)	(-0.39499)	(3.96653)
AR(1)	0.979923641	1.004161807	0.843321057	0.916550907	0.978175425
	(25.25275)	(32.44179)	(23.52458)	(29.86192)	(28.24207)
AR(2)	-0.004558631	-0.030266902	0.073999012	0.012294968	-0.000814682
	(-0.11791)	(-0.99633)	(2.06193)	(0.40664)	(-0.02347)
ECBMPSI	-6.38E-05	-1.77E-05	0.000354421	6.55E-05	-1.33E-05
	(-3.76021)	(-1.43703)	(8.64317)	(3.21811)	(-0.84423)
FEDMPSI	-1.56E-05	-9.08E-06	0.00012986	4.28E-06	-3.48E-06
	(-0.76360)	(-0.67776)	(1.91890)	(0.17069)	(-0.17016)
VIX	3.21E-05	-5.68E-06	-0.000506029	-0.000118843	-1.43E-05
	(1.02251)	(-0.23751)	(-5.05801)	(-3.45900)	(-0.44009)
EUFF	0.000232072	0.000167898	0.00049668	0.00033029	0.000207224
	(2.90338)	(2.79664)	(2.40693)	(3.62928)	(2.74896)
USFF	0.003782914	-0.022698382	0.031421184	-0.005660027	0.005591396
	(0.41041)	(-5.58385)	(1.36264)	(-0.77067)	(0.73970)
ECBMPSIxEUFF	5.07E-07	9.98E-08	-3.00E-06	-4.67E-07	9.39E-08
	(0.33995)	(0.04511)	(-2.60483)	(-0.25722)	(0.05341)
FedMPSIxUSFF	9.61E-05	0.000126593	-0.000322786	-0.000123882	3.91E-05
	(1.15661)	(2.60826)	(-1.27401)	(-1.44006)	(0.43141)
ECBMPSI(-1)	-9.84E-05	-4.50E-05	-4.40E-05	2.52E-05	-0.000122341
	(-6.04802)	(-3.82370)	(-1.04323)	(1.23591)	(-7.44820)
FEDMPSI(-1)	-7.83E-06	2.00E-07	-5.05E-05	2.24E-05	-8.04E-06
	(-0.33091)	(0.01137)	(-0.66929)	(0.74053)	(-0.35159)
VIX(-1)	-3.20E-06	1.34E-05	0.000396387	1.23E-05	4.50E-05
	(-0.09796)	(0.56519)	(3.97659)	(0.32744)	(1.36415)
EUFF(-1)	-0.000268775	-0.000179378	-0.000440314	-0.000319103	-0.000238008
	(-3.35595)	(-2.99980)	(-2.12237)	(-3.48142)	(-3.15381)
USFF(-1)	-0.006848809	0.021592493	-0.025821706	0.009062635	-0.007674086
	(-0.73601)	(5.10121)	(-1.10447)	(1.19827)	(-1.00376)
ECBMPSI x EUFF(-1)	7.55E-07	3.79E-07	4.07E-07	-1.97E-07	9.63E-07
	(0.39771)	(0.16005)	(0.32859)	(-0.11443)	(0.43688)
FedMPSI x USFF(-1)	2.97E-05	-5.91E-05	2.33E-05	-8.44E-05	3.24E-05
	(0.30688)	(-0.96958)	(0.07386)	(-0.83846)	(0.31970)
Variance	1.33E-06	6.76E-07	1.28E-05	2.00E-06	1.11E-06
	(5.80684)	(4.63928)	(20.96656)	(9.68178)	(5.12567)
DoF	10	10	10	10	10
	(4.22064)	(5.77344)	(10.42657)	(7.30237)	(4.13671)
R-sq	0.972376289	0.972372291	0.971365907	0.96863409	0.912137452
DW	2.023112661	2.00801618	1.999491617	2.006587511	2.016404814

Notes: Dependent variables are obtained through 3-stage BEKK filter as outlined in section 2.1; model specification follows conditional auto-regressive dynamic lag representation with error-correction terms as presented in section 2.2;t-statistics are reported in paranthesis R-sq: adjusted R-squared; DW: Durbin-Watson statistic.

Table C.12 BEKK Covariances – Corporate Markets

	XCORP - US_CORP	XCORP_HY - US_CORP	XCORP - US_CORP_HY	XCORP_HY - US_CORP_HY
	0.002264068	0.0024009	0.03525905	-0.007117743
	(1.05026)	(0.33181)	(5.85832)	(-1.78634)
AR(1)	0.812131003	0.872487717	0.279444736	0.793400024
	(27.64732)	(30.45152)	(10.66421)	(21.12385)
AR(2)	0.077177546	0.004575616	-0.128841986	0.069487576
	(2.65247)	(0.17197)	(-4.56040)	(1.83550)
ECBMPSI	-2.38E-05	-0.000124981	-1.15E-05	0.000321463
	(-0.72460)	(-1.68653)	(-0.13831)	(6.91566)
FEDMPSI	6.66E-05	4.66E-05	-3.42E-05	0.000153351
	(1.64588)	(0.34308)	(-0.31998)	(1.90187)
VIX	9.81E-05	0.001527993	-0.000193166	-0.000395438
	(1.61934)	(8.88200)	(-0.93406)	(-3.01568)
EUFF	0.000569017	0.000686307	0.001259394	0.000847766
	(3.97766)	(1.54406)	(2.93016)	(3.64667)
USFF	-0.048851037	-0.093869419	-0.172555524	0.036420949
	(-3.99137)	(-3.15535)	(-5.48277)	(1.31417)
ECBMPSIxEUFF	1.37E-07	1.05E-06	-1.87E-07	-2.64E-06
	(0.06530)	(0.56179)	(-0.09770)	(-2.40488)
FedMPSIxUSFF	-0.000483261	-6.04E-05	0.000684288	-0.000412833
	(-3.64161)	(-0.12378)	(1.67544)	(-1.19655)
ECBMPSI(-1)	-0.000110689	-0.000443541	-0.000663335	-0.000109459
	(-3.62990)	(-5.66110)	(-7.77097)	(-2.11026)
FEDMPSI(-1)	-1.15E-05	-0.000159235	-2.82E-05	-7.64E-05
	(-0.23598)	(-1.22199)	(-0.19754)	(-0.82106)
VIX(-1)	-0.000104023	-0.000969209	0.000296068	0.000338548
	(-1.71546)	(-5.09580)	(1.46199)	(2.71159)
EUFF(-1)	-0.00059124	-0.000759616	-0.00139731	-0.000802083
	(-4.15600)	(-1.69918)	(-3.25594)	(-3.42790)
USFF(-1)	0.055613727	0.089634888	0.163189352	-0.029175335
	(4.51564)	(3.00771)	(5.14694)	(-1.04059)
ECBMPSI x EUFF(-1)	8.53E-07	4.18E-06	5.50E-06	1.09E-06
	(0.49774)	(2.49577)	(2.77661)	(0.90639)
FedMPSI x USFF(-1)	0.000198828	0.000485022	-0.000153561	0.00011919
	(1.31292)	(1.01838)	(-0.28034)	(0.28968)
Variance	4.75E-06	3.96E-05	4.31E-05	1.72E-05
	(13.52029)	(15.75502)	(14.29304)	(20.01489)
DoF	10	10	10	10
	(7.53078)	(8.82808)	(11.70225)	(10.81851)
R-sq	0.968544763	0.960367978	0.911089505	0.910673315
DW	2.012141453	1.976888168	2.011873152	2.013541827

Notes: Dependent variables are obtained through 3-stage BEKK filter as outlined in section 2.1; model specification follows conditional auto-regressive dynamic lag representation with error-correction terms as presented in section 2.2; t-statistics are reported in paranthesis R-sq: adjusted R-squared; DW: Durbin-Watson statistic.

C.4 RiskMetrics Estimates

Table C.13 RM Variances

	var(US_OIS)	var(US10Y)	var(US_CORP)	var(US_CORP_HY)	var(XOIS)	var(XBUND)	var(XCORP)	var(XCORP_HY)
c	-0.000362683	0.052934431	0.005276603	0.055837955	-0.015812484	0.024265175	0.019264348	-0.0082256
	(-0.08705)	(5.93270)	(0.67039)	(5.47489)	(-0.84862)	(4.67943)	(2.11492)	(-0.60803)
AR(1)	0.953501158	0.884570114	0.92707222	0.885262352	0.976916133	0.995187346	0.979252806	0.876567839
	(38.40626)	(22.47852)	(29.67942)	(21.79590)	(36.60758)	(37.37835)	(43.82025)	(30.51461)
AR(2)	-0.059513385	0.011182208	-0.028459164	-0.023791921	-0.093765244	-0.081656444	-0.056244308	0.031548099
	(-1.87544)	(0.28454)	(-0.94892)	(-0.58050)	(-2.81810)	(-2.83238)	(-2.37440)	(1.08826)
ECBMPSI	6.10E-05	-0.000644194	-0.000163064	-0.000897569	-0.000379085	1.26E-05	0.00070723	0.000983243
	(0.72167)	(-5.23150)	(-2.22294)	(-4.92988)	(-2.67918)	(0.17186)	(4.87808)	(4.63737)
FEDMPSI)	1.26E-05	-5.27E-05	-1.79E-05	5.43E-05	-0.000262627	-2.51E-05	-1.33E-05	0.000335081
	(0.17229)	(-0.36631)	(-0.12721)	(0.32180)	(-0.86791)	(-0.19777)	(-0.07137)	(-1.33117)
VIX	2.72E-05	0.000450973	0.00113599	-1.88E-05	5.19E-05	-5.91E-05	-0.000331416	0.001304384
	(0.33654)	(1.80975)	(6.24304)	(-0.05444)	(0.08417)	(-0.31474)	(-1.11981)	(3.87879)
EUFF	0.000308105	-0.000897345	-1.43E-05	-0.001431124	-0.000313827	0.00139636	0.002122317	0.00069425
	(1.21487)	(-1.54822)	(-0.02563)	(-2.09480)	(-0.28491)	(3.41767)	(3.43158)	(0.76491)
USFF	-0.044857284	-0.009979475	0.008115177	-0.001621585	-0.005827883	0.040741583	0.675632619	0.005540676
	(-4.46444)	(-0.15437)	(0.09988)	(-0.02061)	(-0.04024)	(1.18556)	(12.77860)	(0.06017)
ECBMPSIxEUFF	-4.27E-07	5.19E-06	1.24E-06	7.10E-06	3.81E-06	-2.75E-07	-6.22E-06	-8.38E-06
	(-0.06483)	(2.37750)	(0.75188)	(2.41064)	(1.63656)	(-0.14526)	(-2.19512)	(-2.49716)
FedMPSIxUSFF	-0.000105658	0.000794354	0.000587147	0.000456605	0.002009197	0.000206767	0.000621057	-0.001137487
	(-0.34572)	(1.39682)	(1.35108)	(0.57061)	(2.34151)	(0.33580)	(0.95652)	(-0.92221)
ECBMPSI(-1)	-3.77E-05	-0.000524049	-0.000398969	-0.000104752	0.000459287	-0.000731282	-0.001247668	-0.000523618
	(-0.47161)	(-4.03450)	(-4.90991)	(-0.53798)	(2.28649)	(-10.79629)	(-8.76027)	(-2.70671)
FEDMPSI(-1)	3.36E-05	-5.49E-05	-4.53E-05	-7.43E-05	0.000148062	-5.08E-05	-4.38E-05	-9.26E-05
	(0.47412)	(-0.32755)	(-0.29240)	(-0.37718)	(0.48330)	(-0.37742)	(-0.20408)	(-0.35368)
VIX(-1)	-3.86E-06	-0.000205389	-0.000706303	0.000279167	-2.03E-05	0.00018909	0.000341678	-0.000963524
	(-0.04149)	(-0.81012)	(-3.52654)	(0.83376)	(-0.03435)	(1.00075)	(1.12596)	(-2.69262)
EUFF(-1)	-0.000312445	0.000513163	-7.80E-05	0.001042326	0.000458417	-0.001573085	-0.002243789	-0.000678761
	(-1.24413)	(0.88589)	(-0.13902)	(1.50486)	(0.42032)	(-3.84622)	(-3.62616)	(-0.73968)
USFF(-1)	0.050193594	-0.013359648	-0.002706972	-0.017476487	-0.002113428	-0.052709914	-0.684065691	0.006457033
	(4.87816)	(-0.20585)	(-0.03290)	(-0.22096)	(-0.01460)	(-1.51895)	(-13.05156)	(0.06995)
ECBMPSI x EUFF(-1)	1.75E-07	4.39E-06	3.84E-06	7.94E-07	-4.06E-06	6.01E-06	1.02E-05	4.67E-06
	(0.02821)	(1.97816)	(2.63920)	(0.26677)	(-1.57169)	(3.10007)	(3.88522)	(1.30096)
FedMPSI x USFF(-1)	-6.12E-05	-0.000188111	-0.000223268	-9.27E-05	-0.000868015	0.000220692	-6.58E-05	0.000426784
	(-0.20577)	(-0.25413)	(-0.46146)	(-0.09699)	(-0.94667)	(0.36117)	(-0.08456)	(0.36966)
Variance	4.42E-06	7.97E-05	3.80E-05	0.000107959	8.32E-05	3.00E-05	7.79E-05	0.000113609
	(9.89425)	(11.98077)	(14.40994)	(11.48483)	(13.30896)	(12.36824)	(14.06522)	(12.99541)
DoF	10	10	10	10	10	10	10	10
	(8.11252)	(6.82994)	(9.65249)	(6.64896)	(13.60907)	(11.55123)	(11.59219)	(13.63946)
R-sq	0.868571059	0.893569157	0.893808961	0.883141074	0.878075128	0.877476463	0.879514948	0.880729028
DW	1.987741565	2.002604964	1.984797849	1.97990484	2.008860798	1.994298508	1.985400254	1.993747003

Notes: Dependent variables are obtained through 3-stage RM filter as outlined in section 2.1; model specification follows conditional auto-regressive dynamic lag representation with error-correction terms as presented in section 2.2;t-statistics are reported in paranthesis R-sq: adjusted R-squared; DW: Durbin-Watson statistic.

Table C.14 RM Covariances – European Markets

	XBUND - XOIS	XCORP - XOIS	XCORP_HY - XOIS	XCORP - XBUND	XCORP_HY - XBUND	XCORP - XCORP_HY
c	-0.019731187	-0.023968883	-0.004227832	0.015012289	0.007089207	0.014647666
	(-4.76123)	(-3.32941)	(-1.04375)	(2.73780)	(1.90965)	(2.86280)
AR(1)	0.829868678	0.835669091	0.828871462	0.999850527	0.832010596	0.828015653
	(12.49065)	(13.01135)	(19.46130)	(40.47501)	(22.46250)	(21.32728)
AR(2)	0.040361144	0.011415003	-0.038580429	-0.087290343	0.036398402	0.033759615
	(0.64053)	(0.19216)	(-0.92945)	(-3.20366)	(0.94010)	(0.83525)
ECBMPSI	0.000477506	0.000271146	1.73E-05	0.000387279	0.000260382	0.000153723
	(8.69589)	(4.11496)	(0.34491)	(5.22379)	(5.45004)	(2.51864)
FEDMPSI	1.25E-05	9.08E-05	-2.13E-05	-4.59E-05	-7.64E-06	6.93E-05
	(0.15051)	(0.77847)	(-0.26769)	(-0.37428)	(-0.12291)	(0.82278)
VIX	-4.85E-05	5.33E-05	-1.74E-05	-0.000175681	-0.000177946	0.000227815
	(-0.33507)	(0.26500)	(-0.17165)	(-0.74869)	(-1.85255)	(1.59394)
EUFF	0.001063358	0.000995971	0.000258071	0.001851104	0.000599166	0.000921743
	(4.12011)	(2.33406)	(1.09131)	(4.61280)	(2.63493)	(2.94884)
USFF	-0.004791539	-0.038127947	-0.00860569	0.028326564	0.051079909	0.06172389
	(-0.15250)	(-1.06145)	(-0.31048)	(0.81700)	(3.00574)	(1.68927)
ECBMPSIxEUFF	-3.64E-06	-1.59E-06	2.47E-07	-3.37E-06	-2.13E-06	-1.47E-06
	(-1.37287)	(-1.31729)	(0.08636)	(-1.61265)	(-1.62428)	(-0.91870)
FedMPSIxUSFF	-0.000189111	-0.000979532	-8.09E-05	0.000368721	2.55E-05	-0.000239174
	(-0.70215)	(-2.63685)	(-0.35252)	(0.72752)	(0.09352)	(-0.72225)
ECBMPSI(-1)	0.00025024	0.000445576	0.000136281	-0.000783173	-0.000339799	-0.000558013
	(4.56418)	(5.79015)	(2.59187)	(-11.64256)	(-8.24709)	(-10.12462)
FEDMPSI(-1)	-4.50E-05	-5.42E-05	6.58E-05	-8.69E-06	1.03E-05	-7.15E-05
	(-0.52212)	(-0.44049)	(0.81745)	(-0.06331)	(0.13752)	(-0.73193)
VIX(-1)	9.66E-05	-5.97E-06	-3.72E-05	0.000258615	6.81E-05	-0.000184304
	(0.64134)	(-0.02832)	(-0.34515)	(1.18682)	(0.64881)	(-1.20627)
EUFF(-1)	-0.000903234	-0.000810528	-0.000222691	-0.001955799	-0.000649088	-0.001040321
	(-3.50907)	(-1.89272)	(-0.93492)	(-4.85718)	(-2.84454)	(-3.34936)
USFF(-1)	0.003233276	0.044496962	0.012259794	-0.036484986	-0.049152564	-0.058255295
	(-0.10135)	(1.25245)	(0.43777)	(-1.04805)	(-2.84462)	(-1.58022)
ECBMPSI x EUFF(-1)	-2.08E-06	-3.75E-06	-1.32E-06	6.60E-06	3.09E-06	4.90E-06
	(-0.86343)	(-2.28351)	(-0.45957)	(3.19825)	(2.45678)	(2.95791)
FedMPSI x USFF(-1)	0.000299049	0.000528089	-0.000342443	-6.39E-05	-0.000176287	0.000241251
	(1.07728)	(1.27505)	(-1.39651)	(-0.11215)	(-0.58709)	(0.63973)
Variance	1.27E-05	2.67E-05	1.06E-05	3.19E-05	1.32E-05	2.32E-05
	(16.30013)	(14.51976)	(22.05718)	(13.56895)	(20.46047)	(16.70142)
DoF	10	10	10	10	10	10
	(11.90911)	(13.79707)	(12.61364)	(12.14656)	(11.73702)	(11.18624)
R-sq	0.877952069	0.877389625	0.877300317	0.877273139	0.877144372	0.879197647
DW	1.999452564	2.00865946	1.989777469	2.001577378	2.00550298	2.010645219

Notes: Dependent variables are obtained through 3-stage RM filter as outlined in section 2.1; model specification follows conditional auto-regressive dynamic lag representation with error-correction terms as presented in section 2.2;t-statistics are reported in paranthesis R-sq: adjusted R-squared; DW: Durbin-Watson statistic.

Table C.15 RM Covariances – US Markets

	US10Y -DUS_OIS	US_CORP - US_OIS	US_CORP_HY - US_OIS	XOIS - US_OIS	US_CORP - US10Y	USCORP_HY - US10Y	US_CORP_HY - US_CORP
c	0.004453781	-0.001853096	0.004928963	-0.003188267	-0.009011358	0.052987233	-0.009887652
	(1.92973)	(-1.07440)	(1.58865)	(-3.52576)	(-2.12243)	(5.96988)	(-2.25595)
AR(1)	0.883803455	0.880140216	0.891873609	0.853425687	0.816844911	0.867902394	0.745103874
	(30.79424)	(27.84710)	(35.08846)	(21.38199)	(25.29271)	(19.93704)	(22.34280)
AR(2)	0.023261224	-0.008369054	0.017714774	-0.03374931	0.056994596	0.006096583	0.103517225
	(0.74771)	(-0.27515)	(0.62381)	(-0.85624)	(1.77254)	(0.14077)	(3.12203)
ECBMPSI	5.34E-05	0.000167717	9.63E-05	4.12E-05	0.00014177	-0.000764166	0.000114626
	(1.11736)	(6.94721)	(1.56757)	(3.32852)	(2.93676)	(-5.82548)	(2.26895)
FEDMPSI)	-2.10E-06	3.34E-05	1.54E-06	5.12E-06	0.000109038	-1.76E-05	9.76E-05
	(-0.04681)	(1.03646)	(0.02464)	(0.28953)	(1.19787)	(-0.12168)	(1.06220)
VIX	6.92E-05	-0.000249726	1.43E-05	1.16E-05	-0.000666782	0.00021362	-0.000373418
	(1.02229)	(-5.24610)	(0.14645)	(0.39727)	(-5.71393)	(0.79003)	(-2.53401)
EUFF	0.00025943	0.000244815	0.00030513	0.00022277	0.000374164	-0.000994059	0.000609509
	(1.66312)	(1.89964)	(1.39477)	(2.90298)	(1.34382)	(-1.68943)	(2.02314)
USFF	-0.026125275	0.006754359	-0.036601543	0.003485347	0.033814742	0.001302094	0.031712845
	(-2.76328)	(0.50142)	(-3.04972)	(0.63516)	(0.69469)	(0.02018)	(0.86936)
ECBMPSIxEUFF	-4.19E-07	-1.30E-06	-7.45E-07	-3.34E-07	-1.22E-06	6.07E-06	-8.98E-07
	(-0.11994)	(-0.59270)	(-0.19215)	(-0.13391)	(-0.63754)	(-2.60917)	(-0.49192)
FedMPSIxUSFF	2.64E-05	-0.00019645	2.12E-06	-0.000104648	-0.00055273	0.00067977	-0.000498087
	(-0.16185)	(-1.90658)	(-0.00890)	(-1.79056)	(-1.97174)	(1.10450)	(-1.67648)
ECBMPSI(-1)	-0.000219827	1.55E-05	-0.000243086	5.63E-05	0.000413282	-0.000296262	0.000427874
	(-4.73006)	(0.58436)	(-3.80318)	(4.08571)	(7.97150)	(-2.11585)	(7.68852)
FEDMPSI(-1)	8.52E-06	-1.99E-05	1.67E-05	-1.42E-06	-1.17E-05	-5.63E-05	-1.79E-05
	(0.16606)	(-0.50947)	(0.24376)	(-0.07158)	(-0.11995)	(-0.32555)	(-0.17396)
VIX(-1)	-2.33E-05	0.000147557	3.10E-05	1.09E-05	0.000384831	-2.95E-05	0.000133761
	(-0.35817)	(2.90867)	(0.33838)	(0.36620)	(3.16343)	(-0.10988)	(0.95163)
EUFF(-1)	-0.000300119	-0.000217045	-0.000349435	-0.000200367	-0.000271791	0.000624459	-0.000505249
	(-1.92752)	(-1.67990)	(-1.59919)	(-2.62353)	(-0.97026)	(1.05154)	(-1.66220)
USFF(-1)	0.027207009	-0.006942412	0.03749055	-0.000491469	-0.031416798	-0.023086813	-0.02641782
	(2.77351)	(-0.51044)	(3.02704)	(-0.08817)	(-0.64098)	(-0.35524)	(-0.71789)
ECBMPSI x EUFF(-1)	1.73E-06	-2.58E-07	1.86E-06	-4.57E-07	-3.71E-06	2.42E-06	-3.72E-06
	(0.52876)	(-0.12064)	(0.49602)	(-0.18185)	(-1.85242)	(1.00683)	(-1.99368)
FedMPSI x USFF(-1)	8.55E-06	0.00012819	2.04E-05	9.81E-07	0.000143278	-0.000151855	0.000147308
	(0.04365)	(1.02435)	(0.07569)	(0.01541)	(0.45377)	(-0.18375)	(0.40652)
Variance	4.27E-06	2.33E-06	6.98E-06	7.51E-07	1.98E-05	8.06E-05	2.16E-05
	(11.08003)	(9.60769)	(23.93671)	(5.61883)	(18.93904)	(11.67223)	(18.98847)
DoF	10	10	10	10	10	10	10
	(8.69805)	(12.49187)	(9.70447)	(7.12321)	(10.16098)	(6.82575)	(11.22382)
R-sq	0.879872614	0.879543793	0.882116323	0.881935176	0.893045472	0.881437156	0.893022664
DW	2.003580714	1.962404859	2.002064226	1.996555602	1.99939122	1.997017199	2.012380837

Notes: Dependent variables are obtained through 3-stage RM filter as outlined in section 2.1; model specification follows conditional auto-regressive dynamic lag representation with error-correction terms as presented in section 2.2;t-statistics are reported in paranthesis R-sq: adjusted R-squared; DW: Durbin-Watson statistic.

Table C.16 RM Covariances – Money Markets

	XOIS - US_OIS	XBUND - US_OIS	XCORP - US_OIS	XCORP_HY - US_OIS	XOIS - US10Y	XOIS -US_CORP	XOIS - US_CORP_HY
c	-0.003188267	-0.000479323	-0.00243097	-0.000835502	-0.011300723	0.000389056	-0.009234434
	(-3.52576)	(-0.37989)	(-2.11842)	(-0.49328)	(-2.95019)	(0.11177)	(-2.27826)
AR(1)	0.853425687	0.764364082	0.730571463	0.863992079	0.826791122	0.645338204	0.883702205
	(21.38199)	(22.87794)	(27.07116)	(24.69881)	(20.81027)	(24.34488)	(23.70400)
AR(2)	-0.03374931	0.081747714	0.009857919	0.06002758	0.028278456	0.163834321	-0.021082643
	(-0.85624)	(2.12857)	(0.33047)	(1.85892)	(0.68755)	(5.39259)	(-0.48396)
ECBMPSI	4.12E-05	9.59E-05	0.00011565	7.55E-05	4.47E-05	5.97E-05	-2.91E-05
	(3.32852)	(4.91573)	(6.72788)	(2.87062)	(0.95758)	(1.47447)	(-0.59621)
FEDMPSI	5.12E-06	1.73E-05	-2.51E-06	2.23E-05	8.15E-05	-7.00E-05	0.000108606
	(0.28953)	(0.73092)	(-0.11896)	(0.88980)	(0.96135)	(-1.06578)	(1.26143)
VIX	1.16E-05	-5.57E-05	-0.000113996	-0.000238682	6.12E-05	-0.000172125	-5.10E-05
	(0.39727)	(-1.66556)	(-3.07491)	(-5.67907)	(0.45374)	(-1.97688)	(-0.31078)
EUFF	0.00022277	0.000292049	0.000197981	-8.00E-05	0.001190312	0.000484766	0.001365634
	(2.90298)	(3.13000)	(2.30285)	(-0.64711)	(4.25063)	(2.39785)	(4.61926)
USFF	0.003485347	0.015705985	-0.015669799	0.004005625	0.025487008	0.043716408	0.033567688
	(0.63516)	(2.30408)	(-3.25093)	(0.49091)	(0.59504)	(2.50479)	(0.77508)
ECBMPSIxEUFF	-3.34E-07	-7.49E-07	-9.55E-07	-7.07E-07	-1.62E-07	-2.92E-07	3.85E-07
	(-0.13391)	(-0.35857)	(-0.45296)	(-0.25207)	(-0.13372)	(-0.23155)	(0.24862)
FedMPSIxUSFF	-0.000104648	-8.82E-05	9.03E-05	2.87E-05	-0.00089063	0.000456567	-0.000871008
	(-1.79056)	(-0.89393)	(1.20519)	(0.29995)	(-3.41874)	(2.16647)	(-3.21379)
ECBMPSI(-1)	5.63E-05	-9.07E-05	-3.11E-05	-1.41E-05	0.000273448	9.11E-05	0.000335893
	(4.08571)	(-4.53231)	(-1.64715)	(-0.53311)	(5.20496)	(2.29097)	(5.90408)
FEDMPSI(-1)	-1.42E-06	-1.48E-05	-9.08E-06	3.39E-06	-4.90E-05	7.83E-05	-6.47E-05
	(-0.07158)	(-0.48456)	(-0.33519)	(0.09892)	(-0.58499)	(1.11097)	(-0.75640)
VIX(-1)	1.09E-05	9.15E-05	0.000112358	0.000177967	-1.52E-05	6.84E-05	9.80E-05
	(0.36620)	(2.56087)	(3.09405)	(4.07588)	(-0.11073)	(0.76056)	(0.59185)
EUFF(-1)	-0.000200367	-0.000293507	-0.000176296	9.40E-05	-0.00111287	-0.000474307	-0.001305553
	(-2.62353)	(-3.18545)	(-2.05422)	(0.76216)	(-3.95286)	(-2.33009)	(-4.39096)
USFF(-1)	-0.000491469	-0.013148029	0.015986363	-0.004627455	-0.015296777	-0.044076992	-0.024068937
	(-0.08817)	(-1.88499)	(3.20034)	(-0.55100)	(-0.35479)	(-2.57453)	(-0.55121)
ECBMPSI x EUFF(-1)	-4.57E-07	7.21E-07	2.55E-07	4.35E-08	-2.16E-06	-9.68E-07	-2.63E-06
	(-0.18185)	(0.32758)	(0.13025)	(0.01658)	(-1.41636)	(-0.72267)	(-1.42281)
FedMPSI x USFF(-1)	9.81E-07	4.75E-05	-2.30E-05	-4.10E-05	0.000483572	-0.000572706	0.000437193
	(-0.01541)	(0.40566)	(-0.24446)	(-0.33832)	(1.85996)	(-2.85955)	(1.51190)
Variance	7.51E-07	1.40E-06	1.37E-06	2.16E-06	1.59E-05	7.41E-06	1.83E-05
	(5.61883)	(7.47093)	(7.97053)	(9.74009)	(18.44698)	(29.26518)	(18.20298)
DoF	10	10	10	10	10	10	10
	(7.12321)	(5.94760)	(9.94549)	(9.50293)	(12.29994)	(8.24933)	(13.03442)
R-sq	0.881935176	0.88137407	0.880874595	0.882187881	0.880868518	0.892939248	0.882788451
DW	1.996555602	1.994799916	1.99867723	1.983756222	2.024688437	2.02303203	2.022500978

Notes: Dependent variables are obtained through 3-stage RM filter as outlined in section 2.1; model specification follows conditional auto-regressive dynamic lag representation with error-correction terms as presented in section 2.2;t-statistics are reported in paranthesis R-sq: adjusted R-squared; DW: Durbin-Watson statistic.

Table C.17 RM Covariances – Treasury Markets

	XBUND - US10Y	XCORP - US10Y	XCORP_HY - US10Y	XBUND - US_CORP	XBUND - US_CORP_HY
c	0.024834873	0.015616964	-0.00919612	-0.000403534	0.023881409
	(5.58861)	(3.08644)	(-2.00132)	(-0.16241)	(4.68300)
AR(1)	0.868261365	0.880497263	0.803408252	0.822852625	0.866212184
	(22.83452)	(28.92753)	(22.35960)	(26.92166)	(25.51443)
AR(2)	0.01059031	-0.041210718	0.093271378	0.036075642	0.007433039
	(0.28405)	(-1.33695)	(2.58548)	(1.16813)	(0.21458)
ECBMPSI	-0.000283419	-0.000151083	0.000486907	0.000103595	-5.52E-05
	(-4.58795)	(-2.14170)	(8.57690)	(3.04104)	(-0.77080)
FEDMPSI)	-6.67E-05	-6.53E-05	0.000180665	4.95E-06	-1.34E-05
	(-0.73755)	(-0.70364)	(1.85228)	(0.10548)	(-0.12017)
VIX	0.000148958	-3.37E-05	-0.000728559	-0.000227114	-6.38E-05
	(1.06422)	(-0.20595)	(-5.03413)	(-3.47800)	(-0.36071)
EUFF	0.001043431	0.001158216	0.000722883	0.000626437	0.00114115
	(3.02062)	(3.13435)	(2.42706)	(3.76743)	(2.98247)
USFF	0.017353781	-0.159613086	0.046031659	-0.011516828	0.030718366
	(0.42406)	(-5.85816)	(1.44718)	(-0.82048)	(0.74162)
ECBMPSIxEUFF	2.23E-06	9.03E-07	-4.13E-06	-7.24E-07	3.43E-07
	(1.26920)	(0.53304)	(-3.36593)	(-0.45464)	(0.17161)
FedMPSIxUSFF	0.000426004	0.000892291	-0.000445751	-0.00022006	0.000198475
	(1.15888)	(2.65026)	(-1.20902)	(-1.40069)	(0.40309)
ECBMPSI(-1)	-0.000436201	-0.000356541	-0.00010036	4.02E-05	-0.000646451
	(-7.79230)	(-5.39357)	(-1.75025)	(1.12998)	(-9.20619)
FEDMPSI(-1)	-3.18E-05	-5.04E-06	-7.85E-05	4.06E-05	-3.93E-05
	(-0.30437)	(-0.04129)	(-0.72303)	(0.71116)	(-0.31740)
VIX(-1)	-6.70E-06	9.19E-05	0.000573941	2.95E-05	0.0002543
	(-0.04619)	(0.55753)	(3.99455)	(0.40774)	(1.40152)
EUFF(-1)	-0.001215311	-0.001252913	-0.000647025	-0.000609314	-0.001315672
	(-3.50032)	(-3.39610)	(-2.16304)	(-3.64309)	(-3.42405)
USFF(-1)	-0.030682398	0.151655555	-0.038937317	0.016527326	-0.041537974
	(-0.74231)	(5.43150)	(-1.20576)	(1.14143)	(-0.99330)
ECBMPSI x EUFF(-1)	3.32E-06	2.98E-06	8.88E-07	-3.14E-07	5.06E-06
	(1.96698)	(1.72773)	(0.69599)	(-0.19854)	(2.66253)
FedMPSI x USFF(-1)	0.000127693	-0.000375099	5.26E-05	-0.000151118	0.000167576
	(0.29683)	(-0.88416)	(0.11579)	(-0.81975)	(0.30354)
Variance	2.63E-05	3.30E-05	2.65E-05	7.25E-06	3.28E-05
	(13.29229)	(15.98635)	(18.99253)	(34.80415)	(12.55588)
DoF	10	10	10	10	10
	(9.43897)	(10.82912)	(10.45334)	(8.13857)	(10.77618)
R-sq	0.87956103	0.877250808	0.875979313	0.892889557	0.881786522
DW	2.024378038	2.005165061	2.003177461	2.006300119	2.017373115

Notes: Dependent variables are obtained through 3-stage RM filter as outlined in section 2.1; model specification follows conditional auto-regressive dynamic lag representation with error-correction terms as presented in section 2.2;t-statistics are reported in paranthesis R-sq: adjusted R-squared; DW: Durbin-Watson statistic.

Table C.18 RM Covariances – Corporate Markets

	XCORP - US_CORP	XCORP_HY - US_CORP	XCORP - US_CORP_HY	XCORP_HY - US_CORP_HY
c	0.003519231	0.002404425	0.01807489	-0.008188955
	(1.12958)	(0.43423)	(2.98499)	(-1.59069)
AR(1)	0.737260656	0.851299154	0.897455515	0.784968647
	(25.31991)	(29.86816)	(33.00865)	(20.76156)
AR(2)	0.08270923	0.030918262	-0.04750425	0.086041627
	(2.72305)	(1.18729)	(-1.64640)	(2.24790)
ECBMPSI	-4.08E-05	-0.000122504	9.57E-06	0.000382922
	(-1.00488)	(-2.23631)	(0.11034)	(6.27843)
FEDMPSI)	9.71E-05	4.20E-05	-3.06E-05	0.000193962
	(1.62945)	(0.40707)	(-0.28229)	(1.83873)
VIX	0.000144062	0.001174157	-0.00016384	-0.00051801
	(1.63109)	(8.99368)	(-0.78850)	(-3.03061)
EUFF	0.000843113	0.000500677	0.001355394	0.00110585
	(-4.04653)	(-1.47172)	(-3.12916)	(-3.62912)
USFF	-0.073377995	-0.071914363	-0.166200738	0.048609963
	(-4.03366)	(-3.17729)	(-5.28222)	(1.38308)
ECBMPSIxEUFF	2.51E-07	9.77E-07	-3.57E-07	-3.16E-06
	(0.14414)	(0.51237)	(-0.18521)	(-2.46618)
FedMPSIxUSFF	-0.00071061	-3.99E-05	0.000633909	-0.000508631
	(-3.64767)	(-0.11061)	(1.53951)	(-1.11263)
ECBMPSI(-1)	-0.000159681	-0.000353334	-0.000610899	-0.00018365
	(-3.65786)	(-6.36782)	(-6.87536)	(-2.72179)
FEDMPSI(-1)	-1.82E-05	-0.000116171	-1.15E-05	-0.000104864
	(-0.25221)	(-1.16322)	(-0.07893)	(-0.86491)
VIX(-1)	-0.000160062	-0.000729003	0.000276269	0.00043903
	(-1.78503)	(-5.08054)	(1.34446)	(2.70128)
EUFF(-1)	-0.000877233	-0.000565832	-0.001480778	-0.001052985
	(-4.22928)	(-1.65267)	(-3.42559)	(-3.43369)
USFF(-1)	0.083674845	0.072308929	0.160928303	-0.038790803
	(4.57387)	(3.17975)	(5.05918)	(-1.08971)
ECBMPSI x EUFF(-1)	1.24E-06	3.27E-06	5.03E-06	1.73E-06
	(0.69134)	(1.75953)	(2.46535)	(1.25442)
FedMPSI x USFF(-1)	0.000295602	0.000377324	-0.000227648	0.000177431
	(1.32070)	(1.06041)	(-0.41437)	(0.32952)
Variance	1.04E-05	2.30E-05	4.38E-05	2.95E-05
	(22.65801)	(15.74014)	(14.34950)	(19.12747)
DoF	10	10	10	10
	(9.39408)	(7.94162)	(11.80036)	(10.93348)
R-sq	0.89272307	0.89425672	0.87985129	0.878994032
DW	2.016119859	1.975812075	2.005686271	2.016421711

Notes: Dependent variables are obtained through 3-stage RM filter as outlined in section 2.1; model specification follows conditional auto-regressive dynamic lag representation with error-correction terms as presented in section 2.2;t-statistics are reported in paranthesis R-sq: adjusted R-squared; DW: Durbin-Watson statistic.

C.5 Additional Figures for Section 3.4

Fig. C.1 RiskMetrics Variances and Covariances

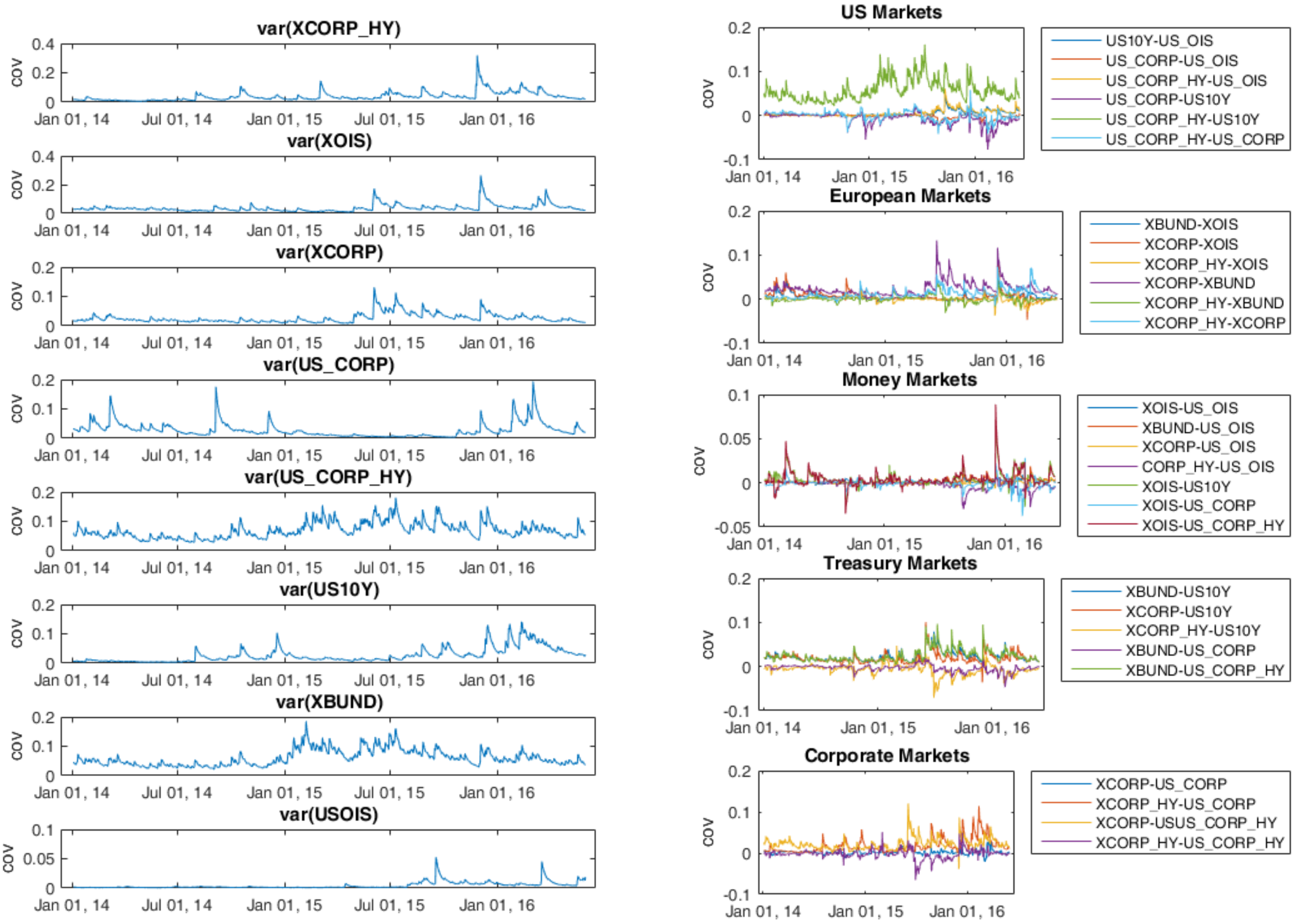
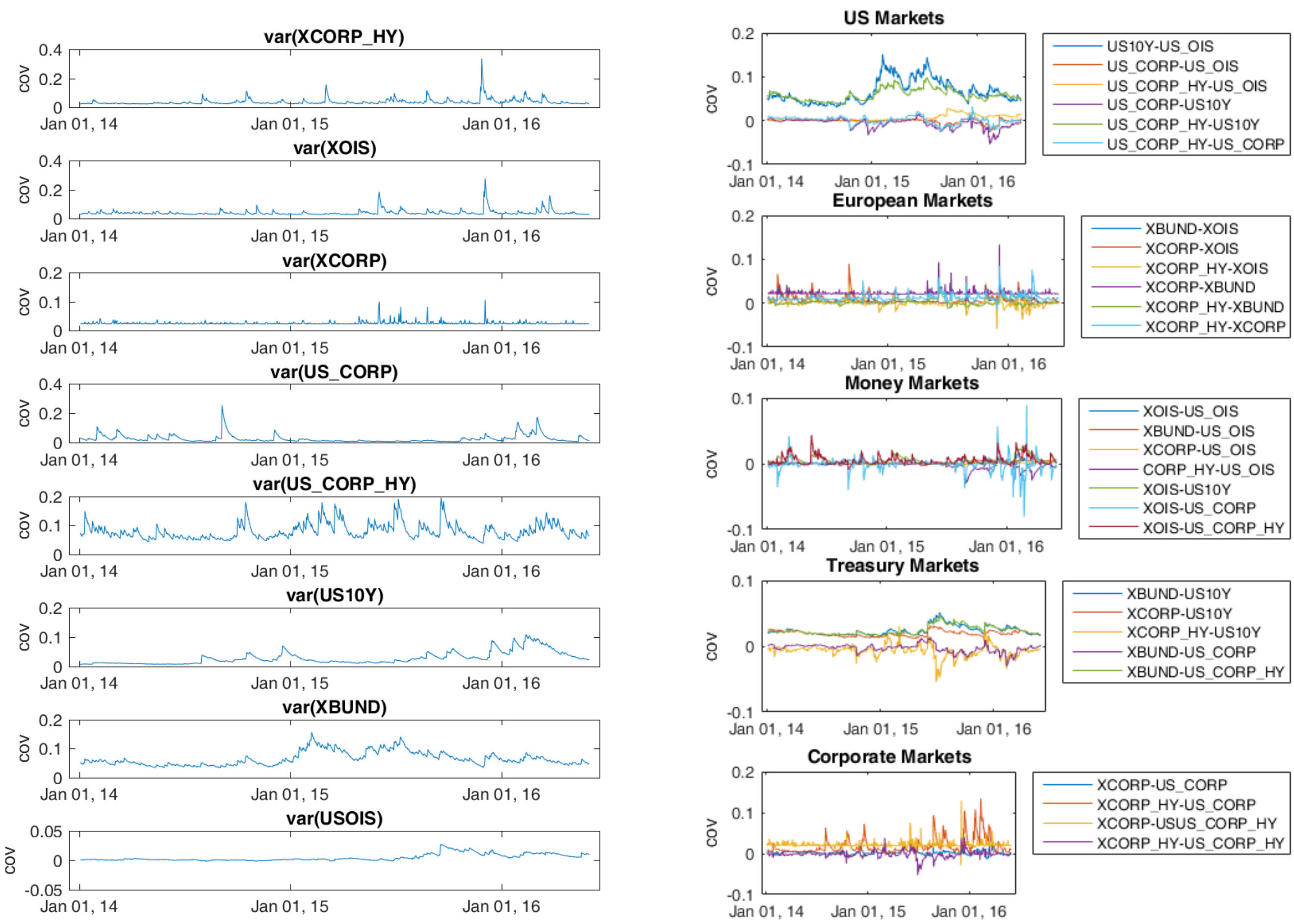


Fig. C.2 BEKK Variances and Covariances



Appendix D

Index Construction

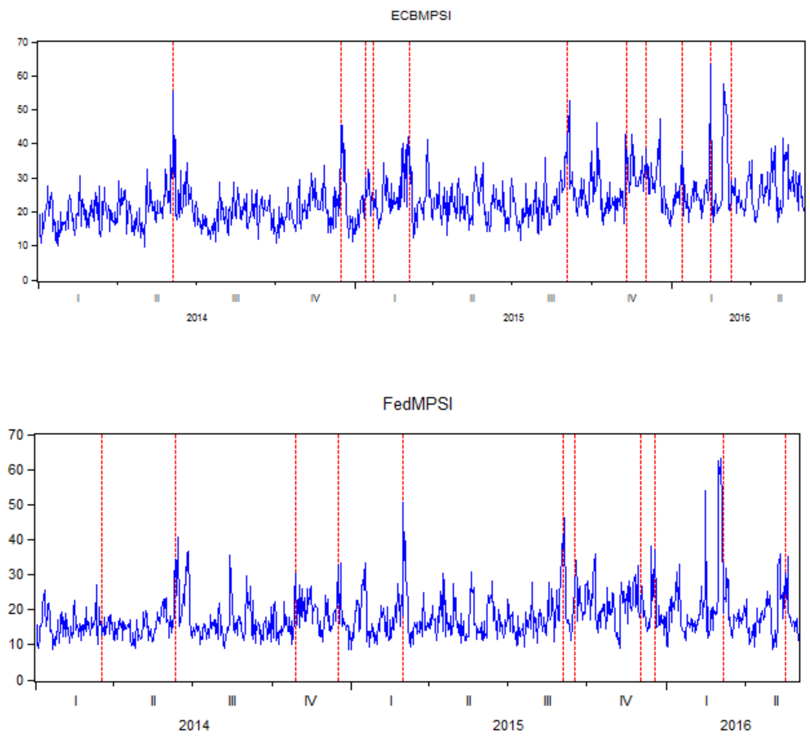
The Monetary Policy Search Index (MPSI) uses an index based on a number of search queries related to one particular central bank investigated. The index is constructed following the approach of Da et al. [2015] in that the search topics "European Central Bank" and "Federal Reserve System" are entered into the Google Trends user interface, which returns a list of related top searches, which will then enter each index, weighted by the impact value assigned by Google. Search terms that are ambiguous or unrelated will be excluded. It is crucial to stress at this stage that weights are not constructed through data-mining approaches such as using uninformed correlation measures, but instead are based on Google's measure of *related searches*, which gives correlations based on search terms the same users also entered and hence avoids spurious relationships.

The search indices for ECB and Fed related searches are plotted in figure 2. The vertical lines represent identified events, which are given in table 22 below. We can observe that the indices that the indices are clearly heteroskedastic and can identify several volatility spikes and clusters that coincide with policy events. The most significant events seem to be relating to the launch and extension of asset purchases for the ECB and interest rate hikes for the Fed, which is in line with the patterns we observed for the fixed income series. Identifying certain relevant events using our indices is not a comprehensive exercise, which would compromise one of the reasons for using such measures, but provides evidence that the MPSI can replicate policy events and do not just follow noise.

Tables D.2 and D.3 give events identified around observed spikes in MPSI. Events are identified with Google searches of search terms employed in the indices in small (1-2 day) windows around observed index spikes.

Search words used for the construction of the MPSI search indices are reported in table D.1 below. Search word selection is based on querying the search topics "European Central Bank" and "Federal Reserve System" with the Google Trends UI, where the search is limited to News Search only. Google reports a number of statistics with each search term queried. We use "related queries" from which we select the most popular search queries. The given metric for those related queries is then used as a weight in our indices. These metrics are described in the Google Trends UI as "Scoring is on a relative scale where a value of 100 is the most commonly searched query, 50 is a query searched half as often, and a value of 0 is a query searched for less than 1% as often as the most popular query." We follow the same approach in the construction of our control indices.

Fig. D.1 Google Search Indices and Identified Events



Notes: Vertical lines represent individual identified events. Vertical axis gives a search volume index value based on normalised index values obtained through Google Trends for individual search words. Data source: Google Trends (www.google.com/trends)

Table D.1 MPSI Indices – Search Words

Index	Search Words	weight
MPSI	European Central Bank	100
	ECB	55
	ECB rate	40
	EZB	25
	BCE	15
	Banco Central Europeo	5
	Banca Centrale Europea	5
	Europaeische Zentralbank	5
	Banque Centrale Europeenne	5
MPSI*		
	Federal Reserve	100
	Fed	65
	Federal Reserve System	60
	Fed interest	5
	Fed rate	5
	Federal Reserve Bank	5
	The Fed	5

Table D.2 Identified ECB Events

Date	Event
05/06/2014	GC Meeting: Deposit rate from 0% to -0.1%; Refi rate from 0.25% to 0.15%; 4yr TLTRO, QE hint
16/12/2014	Bundesbank's Weidmann raises concern over QE
14/01/2015	ECJ Advocate General Approves of OMT
05/03/2015	GC meeting: Announcement to start purchases, as markets raise doubts on ECB's ability to conduct purchases; ELA extension (Greece)
09/03/2015	Benoit Coere confirms EUR3.2bn in purchases (as targeted)
03/09/2015	GC meeting: Hint towards further asset purchases
11/11/2015	Rumors ECB might engage in municipal bond purchases
03/14/2015	12/2015 GCM minutes released
21/01/2016	GC meeting: Draghi hints further asset purchases
15/02/2016	Dovish Draghi Speech at EP
10/03/2016	GC meeting: Deposit rate cut to -0.4; QE extension to EUR80bn/m, incl. corporate bonds

Table D.3 Identified Fed Events

Date	Event
14/06/2014	Stanley Fisher appointed FOMC vice chair
29/10/2014	QE ended
17/12/2015	FOMC "patient to raise rates"
02/03/2015	Appointment of Patrick Harker to succeed Charles Plosser at Phil. Fed
04/09/2015	Disappointing jobs report
17/09/2015	Dovish FOMC meeting
02/12/2015	Yellen hints rate hike
18/12/2015	First rate hike
07/03/2016	Comments from Fed's Brainard and Fisher
18/05/2016	FOMC minutes

Appendix E

Proofs

E.1 CIP Arbitrage Bounds

Following Sushko et al. [2017], we assume foreign exchange swap markets, where arbitrageurs face the following end-period wealth constraints

$$\begin{aligned} E_t[W_{t+1}] &= W_t + (W_t - x_{t,f})y_t + [1-\theta_t]x_{t,f}(f_t^B + y_t^* - s_t^A) + \theta_t x_{t,f}(E_t[s_{t+1}^B] + y_t^* - s_t^A), \\ &\quad \text{if } f_t - s_t > y_t - y_t^* \quad \text{and} \qquad \text{(E.1)} \\ E_t[W_{t+1}^*] &= W_t^* + (W_t^* - x_{t,f})y_t^* + [1-\theta_t]x_{t,f}(f_t^A + y_t - s_t^B) + \theta_t x_{t,f}(E_t[s_{t+1}^A] + y_t - s_t^B), \\ &\quad \text{if } f_t - s_t < y_t - y_t^*. \qquad \text{(E.2)} \end{aligned}$$

W_t denotes the arbitrageurs wealth at time t, y_t the interest rate of underlying assets in the arbitrage portfolio, $x_{t,f}$ are the US$ amount of FX swaps, f_t^B and f_t^A are forward bid and ask exchange rates and s_t^B and s_t^A respective spot rates. θ_t is a probability capturing counterparty default risk, which is arising from collateral for swapped cash-flows being denominated in foreign currencies. CIP requires the forward spread to equal rate differences, in which case there would be complete arbitrage on swap markets. The cases given in E.1 and E.2 are therefore bounds following from the failure of CIP. In E.1, a domestic CIP arbitrageur generates wealth in $t+1$ through interest earned on domestic assets, (hedged) interest earned on foreign assets (denoted *) or arbitrage profits, arising from exploiting differences between forward rates at t and expected spot rates at $t+1$. A foreign CIP arbitrageur takes the counterparty position on swap markets, switching bid and ask rates on swap markets as well as domestic and foreign interest rates. The inequalities between the forward spread and rate differences in E.1 and E.2 arise from the collateral exposed to counterparty risk, when $\theta > 0$.

Assuming an exponential utility function, $-E_t[(-\rho W_{t+1})]$, gives the following certainty-equivalent objective function for E.1

$$\max_{x_{t,f}}\{W_{t+t}\} = W_t(1+y_t) + x_{t,f}(f_t^B - S_t^A + y_t^* - r_t) - \frac{\rho}{2}\theta_t x_{t,f}^2 \sigma_s^2 \qquad \text{(E.3)}$$

which, imposing market clearing, $x_{t,f} = D_t^{XC} - \Lambda$, gives the forward rate as [1]

$$f_t^B = s_t^A + y_t - y_t^* + \theta_t \rho \sigma^2 D_t^{XC} - \Lambda, \tag{E.4}$$

where D_t^{XC} captures shocks to swap demand, where $D_t^{*,XC} \equiv -D_t^{XC}$, and Λ captures frictions arising from liquidity and transaction costs.[2]

From the CIP relationship, a negative cross-currency basis follows

$$\begin{aligned} CIP_{i,t}^{-} &\equiv r_{i,t} - (r_{i,t}^* + f_t - s_t) \\ &\geq \theta_t \rho \sigma_s^2 D_t^{XC} - \Lambda \end{aligned} \tag{E.5}$$

and equivalently

$$\begin{aligned} CIP_{i,t}^{+} &\equiv r_{i,t} - (r_{i,t}^* + f_t - s_t) \\ &\leq \theta_t \rho \sigma_s^2 D_t^{XC} = \Lambda, \end{aligned} \tag{E.6}$$

which are the arbitrage bounds, given in section 3.1. □.

E.2 Proof of Eq. (7)

Substituting 4.6 into 4.7 and assuming swap market equilibrium we get

$$\begin{aligned} \hat{b} \quad &\equiv \quad \left[\frac{1}{T} \sum_{i=1}^{T} \mathbb{E}\mathbf{r}_{t+i} + CP(\boldsymbol{x}, \iota) \times VP(\gamma, \lambda(\sigma, \omega(S, \xi), \bar{b}, \gamma), \Sigma\Sigma') \right] \\ &- \quad \left(\left[\frac{1}{T} \sum_{i=1}^{T} \mathbb{E}\mathbf{r}_{t+i}^* + CP(\boldsymbol{x}, \iota)^* \times VP(\gamma, \lambda(\sigma, \omega(S, \xi), \bar{b}, \gamma), \Sigma\Sigma')^* \right] + f_t - s_t \right) \\ &+ \quad \theta_t \rho \sigma_s^2 (\sigma^2, \sigma^{2*}) D_t^{XC}(y, y^*) + \Lambda(r, r^*, r_{REPO}, r_{REPO}^*, f^A, f^B). \end{aligned} \tag{E.7}$$

Rearranging gives 4.7. □

[1] We apply the same logarithmic approximation as Sushko et al. [2017], i.e. $F/S - (1+r)/(1+r^*) \approx f - s - r + r^*$, where $f \equiv \log(F)$ and $s \equiv \log(S)$.

[2] $\Lambda_t = c[(y_t^{*,REPO} - y_t^*) - (y_t^{REPO} - y_t^)] + [(f_t^B - s_t^A) - (f_t^A - s_t^B)]$, which gives frictions arising from wholesale funding costs (where y_t^{REPO} gives repo rates) and liquidity costs arising from bid-ask spreads. Both are assumed constant and exogenous in the following, giving the expression in E.3

Appendix F

Additional Tables for Chapter 4

F.1 Structural Stability

The presence of structural breaks in the data would bias the estimates. We therefore test for the presence of unspecified breaks using a Quandt-Andrews breakpoint test. To proceed with the test, we employ the full mean specification as given in 4.8 and test for unknown breaks in all parameters, choosing standard interval sizes. We execute the tests for all models and compare results for restricted and unrestricted samples. Results are given in table F.1 below.

Table F.1 Quand-Andrews Breakpoint Tests

	3M		1Y		2Y		5Y	
Statistic	Full	Restr.	Full	Restr.	Full	Restr.	Full	Restr.
Maximum LR F-statistic	0.0171	0.0009	0.0084	0.0257	0.0046	0	0.0099	0.0082
Maximum Wald F-statistic	0.0171	0.0009	0.0084	0.0257	0.0046	0	0.0099	0.0082
Exp LR F-statistic	0.4499	0.0043	0.2256	0.0883	0.016	0.0016	0.0464	0.0616
Exp Wald F-statistic	0.0882	0.0003	0.0175	0.0272	0.0034	0.0001	0.0054	0.0122
Ave LR F-statistic	0.3183	0.0007	0.1356	0.0239	0.0014	0.0001	0.0101	0.0131
Ave Wald F-statistic	0.3183	0.0007	0.1356	0.0239	0.0014	0.0001	0.0101	0.0131
Suggested Date	12/04/2015	09/07/2014	12/04/2015	2/18/2015	12/04/2015	1/28/2015	11/28/2015	1/16/2015

Based on maximum test statistics, the null of no breaks is rejected for all models with break dates corresponding around late November-early December for all models. Expected and average test statistics are more ambiguous for models of the 3m and the 1y basis. The dates suggested fall within the area of sample restriction, for which we have previously detected outliers. We also detect evidence for the presence of breaks in the restricted sample. However, the breaks do neither correspond with particular dates across models nor with outliers detected in residual. Conducting a series of Bai-Perron multiple breakpoint tests, largely confirms the assumption of only one break in December 2015.[1] Results of Bai-Perron tests are given in table **??** below.

[1] For the 3m-basis the Bai-perron test suggests two breakpoints. However, the suggested second breakpoint does not correspond with the breakpoint suggested in Quandt-Andrews tests for the restricted sample and we hence proceed with the assumption of only one break.

Given the aforementioned results, we proceed with the assumption of structural stability with respect to the restricted sample.

Table F.2 Bai-Perron Tests

Bai-Perron	3m	1y	2y	5y
Scaled F-statistic (1 vs. 2 breaks)	24.21997	10.0691	16.05189	15.46783
1st break	12/04/2015	1/21/2016	12/04/2015	10/16/2015
2nd break	11/04/2014	NA	NA	NA

F.2 Endogeneity

Covariates in our models may be suffering from endogeneity problems. Whilst this can be due to several causes, we judge that these would most likely be due to simultaneity. We therefore investigate Granger-Causality for each respective cross-currency basis with respect to all covariates, based on a stationary reduced form VAR. Results are given in tables 15 and 16 below.

Table F.3 Granger Causality Tests: Full Sample

Dependent Variables	Independent Variables			
	DCIP3m	DCIP1Y	DCIP2Y	DCIP5Y
D(100*FF)	0.463	0.0361	0.3389	0.6238
D(100*(S-FWD))	0.4986	0	0.0321	0.1746
D(100*REPO)	0.2973	0.5019	0.7266	0.7174
D(100*LIQUIDITY)	0.9908	0.0097	0.6211	0.0279
D(EPU)	0.5131	0.139	0.1937	0.1355

Based on the full sample, there is evidence of reverse causality for several covariates, in that they are Granger-caused by the respective dependent variables. These endogeneity problems are likely caused by the presence of outliers in the full sample. We therefore repeat the tests for the restricted sample.

Table F.4 Granger Causality Tests: Restricted Sample

Dependent Variables	Independent Variables			
	DCIP3m	DCIP1Y	DCIP2Y	DCIP5Y
D(100*FF)	0.7602	0.0584	0.6567	0.7264
D(100*(S-FWD))	0.1536	0	0.3051	0.2651
D(100*REPO)	0.9064	0.2699	0.7467	0.4402
D(100*LIQUIDITY)	0.7371	0.4523	0.9154	0.6216
D(EPU)	0.5867	0.314	0.2053	0.2122

For the restricted sample, most endogeneity problems through reversed causality disappear. For the one year basis, however, the futures- and the forward spreads remain endogenous, where estimates are significant for forward spreads only. This is likely due to the particular dynamics of this market segment, as discussed in section 4.3.1 above. Since there are no further endogeneity problems, we abstain from applying an instrument in this case and refer to results for the 3m and 2y basis instead.

F.3 Additional Tables for Section 4.6

Table F.5 CCBS Regressions including EPU and CDS

	3m	1y	2y	5y	3m	1y	2y	5y
Mean	Excl. Outliers				Incl. Outliers			
GARCH	-6.676 ***	-0.018	-0.001	-0.008	0.001	0.023	0.001	-0.007
C	-1.643 ***	-0.026	0.007	-0.011	-0.015	-0.017	0.017	0.003
FF	0.078 ***	0.040	-0.083 ***	-0.097 ***	0.047 *	-0.031	-0.085 ***	-0.052 **
FWD	0.007 ***	-10.156 ***	-4.768 ***	-1.456 ***	0.002 ***	-7.310 ***	-4.524 ***	-1.490 ***
REPO	-0.005	-0.020	-0.081 ***	-0.078 ***	-9.411 ***	0.002	-0.039 ***	-0.037 ***
LIQUIDITY	2.925	3.853	-0.902 **	1.002 ***	0.001	4.346 *	-0.829 **	1.144 ***
CIP_{t-1}	0.682	-0.069 *	0.021	0.004	0.051 **	-0.068 **	0.028	0.006
CDSUS				-0.074 ***				-0.051 ***
CDSEUR				-0.006				-0.009 ***
Variance								
C(8)	-0.229 ***	-0.275 ***	-0.489 ***	-0.454 ***	-0.221 ***	-0.087 ***	-0.430 ***	-0.454 ***
ARCH	-0.003	0.388 ***	0.059	0.200 **	0.117 ***	0.221 ***	0.155 ***	0.200
Leverage	0.100 ***	0.134 *	0.192 ***	0.206 ***	0.032	-0.059	0.209 ***	0.206 ***
GARCH	0.064 *	0.102	0.452 ***	0.441 ***	0.563 ***	0.357 ***	0.542 ***	0.441 ***
VIX	-0.002	0.065	0.071	-0.039	-0.047	-0.020	0.113 ***	-0.039
FXV	0.002	-0.104	0.400 ***	0.359 **	0.142	-0.079	0.430 ***	0.359 ***
CPRISK	0.390	17.998 *	-12.415	-9.011	9.636 **	11.013 **	12.035 ***	-9.011 ***
MPSI	0.001	-0.002	0.013	-0.011	0.041 ***	-0.013	-0.002	-0.011 *
EPU	0.000	-0.006 ***	-0.013 ***	-0.012 ***	-0.015 ***	-0.011 ***	-0.016 ***	-0.012 ***
t-DoF	3.000	3.000	3.000	3.000	3.000	3.000	3.000	3.000
R2	0.186	0.028	0.070	0.077	0.017	0.022	0.076	0.065
SER	0.894	0.976	0.730	0.752	1.207	1.287	0.820	1.001
BIC	2.425	2.676	1.995	2.177	2.617	2.884	2.066	2.359
DW	2.128	2.267	2.018	1.955	2.001	2.188	1.941	2.023

The table gives estimation output for specifications adding Economic Policy Uncertainty (EPU) in first differences to variances and 5y bank Credit Default Swap indices for US and European to the 5y basis. Dependent variables are 3m-5y CCBS rates. Estimation of all models via maximum likelihood assuming t-distributed errors and optimisation using the Eviews legacy algorithm with Marquard steps. BIC gives the Schwarz-Bayes Information Criterion, DW the Durbon-Watson Statistic and SER the standard error of the regression; Significance levels: $^{*} < 10\%, ^{**} < 5\%, ^{***} < 1\%$.

Table F.6 CCBS Regressions Accounting for Timing of Exchange Trading Hours

	3m		1y		2y		5y		3m		1y		2y		5y	
Mean	Excl. Outliers								Incl. Outliers							
GARCH	0.012		-0.397	**	-1.223	*	-0.081	*	0.004		-0.049		0.015		-0.008	
C	-0.010		-0.038		-0.761	*	-0.051		-0.023		0.006		0.013		-0.002	
FF^{sync}	0.023		-0.019		-0.149	***	-0.123	***	0.006		-0.002		-0.072	***	-0.087	***
FWD	-0.001		-18.983	***	0.225		0.020		0.000		-13.187	***	-0.530		-0.116	
$REPO_{t-1}$	0.013		-0.025		-0.049	***	-0.049	***	0.005		-0.012		-0.004		-0.021	*
$LIQUIDITY_{t-1}$	-3.516		3.199		-0.872	**	1.153	***	-8.752	***	5.760	**	-0.635		1.144	***
CIP_{t-2}	0.060	**	-0.009		-0.103	***	0.023		0.054	**	-0.050		-0.047	**	0.021	
Variance																
C(8)	-0.380	***	-0.275	***	-0.606	***	-0.459	***	-0.340	***	-0.142		-0.969	***	-0.554	***
ARCH	0.115	*	0.388	***	-0.063		0.275	***	0.153	***	0.435	***	0.345	***	0.377	***
Leverage	0.039		0.134	*	-0.036		0.241	***	-0.030		0.061		-0.030		0.190	***
GARCH	0.275	**	0.102		-0.054		0.381	***	0.093		-0.463	***	-0.430	***	-0.073	
VIX	-0.237	***	0.065		-0.030		-0.179	***	-0.210	***	0.012		-0.133	***	-0.172	***
FXV_{t-1}	-0.316	**	-0.104		0.197	*	0.233	*	-0.330	**	0.272	**	0.181	*	0.073	
$CPRISK^{sync}$	-12.260	*	17.998	*	2.405		-11.589	*	-16.524	***	5.351	*	-0.341		4.570	
$MPSI_{t-1}$	0.046	***	-0.002		0.001		-0.009		0.050	***	-0.003		0.024	***	-0.014	
t-DoF	3.000		3.000		3.000		3.000		3.000		3.000		3.000		3.000	
R2	0.005		0.091		0.081		0.023		0.008		0.048		0.025		0.022	
SER	0.989		0.944		0.729		0.773		1.213		1.270		0.846		1.023	
BIC	2.488		2.632		2.100		2.237		2.646		2.832		2.200		2.431	
DW	1.946		2.232		2.038		1.930		1.942		2.217		1.866		2.013	

The table gives results, correcting for delayed pricing of some of the underlying variables through time-zone differences between exchanges considered. Dependent variables are first lags of 3m-5y CCBS rates. FF^{sync} and $CPRISK^{sync}$ gives lags only the European part in respective variables. Estimation of all models via maximum likelihood assuming t-distributed errors and optimisation using the Eviews legacy algorithm with Marquard steps. BIC gives the Schwarz-Bayes Information Criterion, DW the Durbon-Watson Statistic and SER the standard error of the regression; Significance levels: $^{*} < 10\%, ^{**} < 5\%, ^{***} < 1\%$.

Appendix G

Estimation Problems

Estimation of GARCH-type models is non-trivial and covergence problems are common. This appendix outlines typical MLE convergence problems for GARCH-type models and illustrates a case study based on EGARCH models of the daily three month USD/EUR Cross-Currency basis. Our illustrations are based on the follwing model:

$$\begin{aligned}
dCIP &= \beta_0 + \beta_1 \log h_t \ + \beta_2 FF_t + \beta_3 (s - 3mFWD)_t + \beta_4 dLiquidity_t \\
&\quad + \beta_5 dCIP_{t-1} + v_t^{UR}, \\
\text{where} \quad v_t^{UR} &= \varepsilon h_t^{1/2}, \quad \varepsilon \sim IID(0, \Sigma\Sigma'), \\
\text{and} \quad \log h_t &= c_0 + c_1 h_{t-1} + c_2 \left| \frac{v_{t-1}^2}{h_{t-1}} \right| + c_3 \frac{v_{t-1}^2}{h_{t-1}} + c_4 MPSI_t + c_5 dVIX + c_6 \theta_t.
\end{aligned}$$

G.1 Distributional Assumptions

In the following we compare likelihood functions for different distributional assumptions to highlight some potential convergence problems arising from the choice of residual distributions. An application demonstrates results for the specification given above.

G.1.1 Normal Distribution

The loglikelihood of a normal-distributed conditional variance models is

$$l = \sum_{t=1}^{T} \frac{1}{2} \left[-\ln(2\pi) - \ln(h_t) \frac{\varepsilon_t^2}{h_t} \right] \forall \varepsilon.$$

Whilst computationally assuming normality is relatively straightforward, financial data is commonly leptokurtic and hence produces nonnormal residuals. We therefore proceeed with two heavy-tailed distributions.

G.1.2 Student t Distribution

The loglikelihood of a t-distributed conditional variance models is

$$l = \sum_{t=1}^{T} \left[-\frac{1}{2} \log \left(\frac{\pi(\nu-2)\Gamma(\nu/2)^2}{\Gamma((\nu+1)/2)^2} \right) - \frac{1}{2} \log h_t - \frac{(\nu+1)}{2} \log \left(1 + \frac{\varepsilon_t^2}{h_t(\nu-2)} \right) \right],$$

where $\nu > 2$, $\lim_{\nu=2} \varepsilon \to \infty$, and $\lim_{\nu\to\infty} \varepsilon \sim N$.

The student-t distribution allows for heavier tails as the normal distribution and is hence often chosen for applications considering financial data. Its shape parameter is bounded from below by 2, leading to explosive behaviour of variances at the edge of the parameter space.

G.1.3 Generalised Error Distribution

The loglikelihood of a GE-distributed conditional variance models is

$$l = \sum_{t=1}^{T} \left[-\frac{1}{2} \log \left(\frac{\Gamma(1+r)^3}{\Gamma(3/r)(r/2)^2} \right) - \frac{1}{2} \log h_t - \left(\frac{\Gamma(3/r)(\varepsilon_t)^2}{h_t \Gamma(1/r)} \right)^{r/2} \right],$$

where $r > 0$, $\varepsilon \sim N$ for $r = 2$, $\varepsilon \sim Laplace(\mu, b)$ for $r = 1$, $\varepsilon = \infty$ for $r < 1$, and $\lim_{r\to\infty} \varepsilon \sim U(a,b)$.

The GED allows for more flexibility than the t-distribution, with its shape parameter bounded from below by zero. It follows a Laplace distribution for $r = 1$, and is asymptotically uniform distributed for large r. Laplace distributions are double-exponential distributions and have infinitely many derivatives. Estimation therefore generally requires numerical strategies for any $r \leq 1$. Furthermore, GARCH models have ill-behaved variances for $GED(r < 1)$ and estimated GED parameters below are hence disregarded.

G.1.4 Validity of Estimates at the Edge of the Parameter Space

We are particularly interested in the behaviour of estimates when the assumed distribution approaches the limit of its defined parameter space. From the above, it can be easily seen that this is applicable in three cases:

1. $\lim_{h_t=0} l \sim N$,
2. $\lim_{\nu=2} l \sim t$, and
3. $\lim_{r=0} l \sim GED$.

The two cases given above are common for leptokurtic processes, such as the series we consider. It is difficult to define criteria to verify the validity of estimates that are close to but not on the edge of the parameter space. But given knowledge about asymptotic behaviour of estimates described above, we can take a rule of thumb approach based on the credibility of variance estimates and distribution parameters reasonably satisfying the regularity conditions given above. This implies e.g. for GED distribution parameter estimates below one that the GED parameter is fixed to above but close to one and for t-distributed estimates that models giving estimated t-statistics >50 are disregarded.

G.1.5 Application

Table 1 below compares the estimation results across the three distributions discussed. To simplify the estimation, we first specified the model as a simple EGARCH(1,1,1) without any further terms entering the conditional variance process. The data employed is very leptokurtic (kurtosis: 38.8) and we therefore aim for assuming a fat-tailed residual distribution. Furthermore, assuming a normal EGARCH(1,1,1) model does not satisfy strict stationarity as $1-\sum_{i=1}^{4}\beta_i = -0.005 < 0$. Assuming GED or t-distributed innovations both satisfies stationarity but in the case of GED errors convergence can only be achieved by fixing the GED parameter. We chose 1.2, which is the closest value to one (the Laplace distribution) allowing convergence and hence the most leptokurtic available distribution. For the t-distribution the parameter estimate is close to the edge of the parameter space. We do however view this as unproblematic given that estimated standard errors seem credible. Likewise, assuming a GED distribution fixed at $r = 1.2$ gives credible estimates, which leaves with both, GED(1.2) and t(ν) as viable distributions.

Table G.1 EGARCH Models without Conditional Variance Specification

Dist	β_0	β_1	β_2	β_3	β_4	β_5	c_0	c_1	c_2	c_3	Dist. Param.
N	-0.098268	0.150818	0.002073	-0.048448	-19.254	0.053009	-0.055594	0.104483	-0.06981	0.970561	
	(-2.84)	(5.19)	(2.81)	(-2.42)	(-2.52)	(1.73)	-7.06339	(7.81)	(-6.69)	(174.29)	
t	-0.010835	0.015527	0.001089	0.006935	-13.57256	0.045577	4.933772	1.564942	-0.129711	-0.680416	2.014148
	(-0.52)	(0.64)	(2.19)	(0.54)	(-3.30)	(2.33)	(1.47)	(0.95)	(-0.63)	(-13.95)	(-69.63)
GED	-0.000115	0.037929	0.001118	-0.007325	-5.629003	0.009846	-0.478291	0.201041	-0.032233	-0.75369	1.2 (fixed)
	(-0.00)	(1.60)	(1.77)	(-0.40)	(-0.94)	(0.35)	(-7.04)	(6.56)	(-1.75)	(-22.44)	

We repeat the exercise for the fully specified model, including exogenous variables in variances and GARCH-in-mean terms. Results are given in table 2. Both normally and GED distributed errors clearly led to instable GARCH terms as covariance stationarity was not satisfied. The t-distributed model had to be estimated with its degrees of freedom parameter fixed at 3 as errors were otherwise ill-behaved. The resulting estimates are credible and we therefore proceed with the assumption of $\varepsilon \sim t(3)$. Distributional assumptions for the remaining models are justified analogously.

Table G.2 EGARCH-in-Mean Models: Full Specification

Dist	β_0	β_1	β_2	β_3	β_4	β_5	β_6	c_0	c_1	c_2	c_3	c_4	c_5	c_6	Dist. Param.
N	-0.069598	-0.05189	0.10996	0.00269	-0.073545	-24.97	0.051851	0.019976	-0.031187	-0.08533	1.004185	0.017515	-5.665124	0.018183	
	(-2.9)	(-1.6)	(4.28)	(-3.65)	(-4.87)	(-3.54)	(1.83)	(5.67)	(-12.49)	(-12.01)	(460.48)	(1.685)	(-16.01)	(3.64)	
t	-0.071405	-0.041048	0.050077	0.001932	-0.001389	-19.42914	0.053896	-0.289847	0.147218	-0.013718	0.178786	-0.090531	3.650462	0.048591	3 (fixed)
	(-1.16)	(-1.23)	(-2.11)	(-3.52)	(-0.07)	(-4.01)	(-2.09)	(-4.20)	(2.68)	(-0.30)	(1.17)	(-2.51)	(2.76)	(4.50)	
GED	0.000613	0.001408	0.023597	0.000557	-0.01299	-5.076017	0.004971	0.01188	-0.021497	-0.07857	1.003489	0.039542	-3.821427	0.017168	1.2 (fixed)
	(0.01)	(0.03)	(0.82)	(0.81)	(-0.78)	(-0.91)	(0.19)	(4.55)	(-8.67)	(-9.98)	(342.68)	(2.82)	(-7.82)	(2.35)	

G.2 Sample Selection

Whilst leptokurtic processes are common in highly frequent financial data outliers might have an effect on the residual kurtosis of our models. Proceeding with the model-specification given in table 2 we obtain the standardised residual series plotted in figure 8. There is clear evidence of an outlier on 04/12/2015, which follows a surprise decision of the ECB on 03/12/2015 to extend it's EAPP by less then expected as well early misreporting of the policy decision by the financial time. Both is likely to have contributed to abnormally high volatility on markets and we therefore consider a restricted sample ending at 01/11/2015.

Fig. G.1

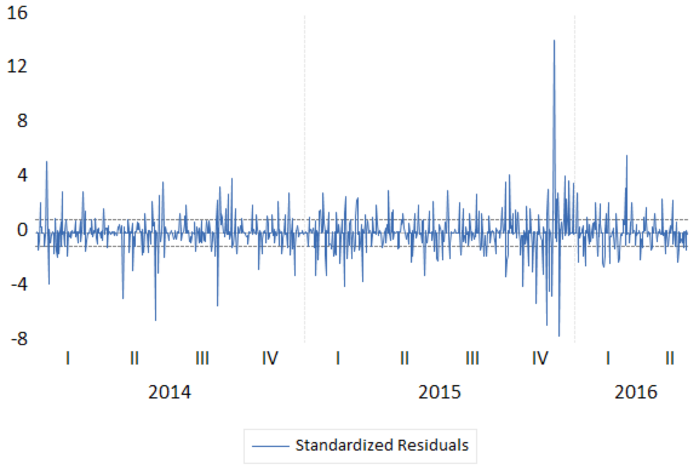


Figure 9 gives the standardised residual for the restricted sample. We can see a clear improvement using the restricted sample. Further residual diagnostics confirm this, with the residual kurtosis dropping from 24.22 to 7.98.

Fig. G.2

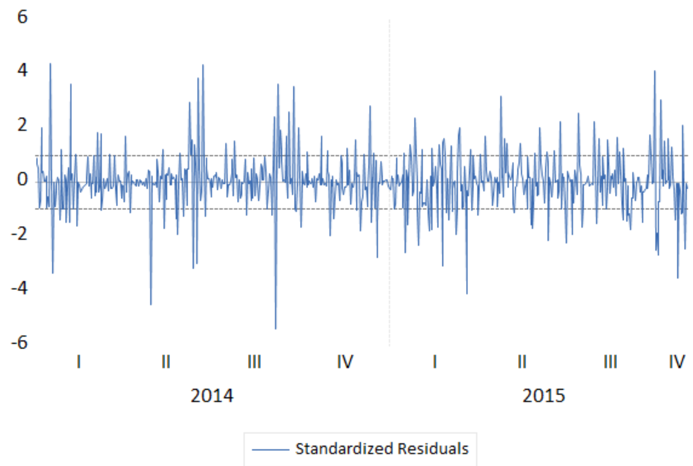


Table 3 gives correlation statistics of squared residuals. In other words, it shows residual GARCH effects. We can observe an improvement in squared residual correlation employing the sample restriction.

Table G.3 Squared Residual Correlation

Full Sample					Restricted Sample			
lags	AC	PAC	Q-Stat	Prob*	AC	PAC	Q-Stat	Prob*
1	-0.007	-0.007	0.0441	0.834	0.048	0.048	1.5329	0.216
2	0.008	0.007	0.094	0.954	-0.013	-0.016	1.6538	0.437
3	0.108	0.108	10.371	0.016	0.144	0.146	15.602	0.001
4	0.005	0.007	10.394	0.034	0.029	0.015	16.179	0.003
5	0.035	0.034	11.501	0.042	0.112	0.117	24.588	0
6	-0.005	-0.016	11.521	0.074	0.034	0.003	25.354	0
7	0.298	0.3	90.616	0	0.035	0.035	26.2	0
8	0.026	0.024	91.204	0	-0.011	-0.048	26.283	0.001
9	-0.003	-0.001	91.212	0	-0.009	-0.014	26.343	0.002
10	0.186	0.135	122.11	0	0.008	-0.018	26.387	0.003

Restricting samples based on observed outliers that show abnormal behaviour is clearly controversial as it rests on a notion of normality that is difficult to defend. In our case we hence view this exercise not as primary evidence but as giving explanations for occasionally bad fits and the high excess kurtosis observed in several models. In this respect it can be regarded as a robustness exercise.

G.3 Computational Problems

In principle, maximisation of a likelihood function can be achieved analytically or numerically. In practise, however, likelihood functions are often too complex to obtain analytical solutions. Therefore, numerical, i.e. iterative, optimisation procedures are commonly applied. Such algorithms effectively try improving likelihoods by guessing some alternative parameter vector θ until a maximum is reached. This requires some initial guess (or starting value), $\theta_{(0)}$, an updating strategy (optimiser) alongside a method determining the size of updating steps, and some convergence criterium to stop the iteration when a maximum is found. Since MLE convergence problems are commonly linked to the failure of numerical optimisation strategies, the following section discusses common problems in more detail. We illustrate again using the model described above.

G.3.1 Optimisation Algorithm

Optimisers commonly approximate derivatives to evaluate first and second order conditions. Second derivative methods evaluate both, the Jacobian (first order derivatives) and the Hessian matrix (second order derivatives). Two optimisers are commonly applied: Newton-Raphson linearises the likelihood function, using a second order Taylor expansion around θ_i such that

$$\begin{aligned} g_i + H_i(\theta_{i+1} - \theta_i) &= 0 \\ \Leftrightarrow \theta_{i+1} &= \theta_i - H_i^{-1} g_i, \end{aligned}$$

where g is a gradient vector for the parameters to be estimated and H denotes the Hessian matrix. The Goldfield-Quandt algorithm updates with a quadratic hill-climbing method based on the modified Hessian such that

$$\theta_{i+1} = \theta_i - H_i g_i,$$

where $-H_i = -H_i + \alpha I$, and I is the identity matrix. Gauss-Newton/BHHH and Marquardt are first derivative optimisers. Whilst the former uses outer product gradient vectors to approximate the Hessian, Marquardt uses a modified hill-climbing algorythm similar to the Goldfield-Quandt optimiser above. It modifies the Gauss-Newton optimiser through applying a ridge-correction to the Hessian, i.e. a correction matrix (the ridge-factor) that improves convergence in cases were the outer product derivatives are near singular. A prominent case where derivative matrices (both Jacobian and Hessian) are close to singular is for flat likelihood functions, i.e. for likelihoods describing noisy processes.

Further step methods are an alternative trust-region method (Dogleg) and a simple line search method. Marquardt steps are commonly assumed as default case. Eviews offers another optimiser, Eviews Legacy, which combines the Gauss-Newton first derivative optimiser with Marquardt or line search steps and allows for backward estimation compatibility.

Computational convergence problems linked to the choice of optimisers typically arise from differentiability problems due to flat shaped likelihood functions. As mentioned above, likelihood functions are flat-shaped for high variances. This is likely to be the case for higher-frequency financial data, that is typically noisy and should for efficient markets even be a martingale process. Differentiability problems then follow if the approximated first differential is constant (or close to constant), in which case the second derivative is zero and hence the Hessian is singular. We believe this to be the primary source of convergence problems in our case.

An indication of convergence problems originating from the choice of optimiser are differences in parameter estimates obtained through applying different optimisation routines and incredible estimates resulting from ill-behaved variance-covariance matrices. To confirm the validity of the optimiser choice we therefore aim to replicate estimates for different optimisation routines. However, following this approach assumes convergence for a set of different optimisers available, which is unrealistic in our case. We therefore restricted the model above by omitting exogenous variables in the conditional variance as well as all covariates in the mean equation apart from the lagged dependent variable. The aim here is to replicate a scenario close to the (assumed) optimally converged specification to be able to replicate estimates. Table 4 gives estimates for the restricted model. We use the Eviews Legacy optimiser as default case and compare estimates with obtained estimates through applying Newton-Raphson as this was the only other optimiser achieving convergence under the assumption of $\sim t(3)$. Obtained parameter estimates are almost identical and both optimisers gave the same log likelihood of -1119.406. We compare the results to those obtained using the Legacy option with outer product gradients in stead of Marquardt steps, which gives a higher likelihood and is hence chosen as the preferred step method.

Table G.4 Comparing Optimisers for Restricted Model $\sim t(3)$

Optimiser	b0	b1	c0	c1	c2	c3
Legacy /Marquardt	-0.018143	0.059352	-0.595726	0.251977	-0.017826	-0.751772
ll: -1119.406	-0.74257	2.565748	-6.275085	6.887861	-0.746425	-19.19811
Newton-Raphson/ Dogleg	-0.018128	0.05935	-0.595724	0.251979	-0.017824	-0.751771
ll: -1119.406	-0.741961	2.565748	-6.275045	6.88799	-0.746329	-19.19865
Legacy/ OPG	-0.021457	0.048434	-0.056243	0.074438	-0.079009	0.983112
ll: -1114.249	-0.879703	2.000003	-3.750596	3.591366	-5.08842	130.9525

We confirm results for the full specification in Table 5. The legacy optimiser was the only algorithm achieving convergence. However, we could estimate results with the different step methods available. Estimates were identical with identical likelihoods. Given the evidence above, we opt for the Legacy optimiser with OPG steps.

Table G.5 Different Step Methods for Unrestricted Model

Optimiser	b0	b1	b2	b3	b4	b5	b6	c0	c1	c2	c3	c4	c5	c6
Legacy /Marquardt	-0.071432	-0.041054	0.050073	0.001932	-0.001387	-19.42956	0.053895	-0.2899	0.147238	-0.013746	0.178619	-0.09053	3.649912	0.048587
ll:-1114.210	-1.169246	-1.232402	2.112072	3.527129	-0.079648	-4.016546	2.095277	-4.206223	2.680749	-0.301871	1.175903	-2.513544	2.765911	4.50774
Legacy/ OPG	-0.071432	-0.041054	0.050073	0.001932	-0.001387	-19.42956	0.053895	-0.2899	0.147238	-0.013746	0.178618	-0.09053	3.649911	0.048587
ll:-1114.210	-1.169247	-1.232402	2.112072	3.527128	-0.079648	-4.016546	2.095277	-4.206223	2.680749	-0.301872	1.175901	-2.513544	2.76591	4.50774

G.3.2 Global Optimality

The choice of initial values and step-sizes can have a decisive impact in the presence of multiple (local) optima. As reasoned above, we assume a flat-shaped likelihood function, which rules out missing optima through the choice of the iteration step-size. Similarly, the presence of multiple optima is unlikely. We do, however, vary initial values multiplying provided starting values, the initial parameter estimates, by 0.1. Obtained estimates and likelihoods are identical and we hence proceed assuming global optimality.

G.4 Higher Order GARCH Processes

First order ARCH-, GARCH, and leverage parameters are commonly assumed for EGARCH models. This is intuitive, since volatility clustering, mean reversion and asymmetry should be expected with no more than one lag. To explore this, we evaluate the full model specification for several GARCH-,ARCH- and leverage orders. Resulting AIC and BIC statistics are given in table 6. NA indicates specifications where no convergence could be achieved. The suggested conditional variance specification was for an EGARCH(5,4,2) model. However, the evolution of information criteria around this specification is not credible and further evaluation of parameter estimates confirmed convergence problems due to ill-behaved derivative matrices. Since furthermore, choosing lag-orders at one was locally optimal and did result in any apparent convergence problems, high order variance specifications were disregarded.

Table G.6 Higher Order ARCH/GARCH Effects for Asymmetry Order 1 and 3

Leverage 1							
ARCH		GARCH					
		1	2	3	4	5	6
1	BIC	-4.189735	-3.520642	2.463245	NA	-4.178545	NA
	AIC	-4.254857	-3.591191	2.387269	NA	-4.265374	NA
2	BIC	-2.400132	-1.688966	2.689285	-4.50942	2.177071	NA
	AIC	-2.470681	-1.764942	2.607882	-4.59625	2.084815	NA
3	BIC	-4.958419	-5.766744	-3.787532	-1.746524	-6.912482	NA
	AIC	-5.034395	-5.848147	-3.874362	-1.838781	-7.010166	NA
4	BIC	-5.663962	-4.95045	-1.194862	-3.948132	-3.939197	-5.294424
	AIC	-5.745364	-5.03728	-1.287119	-4.045816	-4.042307	-5.402961
5	BIC	-2.889076	-5.724518	-5.865227	-3.939197	-5.791324	-5.111937
	AIC	-2.975906	-5.816774	-5.96291	-4.042307	-5.899861	-5.225901
6	BIC	-4.737368	-5.477082	1.667902	-6.047696	-6.171693	-6.168956
	AIC	-4.829624	-5.574765	1.564792	-6.156233	-6.285657	-6.288347
Leverage 2							
1	BIC	-3.434856	2.43349	-3.395959	-5.462803	-7.370048	-5.258123
	AIC	-3.505405	2.357514	-3.477362	-5.549632	-7.462305	-5.355807
2	BIC	-6.726408	-5.688194	-7.823705	-5.145213	NA	NA
	AIC	-6.802384	-5.769596	-7.910535	-5.237469	NA	NA
3	BIC	-2.339721	-2.667202	-4.142392	-2.023637	-5.379462	-7.786988
	AIC	-2.421124	-2.754031	-4.234649	-2.121321	-5.482572	-7.895525
4	BIC	-3.448545	-6.808609	-4.488939	-6.161123	-3.067196	-7.786988
	AIC	-3.535375	-6.900866	-4.586622	-6.264233	-3.175733	-7.895525
5	BIC	-1.492078	-6.670866	-6.111619	-10.60116	-7.705208	-5.560528
	AIC	-1.584335	-6.768549	-6.214729	-10.70969	-7.819172	-5.674492
6	BIC	-3.311077	-2.32244	-3.933804	-7.541437	-6.342892	-5.324531
	AIC	-3.213394	-2.42555	-4.042341	-7.655401	-6.462283	-5.443922

Appendix H

Model Selection for Section 4.5

This appendix gives results for the model selection tests employed to build the EGARCH models in section 4.5. We consider a set of 10 models, given by each column (1)-(10) of the following tables. The model selection is then based on evaluating joint results of the three information criteria (IC), AIC, BIC and HQ, whereby lower IC indicate improvements. We decide based on the average of all three IC and err on the side of BIC in caonflicting cases. Models (1)-(3) test mean specifications. Here we only consider improvements in information through either adding the policy measure FF or the GARCH in mean term, log(GARCH). FF adds significant information in all cases but the 1 year basis. GARCH in mean adds significant information for the 3 months and 2 year basis, as well as the 1 year basis, where the improvement is small and therefore not visible in table H.2 due to rounding effects. We specify variance equations in columns (4)-(8). Generally, the most parsimonious model, (4), tends to provide the best fit but we proceed with model (8) to control for otherwise omitted variables. Models (9) and (10) consider Economic Policy Uncertainty, EPU, in variances as well as both means and variances. Including EPU in means does generally not improve the information content whilst for variances it largely does. We consider this in an robustness exercise.

Table H.1 Model Selection: 3 Month Basis

					Means					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
LOG(GARCH)		-6.88	-6.75	-7.85	-7.89	-7.47	-7.21	-6.75	-0.04	-6.68
C	-0.01	-1.93	-1.69	-1.63	-1.66	-1.54	-1.63	-1.69	-0.03	-1.64
FF			0.08	0.09	0.09	0.09	0.09	0.08	0.03	0.08
FWD	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.01
REPO	0.01	0.00	0.00	-0.01	-0.01	-0.01	-0.01	0.00	0.01	0.00
LIQUIDITY	-3.82	2.74	2.73	2.74	2.67	2.25	2.64	2.73	-3.25	2.92
CIP(-1)	0.06	0.66	0.68	0.70	0.70	0.69	0.69	0.68	0.06	0.68
EPU									0.00	
					Variances					
c	-0.37	-0.27	-0.23	-0.19	-0.20	-0.19	-0.21	-0.23	-0.35	-0.23
ARCH	0.12	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.11	0.00
Leverage	0.05	0.09	0.10	0.09	0.09	0.09	0.09	0.10	0.05	0.10
GARCH	0.26	0.05	0.06	0.07	0.06	0.07	0.07	0.06	0.41	0.06
FXV	-0.13	0.00	0.00		0.00	0.00	0.00	0.00	-0.05	0.00
VIX	-0.10	0.00	0.00			0.00	0.00	0.00	-0.07	0.00
CPRISK	-13.03	0.85	0.38				0.27	0.38	-11.16	0.39
MPSI	0.05	0.00	0.00					0.00	0.05	0.00
EPU									-0.01	0.00
R2	0.01	0.05	0.18	0.18	0.18	0.18	0.18	0.18	0.01	0.19
AIC	2.39	2.32	2.32	2.31	2.31	2.31	2.32	2.32	2.37	2.32
BIC	2.48	2.42	2.42	2.38	2.39	2.40	2.41	2.42	2.48	2.43
HQ	2.42	2.36	2.35	2.34	2.34	2.35	2.35	2.35	2.41	2.36
Sum(IC)	7.29	7.10	7.09	7.03	7.05	7.06	7.08	7.09	7.27	7.10
DW	1.99	2.11	2.13	2.12	2.12	1.91	1.91	2.13	1.99	2.13

Table H.2 Model Selection: 1 Year Basis

	Means									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
LOG(GARCH)		-0.21	-0.21	-0.22	-0.23	-0.25	-0.21	-0.21	-0.28	-0.02
C	-0.01	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03	-0.04	-0.03
FF			0.01	0.01	0.01	0.02	0.01	0.01	0.00	0.04
FWD	-8.61	-10.11	-10.43	-9.22	-9.29	-10.83	-10.43	-10.43	-11.56	-10.16
REPO	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02
LIQUIDITY	3.64	3.41	3.56	4.25	3.83	2.54	3.56	3.56	2.73	3.85
CIP(-1)	-0.07	-0.06	-0.06	-0.05	-0.05	-0.05	-0.06	-0.06	-0.05	-0.07
EPU									0.00	
	Variances									
c	-0.27	-0.27	-0.28	-0.26	-0.27	-0.27	-0.28	-0.28	-0.24	-0.27
ARCH	0.40	0.39	0.40	0.39	0.40	0.38	0.40	0.40	0.32	0.39
Leverage	0.09	0.11	0.11	0.18	0.18	0.17	0.11	0.11	0.15	0.13
GARCH	-0.14	-0.06	-0.07	0.03	0.00	0.00	-0.07	-0.07	0.18	0.10
FXV	-0.09	-0.03	-0.03		0.09	-0.02	-0.03	-0.03	-0.10	-0.10
VIX	0.08	0.08	0.08			0.08	0.08	0.08	0.08	0.06
CPRISK	18.85	17.68	17.60				17.60	17.60	14.90	18.00
MPSI	0.00	0.00	0.00					0.00	0.00	0.00
EPU									-0.01	-0.01
R2	0.03	0.03	0.03	0.04	0.04	0.04	0.03	0.03	0.04	0.03
AIC	2.57	2.57	2.57	2.57	2.57	2.57	2.57	2.57	2.56	2.57
BIC	2.66	2.66	2.67	2.64	2.65	2.66	2.66	2.67	2.68	2.68
HQ	2.60	2.60	2.61	2.60	2.60	2.60	2.60	2.61	2.61	2.61
Sum(IC)	7.83	7.83	7.85	7.80	7.82	7.83	7.83	7.85	7.84	7.85
DW	1.99	2.24	2.25	2.23	2.23	2.23	2.25	2.25	2.23	2.27

Table H.3 Model Selection: 2 Year Basis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Means										
LOG(GARCH)		-0.22	-0.13	-0.10	-0.14	-0.15	-0.13	-0.13	-0.14	0.00
C	0.01	-0.16	-0.10	-0.08	-0.10	-0.11	-0.10	-0.10	-0.11	0.01
FF			-0.08	-0.11	-0.09	-0.08	-0.08	-0.08	-0.07	-0.08
FWD	-4.75	-4.46	-4.39	-4.50	-4.33	-4.42	-4.40	-4.39	-4.65	-4.77
REPO	-0.08	-0.08	-0.08	-0.09	-0.09	-0.09	-0.09	-0.08	-0.08	-0.08
LIQUIDITY	-0.83	-0.90	-0.72	-0.60	-0.73	-0.74	-0.74	-0.72	-1.04	-0.90
CIP(-1)	0.02	0.09	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.02
EPU									0.00	
Variances										
c	-0.31	-0.27	-0.33	-0.33	-0.33	-0.31	-0.31	-0.33	-0.39	-0.49
ARCH	-0.11	-0.10	-0.09	-0.18	-0.09	-0.10	-0.10	-0.09	-0.09	0.06
Leverage	0.25	0.15	0.22	0.31	0.23	0.22	0.22	0.22	0.21	0.19
GARCH	0.49	0.54	0.48	0.41	0.48	0.50	0.50	0.48	0.46	0.45
FXV	0.41	0.23	0.27		0.34	0.28	0.28	0.27	0.32	0.40
VIX	0.05	0.04	0.05			0.05	0.05	0.05	0.06	0.07
CPRISK	-12.07	-6.36	-4.41				-4.10	-4.41	-3.93	-12.42
MPSI	0.00	0.00	0.01					0.01	0.01	0.01
EPU									-0.01	-0.01
R2	0.07	0.09	0.08	0.07	0.08	0.08	0.08	0.08	0.09	0.07
AIC	1.92	1.92	1.91	1.91	1.91	1.91	1.91	0.75	1.88	1.89
BIC	2.01	2.01	2.01	1.98	1.99	1.99	2.00	1.91	1.99	2.00
HQ	1.96	1.95	1.95	1.94	1.94	1.94	1.95	2.01	1.92	1.93
Sum(IC)	5.89	5.88	5.88	5.82	5.83	5.84	5.86	4.68	5.79	5.81
DW	2.02	2.07	2.25	2.03	2.04	2.04	2.04	2.04	2.04	2.02

Table H.4 Model Selection: 5 Year Basis

	Means									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
LOG(GARCH)		-0.08	-0.08	-0.12	-0.10	-0.11	-0.10	-0.08	-0.14	-0.01
C	-0.01	-0.05	-0.04	-0.06	-0.05	-0.06	-0.05	-0.04	-0.08	0.01
FF			-0.11	-0.11	-0.11	-0.11	-0.11	-0.11	-0.11	-0.11
FWD	-1.47	-1.34	-1.26	-1.22	-1.25	-1.27	-1.27	-1.26	-1.25	-1.23
REPO	-0.08	-0.08	-0.08	-0.07	-0.08	-0.07	-0.08	-0.08	-0.07	-0.08
LIQUIDITY	0.83	0.80	0.77	0.76	0.76	0.75	0.70	0.77	0.65	0.78
CIP(-1)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
EPU									0.00	
	Variances									
c	-1.07	-0.57	-0.50	-0.54	-0.51	-0.53	-0.51	-0.50	-0.43	-0.42
ARCH	0.35	0.33	0.28	0.30	0.28	0.29	0.29	0.28	0.22	0.18
Leverage	0.00	0.20	0.24	0.23	0.24	0.23	0.23	0.24	0.19	0.25
GARCH	-0.75	0.22	0.33	0.27	0.32	0.30	0.32	0.33	0.48	0.45
FXV	0.22	0.26	0.27		0.28	0.24	0.25	0.27	0.28	0.40
VIX	0.02	0.02	0.03			0.03	0.03	0.03	0.05	0.03
CPRISK	9.96	-5.42	-6.22				-6.21	-6.22	-1.93	-6.79
MPSI	0.00	-0.01	-0.01					-0.01	0.00	-0.01
EPU									-0.01	-0.01
R2	0.05	0.05	0.06	0.06	0.06	0.06	0.06	0.06	0.07	0.06
AIC	2.10	2.12	2.11	2.10	2.10	2.10	2.11	2.11	2.07	2.08
BIC	2.19	2.21	2.21	2.18	2.18	2.19	2.20	2.21	2.19	2.18
HQ	2.14	2.15	2.15	2.13	2.13	2.14	2.14	2.15	2.12	2.12
Sum(IC)	6.43	6.48	6.46	6.41	6.41	6.43	6.45	6.46	6.38	6.38
DW	1.96	1.92	1.92	1.91	1.91	1.91	1.91	1.92	1.91	1.95