THREE ESSAYS ON VOLATILITY AND INFORMATION CONTENT OF FUTURES MARKETS

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ABSTRACT

This dissertation includes three essays on volatility and information content of futures markets. This work gives new insight into the structural changes in volatility, the information content of global interest rate futures, and the time-series behavior of the volatility term structure.

The first essay examines structural volatility shifts U.S. crude oil and corn futures markets. In trying to capture the interrelations present in the two markets, we take seriously the importance of properly modelling smooth structural shifts. We incorporate trigonometric functions into a multivariate GARCH model of crude and corn futures prices to obtain the empirical volatility response functions and the time-varying correlation coefficient. Although both short-term and long-term futures exhibit shifts in the mean and volatility, volatility shifts do not manifest themselves in the same manner for different maturities.

In the second essay, we investigate the term structure of interest rate futures in the US, Eurozone, United Kingdom, and Switzerland and empirically document five unique results. First, implied USD futures rates contain significantly different information compared to USD spot rates. Second, the four interest rate futures contracts contain similar information that is driven by one common component. Third, implied futures rates contain more information regarding future rate changes than return premiums. Fourth, information shifts are associated with macroeconomic conditions and central bank policies. Finally, significant information shifts occurred during the 2013-2015 time frame, which were greater than those of the great recessionary period of 2008-2009.

The third essay focuses on the Samuelson hypothesis, a proposition that futures volatility declines with maturity. We study the strength of the Samuelson effect over time in ten most actively traded U.S. commodity futures. Capturing the dynamics of the futures volatility term structure with three factors, we show that in most markets the slope factor is strongly negative in certain periods and only weakly or not at all negative in other periods. Consistent with the linkage between carry arbitrage and the Samuelson hypothesis, we find that high inventory levels correspond to a flatter volatility term structure. We also find that a flatter volatility term structure corresponds to lower absolute futures term premiums.

DEDICATION

This dissertation is dedicated to my parents, Yuri Teterin and Olga Teterina, and my grandmother, Tamara Teterina, whose unwavering and selfless support is the reason I have been able to embark on this ten-year journey from first entering undergraduate studies to now completing this dissertation. The heartfelt encouragement of my wife, Jamie Eloff Teterin, and the inspiration from my two sons, Asa and Henry, are what kept me on this path during the hardest moments, and so I dedicate this dissertation to them as well.

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CHAPTER 1: INTRODUCTION

The three essays of this dissertation empirically examine the time-series behavior of volatility and forecasting ability with the emphasis on the futures markets. The key difference between futures and spot markets lies in the maturity dimension present in futures but lacking in spot markets. The ability to observe the maturity term structure of futures prices and volatilities leads to key insights in each of the essays.

The first essay shows that trigonometric functions work well in capturing structural changes in futures volatility and that the presence of trigonometric functions reduces model persistence. Improved model persistence has implications for the quality of volatility forecasts, while the coincident structural volatility changes in the short-term and long-term futures are related to the volatility term structure. The second essay studies the ability of current information to forecast future conditions in interest rate futures markets and finds that the predictive ability varies over time with the substantial portion of variation attributable to global phenomena. The third essay further examines futures volatility term structure by decomposing it into three component factors and tracking the time-series behavior of the factors.

Motivation for the first essay comes from the literature that studies the linkages between corn and crude oil markets and the changes that the two markets have undergone due to increased ethanol production in the U.S. in part mandated by federal law. Existing literature has considered two primary features of the changes in these markets: structural shifts and volatility spillovers. We add to the debate by allowing structural shifts in both the mean and the variance-covariance matrix. It is important to allow for both types of breaks because seminal works of

Perron (1989) and Hillebrand (2005) show that neglected structural change in the mean and variances equations typically results in spurious persistence.

We modify Gallant's (1981) Flexible Fourier Form to allow for breaks in a VAR with GARCH effects by incorporating several low frequency trigonometric components of a Fourier series approximation into the mean and conditional variance equations of a bivariate GARCH model. We show that the means and the variance–covariance matrix of corn and crude oil futures exhibit structural change. Existence of structural change in the variance-covariance matrix is our key contribution to the research on the interaction between petroleum and corn markets because it allows us to reconcile the opposing viewpoints found in the literature. Specifically, the period surrounding the financial crisis of 2008 was marked by increased interaction between the two markets resulting in the rise of conditional correlations, consistent with the traditional view expressed in Enders and Holt (2012) and others; correlations were much lower throughout the rest of the sample period, consistent with Myers et al. (2014).

We also contribute to the literature on structural change by showing that our modification of a well-known trigonometric function approach can control for breaks in the variance-covariance matrix. The variance impulse response function methodology of Hafner and Herwartz (2006) effectively demonstrates that controlling for volatility breaks leads to reduction in volatility persistence. A given shock's dissipation time declines by approximately 50% when we switch from a no-break model to one that controls for mean and volatility breaks. Shorter shock dissipation time is indicative of the principal ability of our approach to alleviate the problem of spurious persistence by controlling for breaks in a GARCH model.

The second essay examines the information content of global interest rate futures. While determining the prevailing information content of forward rates in different countries is

important to policymakers, investors, financial institutions and other economic agents, nearly all existing literature on the estimation of term premia and forecasting rate changes and holding period returns has used data from only a single country, most often the United States (Wright, 2011). Recent studies find that there exist global yield factors that are economically important and explain significant fractions of country yield curve dynamics (Diebold, Li, and Yue, 2008) and that the term premium components of forward rates in the ten major industrialized countries have trended together for the last 20 years (Wright, 2011). These findings fit well within the emerging global financial cycle framework (Miranda-Agrippino and Rey, 2015; Rey, 2015).

We contribute to the existing literature on the cross-country term structure differences in two ways. First, the observed rate in our study is based on the futures market rather than the spot market. Thus, we expect differences between the spot rates and implied futures rates because informed traders are more likely to trade futures contracts rather than making interbank transactions or trading government bonds. Second, instead of imposing a factor structure on the yield curve and studying the factors, we investigate time-series variation in the information content of the term structure by employing simple forecasting regressions involving forward rates.

Our goal is to determine whether interest rate markets in different countries are experiencing convergence in terms of their information content, which would be consistent with the literature on global yield factors and global financial cycle, or if these markets generate distinct information, perhaps due to difference in macroeconomic conditions and monetary policies. To this end, we apply the methodology of Brooks, Cline, and Enders (2015) to global rate-based futures contracts. Specifically, we investigate the information content in four available interest rate futures markets – Eurozone, US, UK, and Switzerland – by assessing the forecasting

power of forward rates in predicting return premiums and future rate changes as in Fama (1984). We find that the four markets contain similar information, while U.S. interest rate futures differ from the spot markets in terms of their information content. Implied forward rates contain more information regarding future rate changes rather than return premiums. While information shifts appear to be related to macroeconomic conditions and monetary policy, the 2013-2015 time frame stands out as a period of widespread information shifts, but relatively contained changes in the macroeconomic indicators.

In the third essay, the focus is on the Samuelson hypothesis – a much-tested proposition that futures volatility increases as expiration date approaches used by Samuelson (1965) as an example within his model of price behavior. While empirical literature over the years has found mixed support for the hypothesis across a variety of markets, time periods, and observation frequencies, theoretical literature has put forth three explanation of the maturity effect. Anderson and Danthine (1983) introduce a state-variable framework within which the hypothesis can be interpreted as a special case when progressively more uncertainty is resolved as the maturity date approaches. Bessembinder et al. (1996) show that the hypothesis will generally be supported in markets where the spot price process contains a mean reverting component. Brooks (2012) develops a futures market representation to show that the hypothesis cannot hold in fully arbitraged markets where the cost-of-carry model holds without the need to assume the existence of a convenience yield.

Our contribution to the literature is empirical in nature as we study the variation in the strength of the Samuelson hypothesis over time in ten most actively traded U.S. commodity futures across three categories: agriculture, energy, and metals. We reduce dimensionality of the research question by borrowing from the interest rate term structure literature (Diebold and Li,

2006) and showing that changes in the shape of the futures volatility term structure can be explained by three dynamic factors whose loadings have the Nelson and Siegel (1987) functional form. Using the slope factor as a measure of strength of the Samuelson effect, we show that, except for natural gas futures, the markets in our study had a statistically flat volatility term structure sometime during the sample period. The fact that the Samuelson effect was absent in corn, soybeans, wheat, crude oil, heating oil, and reformulated blend futures during certain periods is particularly remarkable because at other times the effect was very strong; in contrast, even when the Samuelson effect was present in gold, copper, and silver futures it was not very strong.

Carry arbitrage transactions involving short sales of the underlying commodity become more feasible and the Samuelson effect disappears as per Brooks (2012) only when inventories are sufficiently high; consistent with this notion, we find that high inventory levels correspond to a flatter volatility term structure in corn, crude oil, heating oil, gold, silver and copper futures. Furthermore, the relationship is generally stronger when inventories are above a market-specific threshold. Threshold behavior lends support to the carry arbitrage explanation of the Samuelson hypothesis because other explanations of the hypothesis predict a continuous inventory-slope relationship. In addition, when the volatility term structure flattens, term premiums in all futures markets except for wheat move closer to zero, consistent with the explanation that arbitrageurs provide infinite supply to meet net hedging demand.

CHAPTER 2: SMOOTH VOLATILITY SHIFTS AND SPILLOVERS IN U.S. CRUDE OIL AND CORN FUTURES MARKETS

2.1. Introduction

The recent history of petroleum and agricultural commodity prices is replete with large fluctuations accompanied by sizable changes in their conditional volatilities. Sumner (2009) and Wright (2011) indicate that from 2006 through mid-2008 grains experienced one of the largest percentage price increases in history and that the volatility increases were sustained. For example, corn cash prices rose from $1.87 at the end of 2005 to $5.35 in August 2008. The price reached a maximum of $7.13 in 2013 only to fall to $3.53 by the end of 2015. Similarly, West Texas Intermediate spot prices fluctuated around $55 per barrel in 2005, rose to $145 in July 2008, and began a steady decent to $37 per barrel by the end of 2015. The co-movements between corn and oil futures prices can be seen in Figure 2.1. It appears that the two prices often move together and that both volatilities are far larger in the latter third of the sample than during the 1990s.

Papers such as Hertel and Beckman (2011), Tyner (2010), and Muhammad and Kebede (2009) argue that the increased reliance on biofuels (particularly on ethanol) is a key factor contributing to the increased linkages between the grain and petroleum markets. As part of the Energy Policy Act of 2005, the Renewable Fuel Standard (RFS) requires that an increasing volume of renewable fuels be blended into all gasoline sold in the United States. The RFS required that four billion gallons of renewal fuels be blended into gasoline in 2006. The number rose to nine billion gallons in 2008 and is mandated to rise to 36 billion gallons by 2022.

Moreover, as pointed out by Wetzstein and Wetzstein (2011), U.S. biofuel refining receives a federal tax credit of $0.45 per gallon along with various state subsidies combined with a $0.54 per gallon U.S. ethanol tariff. As a result, in 2011 over 40 percent of the U.S. corn crop was used in ethanol production.

In addition to increased biofuel production, researchers have offered additional explanations for these recent shifts in commodity prices and the accompanying volatility increases. Enders and Holt (2012) suggest that rapid income growth in emerging economies, specifi- cally the so-called BRIC (Brazil, Russia, India, and China) countries, is one of the primary drivers of the price boom, citing increased demand for both agricultural and energy products. Trujillo-Barrera et al. (2012) argue that underinvestment in agriculture, low inventory levels, supply shocks in key producing regions, fiscal expansion and lax monetary policy in many countries, as well as a depreciation of the U.S. dollar, have also contributed to increased commodity price volatility.

In contrast, a number of authors have argued that the relationship between the two prices is not especially tight. For example, Myers et al. (2014) use common trend-cycle decompositions and find that the co-movements between energy and agricultural feedstock prices tend to dissipate in the long-run. Similarly, Wetzstein and Wetzstein (2011) contend that a strong connection between oil and agricultural prices is a “myth.” Their reasoning is that the creation of biofuel capacity entails adjustment costs, non-reversibilities, and uncertainties. As such, biofuel production is not likely to be highly responsive to short- run oil-price changes. In the same vein, papers such as Tyner (2010), Hertel and Beckman (2010), Saghaian (2010) and Zhang et al. (2010) find that changes in government policy and/or non-petroleum input price changes often govern large movements in grain prices.

The aim of the paper is to examine the changing relationship between energy and agricultural markets, as represented by crude oil and corn prices, respectively. Note that Enders and Holt (2012) examine the behavior of real petroleum and agricultural prices over a fifty-year period and identify structural changes in each by estimating shifting-mean autoregressions. Enders and Holt (2014) generalize the procedure and estimate the prices as a mean-shifting vector autoregression (VAR). Nevertheless, both papers treat the conditional variance of each market as a constant, so that they ignore the possibility of volatility shifts and spillovers. In contrast, Zhang et al. (2009) and Trujillo-Barrera et al. (2012) model agricultural and petroleum prices in a multivariate generalized autoregressive conditional heteroscedasticity (GARCH) setting and explore volatility spillovers, but do not allow for structural breaks in mean or variance. It is important to allow for mean and volatility breaks as Perron (1989) and Hillebrand (2005) demonstrate that neglected structural change in the mean and variance equations typically result in spurious persistence.

Our approach is novel in the sense that we allow for breaks in both the mean and variance equations. As in Enders and Holt (2012, 2014), we incorporate several low-frequency trigonometric functions into the mean equations to capture gradual structural change. As in Baillie and Morana (2009), we incorporate several low-frequency trigonometric functions into the conditional variance equations in order to capture the growth of the BRIC countries and the adoption of ethanol standards. Since we model the two processes in a multivariate GARCH framework, a key feature of our methodology is that it allows for smooth shifts in the volatility spillovers between the two markets. A desirable feature of the trigonometric functions is that they enable us to model the mean and volatility shifts as ongoing, rather than pure jump, processes.

We use a modification of Gallant's (1981) Flexible Fourier Form to allow for breaks in a VAR with GARCH effects, and show that the means and the variance-covariance matrix of corn and crude oil futures exhibit structural change. This structural change in volatility is present in both the short-term and the long-term futures contracts. A number of paper such as Baillie and Meyers (1991), Brunetti and Gilbert (2000), and Jin and Frechette (2004) have found that commodity process exhibit long-memory in that conditional volatilities appear to be fractionally integrated. We construct variance impulse response function using the methodology suggested by Hafner and Herwartz (2006) in order to assess whether control- ling for volatility breaks leads to reduction in volatility persistence. We show that a given shock's dissipation time declines by approximately 50% when we switch from a no-break model to one that controls for mean and volatility breaks. Since a longer shock dissipation time corresponds to a model with more persistence, we can conclude that our approach to controlling for breaks in a GARCH model helps alleviate the problem of spurious persistence.

In our analysis, we use daily settlement prices of corn and crude oil futures. There are several reasons for examining futures prices. First, price discovery is an important feature of exchange-traded futures. Informed traders will prefer futures over spot transactions due to low margin requirements and lack of physical product. Second, as shown by Brooks (2012), crude oil and corn futures are characterized more as unarbitraged rather than fully arbitraged markets; thus, futures prices may reflect future expected spot prices.[1] Third, futures markets permit the analysis of the maturity time dimension as well as the calendar time dimension. Therefore, volatility shocks and spillovers can be studied from both short-term and long-term perspectives.

[1] Based on a proxy for the degree to which a futures market is unarbitraged, corn ranked 14th, crude oil ranked 19th, and unarbitraged markets comprised roughly 30 of the 50 markets examined by Brooks. Due to the consumption nature of both corn and WTI as well as the inability to short sell them, both commodities exhibit the Samuelson effect of declining volatility of longer dated futures contracts.

Although we find structural change in the variance-covariance matrix of both the short-term and the long-term futures, it is difficult to tell whether this change manifests itself in the same manner when looking at each maturity separately. To circumvent this issue, we repeat our analysis using the term spread between the long-term and the short-term futures contracts in each market. We find that the variance-covariance matrix of term spreads also exhibits structural change, which indicates that the term structure of volatility in corn and crude oil futures markets changes over time. Thus, even if the term structure of volatility is flat at some point in time, it does not stay flat throughout our sample, which further confirms Brooks' (2012) finding that U.S. corn and crude oil futures markets are unarbitraged. At the same time, we find no evidence that the term structure of futures prices changes over time.

2.2. Data

We obtain daily settlement prices of corn and crude oil futures[2] from Commodity Systems Incorporated, a data vendor. The sample starts on June 1, 1993 and ends on March 19, 2015, totaling 5688 days. We exclude weekends, and forward fill the prices on the weekdays when the futures markets are closed. For each commodity, settlement prices are available for every traded futures contract from the first day it has traded until the last day of trading in the contract.[3] Starting on the first day of our sample, we construct a time-series of settlement prices of the contract with the nearest delivery month, the contract with next nearest delivery month,

[2] Corn futures trade in the open outcry at the Chicago Board of Trade and electronically on the CME Globex platform. Crude oil (West Texas Intermediate) futures trade in the open outcry on NYMEX and electronically on the CME Globex platform.

[3] For crude oil futures, the settlement price of the front month contract is the volume weighted average price of trades occurring on Globex between 14:28:00 and 14:30:00 Eastern Time. The settlements of the second through sixth contract months are determined from Globex spread data. For corn futures, the CME Group staff determines the daily settlement prices by incorporating both Floor-based and Globex-based trading activity between 13:14:00 and 13:15:00 Central Time. The settlement procedure for corn futures is a bit more involved compared to crude oil futures; details can be found at http://www.cmegroup.com/trading/agricultural/files/daily-grains-settlement-procedure.pdf.

and so on up to the longest dated contract that is traded on any day in our sample. Note that a traded contract with the nearest delivery month is termed the first nearby, whereas a contract with the next nearest delivery month is the second nearby, and so forth.

In order to gauge the differences in the volatility interaction between crude oil and corn futures across maturities, for each commodity we select two contracts: a short-term contract and a long-term contract. Specifically, the short-term corn futures contract in our sample is the second nearby; the use of the first nearby contract is not desirable because of the significant decline in trading volume and open interest, as well as the noise associated with trading in the delivery month. Average number of days to expiration of the second nearby corn futures is 115 calendar days. The short-term crude oil futures contract in our sample is the fourth nearby. On average, this contract has 110 days to expiration, so it is closest to the average maturity of the short-term corn futures contract. For instance, July, 2015 is the delivery month of both the second nearby corn futures and the fourth nearby oil futures on the last day in our sample. Both the second nearby corn futures and the fourth nearby crude oil futures are actively traded: throughout our sample, the minimum open interest in these contracts is 28967 and 12113, respectively.[4]

When choosing a long-term contract for each commodity, the primary consideration is ensuring sufficient open interest and volume of trading in the contract. We select the fifth nearby corn futures and the eleventh nearby crude oil futures as our long-term contracts, purposefully choosing the contracts with matching average maturities. These contracts have, on average, 338 and 330 days to expiration, respectively. Across our sample, the minimum open interest in the

[4] To assess the market value of open interest, we multiply the minimum open interest by the futures price corresponding to the day when the minimum open interest is observed and by the contract size. We find that the assessed market values are $381.64 million and $208.83 million for corn and crude oil, respectively.

fifth nearby corn futures is 986, and the average is 52874. For the eleventh nearby crude oil futures, the minimum open interest is 2349 with the average of 22142.

Figure 2.1 presents plots of each of the four time-series. Beginning in 2007, corn futures have experienced significantly higher volatility than in previous years; perhaps, the shocks related to the financial crisis have caused initial increases in volatility, but volatility seems to have remained higher than before the crisis. Crude oil futures have experienced high volatility around the time of the financial crisis, but appear to have returned to the pre- crisis levels of volatility. Finally, the short-term contracts in both commodities appear to be more volatile than the long-term contracts.

As should be anticipated from Figure 2.1, formal testing indicates that each series is difference-stationary using standard Dickey-Fuller tests and the Enders and Lee (2012b) nonlinear tests. Moreover, at conventional significance levels, the null hypothesis of no cointegration could not be rejected for short- and long-term futures.[5]

2.3. Methods

Let us first consider the simple vector autoregression (VAR):

$$\Delta w_t = \eta_0 + \eta_1 t + A_{11}(L)\Delta w_{t-1} + A_{12}(L)\Delta c_{t-1} + \varepsilon_{1t} \tag{2.1}$$

$$\Delta c_t = \delta_0 + \delta_1 t + A_{21}(L)\Delta w_{t-1} + A_{22}(L)\Delta c_{t-1} + \varepsilon_{2t}$$

where w_t is the log of the price of WTI futures at time t, c_t is the log of the price of corn futures at time t, the $A_{ij}(L)$ are polynomials in the lag operator L, and the ε_{it} are independent and identically normally distributed (across time) error terms that might be contemporaneously correlated with variance-covariance matrix H given by

[5] Results of these tests are available from the authors upon request.

$$H = \begin{bmatrix} h_{11} & h_{12} \\ h_{12} & h_{22} \end{bmatrix} \tag{2.2}$$

where $h_{ij} = \mathbb{E}[\varepsilon_{it}\varepsilon_{jt}]$ for $i = 1, 2$ and $j = 1, 2$. Within this standard framework, the spillovers in the model of the mean are captured by the coefficients in the polynomials $A_{ij}(L)$. For example, if all coefficients of $A_{12}(L)$ equal to zero, variable c_t does not Granger-cause variable w_t. Hence, shocks to the corn prices have no lagged effects on the market for oil. Instead, if any of the coefficients of $A_{12}(L)$ differ from zero, shocks to the corn market spill over to the market for oil.

For our purposes there are three important deficiencies in the equations above. First, as discussed in Enders and Holt (2012, 2014), it is important to control for the possibility of structural breaks in equation (2.1). In particular, the acceleration in the growth rates of the BRIC countries and the increased use of ethanol in gasoline production can manifest themselves as changes in the intercept terms η_0 and δ_0.[6] As such, we want to modify equation (2.1) so that the intercept terms can capture such structural changes. Second, the variance-covariance matrix H is such that all values of h_{ij} are time-invariant. Nevertheless, Trujillo-Barrera et al. (2012) demonstrate that the elements of H exhibit conditional volatility. As a result, we estimate the system as a multivariate GARCH process that allows for volatility shocks in one sector to spill over into the other sector. Third, it is likely that the volatility equations themselves exhibit structural change. Hillebrand (2005) shows that neglected structural change in a GARCH process manifests itself as spurious persistence. In order to ensure that our model of the conditional variance is not misspecified, we allow for possible structural change in our estimated multivariate GARCH process.

[6] In principle, structural change can manifest itself in all of the parameters of the VAR. However, in econometric practice, the effect of structural change is typically concentrated in the intercept terms. Hence, we consider what Enders (2010) calls the "partial break" model. This idea also extends to GARCH models.

In order to modify the basic VAR of equation (2.1), we relax the assumption that the intercept terms are constant over time and estimate a model of the form

$$\Delta w_t = \eta_0(t) + \eta_1 t + A_{11}(L)\Delta w_{t-1} + A_{12}(L)\Delta c_{t-1} + \varepsilon_{1t} \tag{2.3}$$

$$\Delta c_t = \delta_0(t) + \delta_1 t + A_{21}(L)\Delta w_{t-1} + A_{22}(L)\Delta c_{t-1} + \varepsilon_{2t}$$

where the notation $\eta_0(t)$ and $\delta_0(t)$ highlights the fact that the intercepts in the mean equations are functions of time.

In order to account for GARCH effects we also modify the variance-covariance matrix such that

$$H_t = \begin{bmatrix} h_{11t} & h_{12t} \\ h_{12t} & h_{22t} \end{bmatrix} \tag{2.4}$$

where the elements h_ijt are time-varying. We can think of h_{11t} and h_{22t} as the conditional variances of ε_{1t} and ε_{2t}, respectively.[7] Since we want to allow for the possibility that the shocks are correlated, denote h_{12t} as the conditional covariance between the two shocks. Specifically, we use the standard BEKK[8] formulation of a multivariate GARCH model so that we ensure that the conditional variances are necessarily positive. Consider the multivariate GARCH process:

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon_{t-1}A + B'H_{t-1}B \tag{2.5}$$

where for our two-variable case,

$$C = \begin{bmatrix} c_{11} & c_{12} \\ c_{12} & c_{22} \end{bmatrix}; A = \begin{bmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{bmatrix}; B = \begin{bmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{bmatrix} \tag{2.6}$$

The essential feature of the BEKK model is that shocks to the variance of one of the variables spill over to the others because, in general, h_{ijt} depends on the squared residuals, cross-

[7] In a GARCH model, the two error processes from equation (2.3) are given by $\varepsilon_{1t} = v_{1t}\sqrt{h_{11t}}$ and $\varepsilon_{2t} = v_{2t}\sqrt{h_{22t}}$, where v_{1t} and v_{2t} are independently normally distributed with zero mean and unit variance.

[8] The BEKK model is developed in Baba, Yoshihisa, Engle, Kraft, and Kroner (1991). Baillie and Myers (1991) use two different parametrizations of the bivariate GARCH model, diagonal VECH and BEKK, to estimate optimal commodity futures hedges. They find that both models appear to provide a good description of the autocorrelation and conditional heteroscedasticity characterizing commodity prices.

products of residuals, and the conditional variances and covariances of all variables in the system.

As it stands, equation (2.5) only captures autoregressive dynamics in the variance-covariance matrix. In order to allow for structural change in the volatility equations, we now discuss how to incorporate time-varying intercepts into the h_{ijt}.

2.3.1. Smooth structural change

Bai and Perron (1998) develop a methodology that can be used to test for the presence of multiple sharp structural breaks in a univariate time-series model. In essence, the methodology entails estimating the model for every possible combination of breaks and selecting the one that maximizes the log likelihood function ($\mathcal{L}^*$). Bai and Perron develop the appropriate critical values for a likelihood ratio test in which $\mathcal{L}^*$is compared to the maximized value of the likelihood function assuming there are no breaks. The situation is more complicated in a VAR because a break in one variable (say w_t) has the potential to cause mean shifts in all of the other variables. As such, it becomes difficult to determine whether a perceived break in w_t is due to a shift in its own parameters or to changes in the parameters of the other variables in the model. Bai, Lumsdaine and Stock (1998) and Qu and Perron (2007) extend the Bai and Perron (1998) methodology to allow for the presence of multiple structural breaks in the coefficients and/or in the variance-covariance matrix of a VAR.

All of these papers assume, however, that the breaks are sharp in that they fully manifest themselves in a single period. In contrast, the work of Enders and Holt (2014) indicates that smooth breaks best characterize the linkages in the corn and oil price relationship. After all, the growth rates of the BRIC countries did not jump to their new higher levels in one particular quarter and the increased use of ethanol is an ongoing process. As such, we believe it reasonable

to model the changes in the VAR coefficients and in the variance-covariance matrix as being smooth rather than sharp.

Fourier series approximation can capture the behavior of any absolutely integrable function to any degree of accuracy. Hence, instead of estimating the number, form, and the size of the breaks, we use Enders and Lee's (2012a) modification of Gallant's (1981) Flexible Fourier Form (FFF) to control for breaks in a VAR. Specifically, Enders and Lee (2012a) demonstrate that their modification of Gallant's FFF can mimic a time-series with multiple structural breaks. Enders and Jones (2015) have shown that the FFF approximation works well in the context of a VAR. In order to understand the nature of the approximation, let $\eta_0(t)$ in equation (2.3) be represented by[9]

$$\eta_0(t) = \eta + \sum_{i=1}^{k} \left[\phi_i \cos\left(\frac{2\pi i t}{T}\right) + \psi_i \sin\left(\frac{2\pi i t}{T}\right) \right] \tag{2.7}$$

where η, ϕ_i, and ψ_i are constants, T is the number of observations, and k is a constant that controls how many cumulative Fourier frequencies are included in the approximation.

The key feature of equation (2.7) is the presence of trigonometric terms $\cos\left(\frac{2\pi i t}{T}\right)$ and $\sin\left(\frac{2\pi i t}{T}\right)$. There are several desirable features of this approximation. In particular, equation (2.7) nests the linear model, and Gallant and Souza (1991) show that the ordinary least squares estimates of ϕ_i and ψ_i in equation (2.7) have a multivariate normal distribution.[10] As such, a test for linearity (that is, whether it is possible to reject the null hypothesis that $\phi_1 = \cdots = \phi_k = \psi_1 = \cdots = \psi_k = 0$) can be conducted using a standard *F* test. Given that the trigonometric terms

[9] We model $\delta_0(t)$ in a similar fashion.
[10] Note that Astill et al. (2014) develop the critical values to test for the presence of deterministic Fourier components in a univariate time-series model that is asymptotically robust to the order of integration of the process in question.

constitute an orthogonal basis, it follows that $\cos\left(\frac{2\pi it}{T}\right)$ and $\sin\left(\frac{2\pi it}{T}\right)$are orthogonal to each other for all integer values of i. As such, testing whether any or all of the ϕ_i and ψ_i jointly equal to zero is possible because the regressors are uncorrelated with each other. Another advantage of equation (2.7) over other approximations, such as a Taylor series expansion in $t, t^2, t^3, \ldots$ is that the trigonometric frequencies are all bounded in $[-1,1]$.

Hence, the use of the FFF transforms the problem of estimating the number, form, and magnitudes of the breaks into one of incorporating the appropriate frequencies into equation (2.7). The key insight into selecting the appropriate value for k is that breaks shift the spectral density function towards zero. As such, since breaks manifest themselves at the low end of the spectrum, the value of k should be small.[11]

As such, our full model of the mean has the form

$$\Delta w_t = \eta_0 + \eta_1 t + \sum_{i=1}^{n}\left[\eta_{ci}\cos\left(\frac{2\pi it}{T}\right) + \eta_{si}\sin\left(\frac{2\pi it}{T}\right)\right] \tag{2.8}$$

$$+A_{11}(L)\Delta w_{t-1} + A_{12}(L)\Delta c_{t-1} + \varepsilon_{1t}$$

$$\Delta c_t = \delta_0 + \delta_1 t + \sum_{i=1}^{n}\left[\delta_{ci}\cos\left(\frac{2\pi it}{T}\right) + \delta_{si}\sin\left(\frac{2\pi it}{T}\right)\right]$$

$$+A_{21}(L)\Delta w_{t-1} + A_{22}(L)\Delta c_{t-1} + \varepsilon_{2t}$$

and the model of the conditional volatility matrix H_t, obtained by performing matrix multiplication in equation (2.5) and adding trigonometric terms, is given by

$$h_{11t} = \sum_{i=1}^{k}\left[\phi_{11i}\cos\left(\frac{2\pi it}{T}\right) + \psi_{11i}\sin\left(\frac{2\pi it}{T}\right)\right] + (c_{11}^2 + c_{12}^2) \tag{2.9}$$

[11] Another way to make the point is to note that Perron(1989) shows that a neglected break in an otherwise stationary series has the effect of making the series behave as a unit-root process.

$$+(\alpha_{11}^2\varepsilon_{1t-1}^2 + 2\alpha_{11}\alpha_{21}\varepsilon_{1t-1}\varepsilon_{2t-1} + \alpha_{21}^2\varepsilon_{2t-1}^2)$$

$$+(\beta_{11}^2 h_{11t-1} + 2\beta_{11}\beta_{21}h_{12t-1} + \beta_{21}^2 h_{22t-1})$$

$$h_{12t} = \sum_{i=1}^{k}\left[\phi_{12i}\cos\left(\frac{2\pi it}{T}\right) + \psi_{12i}\sin\left(\frac{2\pi it}{T}\right)\right] + c_{12}(c_{11} + c_{22})$$

$$+(\alpha_{11}\alpha_{12}\varepsilon_{1t-1}^2 + (\alpha_{11}\alpha_{22} + \alpha_{21}\alpha_{12})\varepsilon_{1t-1}\varepsilon_{2t-1} + \alpha_{21}\alpha_{22}\varepsilon_{2t-1}^2)$$

$$+(\beta_{11}\beta_{12}h_{11t-1} + (\beta_{11}\beta_{22} + \beta_{21}\beta_{12})h_{12t-1} + \beta_{21}\beta_{22}h_{22t-1})$$

$$h_{22t} = \sum_{i=1}^{k}\left[\phi_{22i}\cos\left(\frac{2\pi it}{T}\right) + \psi_{22i}\sin\left(\frac{2\pi it}{T}\right)\right] + (c_{12}^2 + c_{22}^2)$$

$$+(\alpha_{12}^2\varepsilon_{1t-1}^2 + 2\alpha_{12}\alpha_{22}\varepsilon_{1t-1}\varepsilon_{2t-1} + \alpha_{22}^2\varepsilon_{2t-1}^2)$$

$$+(\beta_{12}^2 h_{11t-1} + 2\beta_{12}\beta_{22}h_{12t-1} + \beta_{22}^2 h_{22t-1})$$

Notice that the trigonometric terms in equation (2.8) can capture structural breaks in Δw_t and Δc_t and the trigonometric terms in equation (2.9) can capture structural breaks in the H_t matrix. Note that the specification is general enough that breaks in the mean and variance equations need not be coincident.

2.4. Results

2.4.1. The model of the mean

Given that the series act as difference-stationary processes, we now turn to determining the appropriate lag length in equation (2.8). Since a VAR treats variables symmetrically, each equation contains the same number of lagged terms of Δw_t and Δc_t. As described in Enders (2010), the general-to-specific method of selecting the appropriate lag length entails beginning with a reasonably long lag length and then pruning down the model using likelihood ratio tests. Since we work with daily data, we begin with the lag length of five days based on the *a priori* notion that one week is a sufficiently long period to capture the systems' dynamics. Using the

significance level of five percent, the general-to-specific procedure results in optimal lag length of one day for the system of short-term crude oil and corn futures.[12] For the system of long-term futures, the general-to-specific algorithm optimally selects the lag length of five days.

We next determine the number of Fourier frequencies to include in the models of the mean, equation (2.8), using the general-to-specific method. We begin with five cumulative trigonometric frequencies ($n \leq 5$) so that we do not estimate a large number of unnecessary parameters and because structural breaks manifest themselves in the low end of the spectrum. The general-to-specific method indicates that five cumulative trigonometric frequencies should be included in the model of the short-term futures (reducing the number of frequencies from five to four produces a likelihood ratio test statistic with marginal significance level of 0.038) and in the model of the long-term futures (0.021). Consequently, when we turn to estimating the models of the variance we use five Fourier frequencies in our models of the mean for both short- and long-term futures.

A properly specified model of the mean is essential in assessing the extent to which the error terms exhibit conditional heteroscedasticity. To this end, we employ a series of diagnostic tests to ensure that our VAR in equation (2.8) adequately captures all of the dynamics in the relationship between logarithmic changes of oil and corn futures prices. These tests indicate that our models of the mean for both short-term and long-term futures capture the autoregressive effects sufficiently well. For instance, the Ljung-Box Q-statistics for the residuals from each equation in the short-term model of the mean are $Q(5) = 7.180$ and $Q(10) = 10.185$ for oil, and $Q(5) = 1.277$ and $Q(10) = 9.598$ for corn. None of these statistics are significant at any

[12] Use of alternative significance levels of one and ten percent sometimes results in the different number of lags, but our main results are unaffected by the change.

conventional level, indicating that the residuals from our short-term VAR display no significant sample autocorrelations.

Having ensured that our models of the mean properly capture the autoregressive dynamics in the data, we turn to formal tests for autoregressive conditional heteroscedasticity (ARCH). For the short-term futures, the Ljung-Box Q-statistics for the squared residuals are $Q(5) = 855$ and $Q(10) = 1467$ for oil, and $Q(5) = 687$ and $Q(10) = 1106$ for corn, which are all highly significant at any conventional level. Not surprisingly, performing the McLeod-Li (1983) test using a lag length of five days, we find that the value of the test statistic is $TR^2 = 540$ for oil and $TR^2 = 440$ for corn. The magnitudes of the Ljung-Box and McLeod-Li tests statistics for the long-term futures are similar. Therefore, there is strong evidence of ARCH errors in the models of the mean for both short-term and long-term futures.

2.4.2. The model of the variance

Given that the error terms in the models of the mean for the short-term and long-term futures exhibit conditional heteroscedasticity, we now turn to estimating the multivariate GARCH model given in equation (2.9) that allows for smooth structural changes in volatility; thus, we address the second and third shortcomings of a basic VAR model that we discuss in the methods section.

As in the case of the models of the mean, we estimate the models of the variance using up to five cumulative trigonometric frequencies (*i.e.*, $k \leq 5$) in equation (2.9).[13] Keep in mind that inclusion of trigonometric terms in the variance equations accounts for possible structural changes in conditional volatility, whereas we have already captured possible structural changes

[13] Parameter estimates from these models are available from the authors upon request.

in the means of the series by selecting appropriate models of the mean for the short-term and long-term futures in the previous section.

Comparing the model with only one trigonometric frequency, $k = 1$, to the model with no trigonometric terms, the estimates suggest that the trigonometric terms are statistically significant in both the short-term and long-term futures models: the likelihood ratio test statistic is significant at any conventional level. Thus, we can conclude that there are structural changes in the conditional volatility of the series and that inclusion of trigonometric terms helps account for these changes.

Whereas it is clear that the model with only one Fourier frequency is better than the standard BEKK, models with more cumulative frequencies may offer an even better trade- off between fit and number of regressors. The likelihood ratio test statistic for $k = 5$ is not significant at any conventional level, indicating that the inclusion of Fourier terms with frequency five to the model that already contains four cumulative frequencies is not warranted. On the other hand, the statistic for $k = 4$ is highly significant, suggesting that the restriction that the coefficients of trigonometric terms with frequency four are equal to zero is binding when compared against the model with three cumulative Fourier frequencies. Therefore, the general-to-specific method points to the model with $k = 4$. For the long-term futures, the general-to-specific method also suggests the model with four cumulative Fourier frequencies.

Examining the estimated variance equations, we find that the autoregressive coefficients become smaller after we include trigonometric terms in the model. This observation is consistent with Hillebrand's (2005) finding that neglected structural change in a GARCH model manifests itself as spurious persistence: Fourier terms in our models help account for structural change, so that the models display less persistence.

We use the models with the optimal number of Fourier frequencies in the mean and variance equations ($n = 5$, $k = 4$ for both the short- and long-term models) to perform a series of diagnostic tests. These diagnostic tests reveal that the model of the mean remains properly specified as we cannot reject the null hypothesis that the various Q-statistics for the standardized residuals sequences are equal to zero. We test for remaining GARCH effects and find that for both short- and long-term futures the estimated residuals from the corn equation do not display any remaining conditional volatility, whereas the residuals from the oil equation do. Interestingly, the inclusion of the Fourier terms in the variance equations attenuates the problem of remaining GARCH effects. For example, the Q-statistic for the squared standardized residuals sequence from the oil equation in the short-term model decreases from $Q(10) = 26.969$ to $Q(10) = 22.095$ (note that the one percent critical value is 23.21) when we include four trigonometric frequencies in the variance equations.

2.4.3. Structural changes in volatility

After we estimate our GARCH models with the optimum number of Fourier terms in the mean and variance equations (five Fourier frequencies in the mean and four in the variance), we can obtain the predicted values of the conditional volatility series. Specifically, we use the estimated coefficients and equation (2.9) to obtain predicted values for crude oil conditional variance, $\hat{h}_{11t}$, corn conditional variance, $\hat{h}_{22t}$, and conditional covariance, $\hat{h}_{12t}$. We construct the estimates of conditional correlation as follows

$$\hat{\rho}_{12t} = \frac{\hat{h}_{12t}}{\sqrt{\hat{h}_{11t}\hat{h}_{22t}}} \tag{2.10}$$

In addition to estimated conditional volatility series, we obtain the values of the time-varying intercepts from each member equation in equation (2.9). Since the long-run mean of the series

can be found by scaling the intercept by a function of the autoregressive coefficients from the model, which is a constant, the time-varying intercept is equal to the time-varying long-run mean of the series up to a multiplicative constant. Note that if we did not include trigonometric terms in the variance equations, the intercepts (and the long-run means of the series) would be constant over time. Thus, the time-variation in the intercepts indicates shifts in the long-run means of the series.

In Panels (a), (b), (c) of Figure 2.2, we plot the estimated conditional volatility series from the short-term futures model while overlaying the time-varying intercept from each equation in (9) on the second axis. Looking at the intercept plot in Panel (a), we note that the long- run mean of the crude oil futures volatility seems to have experienced an increase during the period from 1997 to 1999 and since then has been on a slow, but steady decline, returning to pre-1997 levels in 2013. The autoregressive behavior accounted for most of the transient spikes in crude oil conditional volatility, including the sharp increase in 2008-2009.

Panel (b) indicates that the long-run mean of the corn futures volatility has been steadily increasing from 2001 to 2010, with accelerated growth beginning in 2006. Therefore, the corn futures market began experiencing accelerated volatility growth well before the onset of the crisis in financial markets. An important difference between the crude oil and corn futures markets is that in the corn market the increased volatility levels associated with the financial crisis of 2008 were to a larger degree explained by a shift in the long-run mean of the conditional variance, compared to the oil market.

Turning to the correlation plot in Panel (c), we note that the two markets appear to have been weakly related until 2007: the correlation coefficient stayed positive most of the time, but rarely exceeded 0:25. Starting in 2007, the correlation between the two markets increased rapidly

and stayed around 0.50 until 2010, experiencing a short, but steep decline in 2010, before returning to the financial crisis levels until 2012. The correlation since declined to pre-crisis levels. Comparing the estimated correlation series to its time-varying intercept, we note that the shifts in the intercept closely mimic the shifts in the series, so that the observed shifts in the correlation series are for the most part explained by the shifts in its long-run mean, and not by autoregressive behavior. Given that the beginning of the increase in the correlation coefficient roughly corresponds to the onset of the financial crisis, we are inclined to conclude that the increased correlation could be a result of increased integration of the two markets due to ethanol production, as well as a result of systemic effects in the global economy.

In Figure 2.3, we plot the conditional volatility series from the long-term futures model. In comparison to the same plots for the short-term model, the peaks of volatility series in the long-term model are somewhat smaller, as well as the average volatility levels; however, the overall behavior of the series is almost indistinguishable from the short-term model, including the time-variation in the intercepts. Thus, we can conclude that the long-term crude oil and corn futures are slightly less volatile than the short-term futures during both normal times and the episodes of extreme volatility. The nature of correlation between the two markets does not appear to depend on the maturity of the contracts with the exception that the estimated correlation series from the long-term model appears to be noisier.[14]

2.4.4. Variance impulse response function

Hafner and Herwartz (2006) introduce the concept of the volatility impulse response function (VIRF) for multivariate GARCH models. Here we briefly discuss how the VIRF can be

[14] The plots of the data sequences and conditional variances suggest that there are seasonal impulses. Consistent with this observation, we find evidence of annual seasonality with period 22, which corresponds to the number of summers in our sample. Controlling for seasonality does not qualitatively affect our results. A reproduction of our main analyses with seasonal controls is available upon request.

constructed before applying the procedure to our data. Since our BEKK formulation can be easily put into the VECH form, the calculation of the variance impulse responses is not difficult.[15] Specifically, consider the VECH formulation:

$$vech(\boldsymbol{H}_t) = \boldsymbol{C} + \boldsymbol{A}vech(\varepsilon_{t-1}\varepsilon'_{t-1}) + \boldsymbol{B}vech(\boldsymbol{H}_{t-1}) \tag{2.11}$$

where $vech$ is the half-vectorization operator that takes a symmetric $n \times n$ matrix and converts it to an $\frac{n(n+1)}{2} \times 1$ vector by arranging the elements of the lower triangular part of the matrix in a column vector, $\boldsymbol{C}$ is a vector that is a result of half-vectorization of a positive semi-definite matrix, and $\boldsymbol{A}$ and $\boldsymbol{B}$ are full $\frac{n(n+1)}{2} \times \frac{n(n+1)}{2}$ matrices.

Note that we have essentially written out the expressions for the three elements of $vech(\boldsymbol{H}_t)$ for our two-variable case with trigonometric terms in equation (2.9). The exact expressions for $\boldsymbol{C}$, $\boldsymbol{A}$ and $\boldsymbol{B}$ that result from putting our BEKK model in VECH form are available upon request.

As discussed by Hafner and Herwartz (2006), although the recursion governing equation (2.11) is very similar to the one governing a one-lag VAR in the mean, we cannot use a standardized set of shocks to obtain variance impulse responses in a GARCH model since the ε_t terms enter the equations as an outer-product. Instead, we must use a complete vector of shocks to calculate the VIRF. Hafner and Herwarz (2006) offer several interesting ways to create the vector of shocks to enter into the recursion. For the impulse responses to make sense, these shocks must somehow be representative of the data. In our analysis, we pick a vector of shocks, ε_t, that corresponds to a date of some significance.

[15] The VECH formulation is named after the $vech$ operator described in the text.

Given the chosen vector of shocks, using equation (2.11) we can can construct what Hafner and Herwartz (2006) call the conditional volatility profile by taking the difference between the forecast corresponding to the chosen vector of shocks and the forecast corresponding to the zero vector ($\varepsilon_t = 0$). Specifically, the conditional volatility profile is given by

$$vech(\boldsymbol{v}_{t+1}) = \boldsymbol{A} vech(\varepsilon_t \varepsilon_t') \tag{2.12}$$

$$vech(\boldsymbol{v}_{t+k}) = (\boldsymbol{A} + \boldsymbol{B}) vech(\boldsymbol{v}_{t+k-1})$$

Note that the conditional volatility profile is a function of the model coefficients and the shock, and not the data. By analogy with the standard impulse response functions in a VAR, the VIRF is the revision in the forecast due to observing the given shock. Thus, the VIRF is given by

$$vech(\boldsymbol{V}_{t+1}) = \boldsymbol{A} vech(\varepsilon_t \varepsilon_t' - \boldsymbol{H}_t) \tag{2.13}$$

$$vech(\boldsymbol{V}_{t+k}) = (\boldsymbol{A} + \boldsymbol{B}) vech(\boldsymbol{V}_{t+k-1})$$

where, as before, $\boldsymbol{H}_t$ is the covariance matrix for time t. Thus, the shock to the variance is the amount by which $\varepsilon_t \varepsilon_t'$ exceeds its expected value, so that the VIRF now depends on the data through $\boldsymbol{H}_t$.

The historical episode that we consider is the financial crisis of 2008. Since we use daily data, we have to pick a specific day to obtain the vector of shocks to be used for the VIRF. The collapse of Lehman Brothers on September 15, 2008 marks the beginning of the period of extreme turbulence in the U.S. financial markets: during the fall of 2008, the S&P 500 recorded five of its ten worst trading days in history.[16] The first of these five came on September 29, 2008 when the S&P 500 closed 8.79 percent lower than the day before after the U.S. House of Representatives rejected the proposed $700 billion bailout of the financial industry (three days

[16] The complete list can be found at http://money.usnews.com/money/personal-finance/mutual-funds/articles/2012/10/19/october-sell-off-anyone-the-sps-10-worst-trading-days.

later the bailout was passed). We use this date to obtain a vector of shocks for the VIRF as the news of the rejection of the bailout significantly affected both financial and commodity markets.

Figures 2.4 and 2.5 present the volatility impulse responses of the short-term and the long-term futures to the shock of September 29, 2008. We scale the responses by the historical variances at the time of the shock in question as recommended by Hafner and Herwartz (2006). We first focus on the short-term futures VIRF.

In Panels (a), (c), and (e) of Figure 2.4 we plot the impulse responses of the crude oil variance, corn variance, and covariance to the shock using the estimates from the GARCH model with the optimal number of Fourier terms in the mean and variance equations (five Fourier frequencies in the mean and four in the variance). The shock had a significant initial effect on oil and corn variance as it caused each to increase by roughly 30 percent; however, the diffusion of the shock differed noticeably between the two markets. Whereas the shock dissipated relatively quickly in the corn market, almost vanishing after 100 days, it took more than 200 days to dissipate in the oil market. The effect of the shock on the covariance between the two markets was even larger than the effect on the individual variances. The covariance initially increased by more than 60 percent, and the impulse took almost 200 days to dissipate.

In Panels (b), (d), and (f) of Figure 2.4 we plot the impulse responses of the crude oil variance, corn variance, and covariance to the shock using the estimates from the GARCH model without any trigonometric terms in the variance equations. The initial effect of the shock on the individual variances and the covariances remains similar to the case of the GARCH model with Fourier terms in the variance equations; however, the shock takes much longer to dissipate, still appearing to have a significant influence on each variance and the covariance even after 200 days. Thus, when we do not control for structural breaks, the volatility impulse responses appear

similar to those from integrated GARCH (IGARCH) processes. The presence of the Fourier frequencies in our GARCH models make the responses far less persistent.

Focusing now on the long-term futures, we find that the volatility impulse responses in Figure 2.5 closely resemble those of the short-term futures. The initial effect, the diffusion time, and the notable increases in persistence when switching to the model without Fourier terms are almost identical for the VIRF of the short-term and the long-term futures. Based on this observation, we can conclude that the markets perceived the shock of September 29, 2008 to be profound enough to affect both the short-term and the long-term futures to an equal degree.

2.4.5. Analysis of the term spread

For corn and oil futures, we can construct the term spread as the difference between logarithmic changes in the long-term contract and the logarithmic changes in the short-term contract. In order to better assess whether the relationship between corn and oil volatilities differs across maturities, we repeat our analysis using the term spread in corn and oil futures. Specifically, we begin by selecting the optimal lag length in the model of the mean for the spread. Following the lag selection procedure we used in Section 2.4.2, we find that the optimal lag length is five days, just as in the case of long-term oil and corn futures. Next, we estimate six models of the mean by varying the number of included Fourier frequencies from zero to five. The general-to-specific method indicates that trigonometric terms do not belong in the model of the mean.

We can conclude that there were no significant structural changes in the spread between the long-term and the short-term futures prices during our sample period. In other words, the short-term and the long-term futures price series tend to co-break. Structural shifts seem to affect the whole term-structure of futures prices, which is consistent with the interpretation of structural

change as a long-run effect, so that the markets do not expect the effect to dissipate by the expiration date of the long-term futures contract.

Using the specification with five lags and no Fourier frequencies as the model of the mean, we run diagnostic tests to confirm that the error terms exhibit conditional heteroscedasticity, so that it is appropriate to estimate the relationship between the oil futures spread and the corn futures spread as a GARCH process. Thus, we estimate six GARCH models using equations (2.8) and (2.9) by varying the number of trigonometric frequencies included in the variance equations from zero to five. The general-to-specific method selects the model with four Fourier frequencies at the one percent level, indicating that volatility breaks are present in the system of corn and oil futures term spreads.

Our results paint an interesting picture: while structural shifts in the short-term and the long-term futures prices are statistically indistinguishable, the same does not apply to structural breaks in the volatility. This effect is consistent with the findings of Brooks (2012) that corn and crude oil futures markets appear to be unarbitraged. If the markets were arbitraged, we would expect a flat term structure of futures volatility as shown by Brooks (2012). In turn, this implies that any structural change experienced by the volatility of the short-term contract would have to be mimicked by the long-term contract, which we do not observe.

2.5. Conclusion

The purpose of the paper is to examine the interrelationships between prices in the petroleum and grain markets. Grain prices have always reflected the effects of petroleum prices on transport and on fertilizers (since most fertilizers require petroleum or natural gas to manufacture). However, intuition suggests that the interactions between them have become tighter as a result of the increased importance of the BRIC countries and the regulations

requiring increased ethanol production. However, the interactions are not necessarily unidirectional in that the new biofuel technologies mean that grain prices should be reflected in petroleum markets. Nevertheless, researchers such as Myers et al. (2014) and Wetzstein and Wetzstein (2011), contend that impediments like adjustment costs, capacity constraints, and uncertainties imply that short-run price interactions should be weak.

In order to disentangle the two arguments, we utilize a technique allowing for smooth shifts in the price relationships between the two markets. Specifically, we model the interaction between corn and crude oil futures prices as a bivariate GARCH process allowing for smooth structural change in both the mean and variance/covariance matrix. Toward this end, we expand the work of Enders and Holt (2012), Trujillo-Barrera et al. (2012), Enders and Lee (2012a), Bai, Lumsdaine and Stock (1998), Qu and Perron (2007) and Bai and Perron (1998) by using a Fourier series approximation to account for the slow shifts in a multivariate GARCH model of corn and oil prices. Specifically, we generalize the Baillie and Morana (2009) and Enders and Jones (2015) methodologies by incorporating several low frequency trigonometric components of a Fourier series approximation into the mean and conditional variance equations of a bivariate GARCH model.

Our key finding is that the opposing viewpoints on the degree of interaction between petroleum and corn prices each have some validity. In the early part of our sample, the conditional correlation between innovations in the two markets is generally below 0.25. Beginning in 2007 there was a sustained increase in the correlation that can be explained by the traditional view expressed in Enders and Holt (2014) and Trujillo-Barrera et al. (2012). In essence, the adoption of ethanol standards and the uncertainty resulting from the financial crisis likely manifested itself in increase in the conditional correlation. After reaching a peak of more

than 0.5 in 2010, the conditional correlation began to decline back toward its pre-2007 average. Hence, we also support the view of Myers et al. (2014), Wetzstein and Wetzstein (2011), Hertel and Beckman (2010), and Tyner (2010) that the relationship is likely to weaken for a number of reasons.

Neglected structural change in the mean and/or variance-covariance matrix typically results in overstated persistence of parameters. We show that our use of the Flexible Fourier Form to control for structural change leads to quicker shock dissipation in the variance impulse response function. Compared to a standard multivariate GARCH model without smooth breaks, our model with Fourier terms indicates that the markets adjust far more rapidly. Specifically, we construct the variance impulse response function to the shock of September 29, 2008 (the date of the initial rejection by the U.S. House of Representatives of the proposed $700 billion bailout of the financial industry) and find that the number of days required for the shock to dissipate more than doubles when we use the model that does not control for structural change in volatility compared to the model that does. Noting that this shock happened during the time of a significant shift in the variance-covariance matrix, we emphasize that the danger of overestimating the effect of shocks to volatility is greatest during the time of a long-term change in the volatility structure. It is important to note that controlling for structural change mitigates the potential problem of spurious persistence often found in bivariate GARCH models.

Finally, our data set allows us to investigate the relationship of corn and oil futures along the maturity dimension. We find that the structural change in the variance-covariance matrix is present in both the short-term and the long-term futures. When we focus on the spread between the long-term futures price and the short-term futures price for each commodity, we find that there are structural changes in the variance equations in the GARCH model of the term spreads,

indicating that the variance-covariance matrices of the short-term and the long-term futures do not co-break. In other words, the term structures of volatility in these markets, including the correlation term structure, change over time. This is further evidence that the U.S. corn and crude oil futures markets are unarbitraged, so that the term-structure of volatility in each market is not flat. On the other hand, there are no structural breaks in the model of the mean of terms spreads, hinting that the term structure of futures prices in the corn and oil markets does not change over time.

2.6. References

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Figure 2.1. Futures Settlement Prices.

Panels (a) through (d) present the evolution of short-term and long-term corn and crude oil futures settlement prices throughout our sample period. In each panel, the futures prices are normalized by the price of the contract on June 1, 1993, and the resulting index is plotted on the vertical axis.

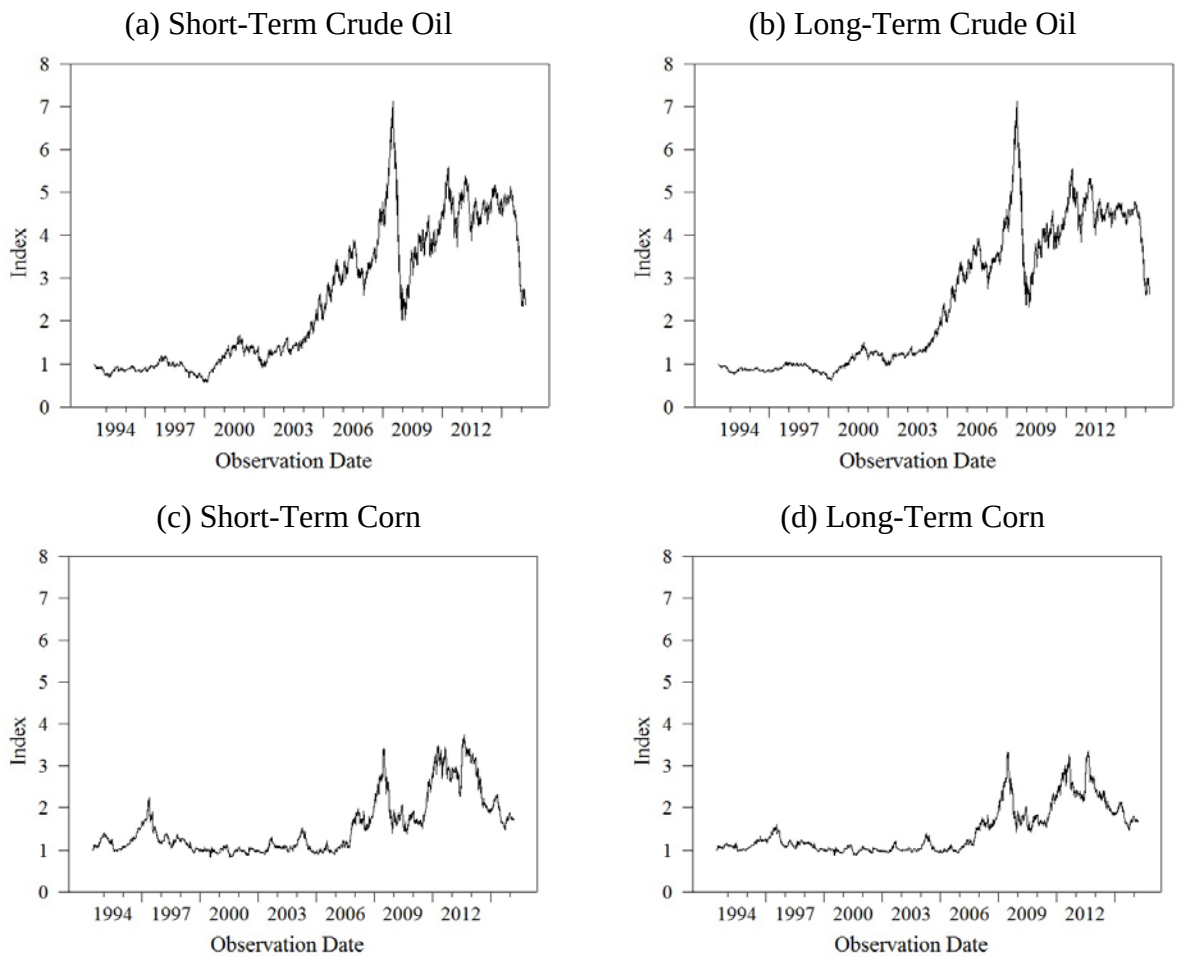
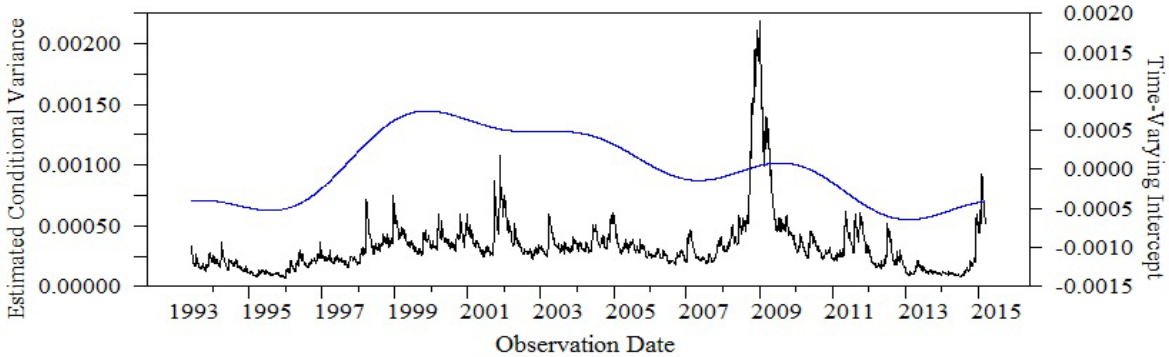


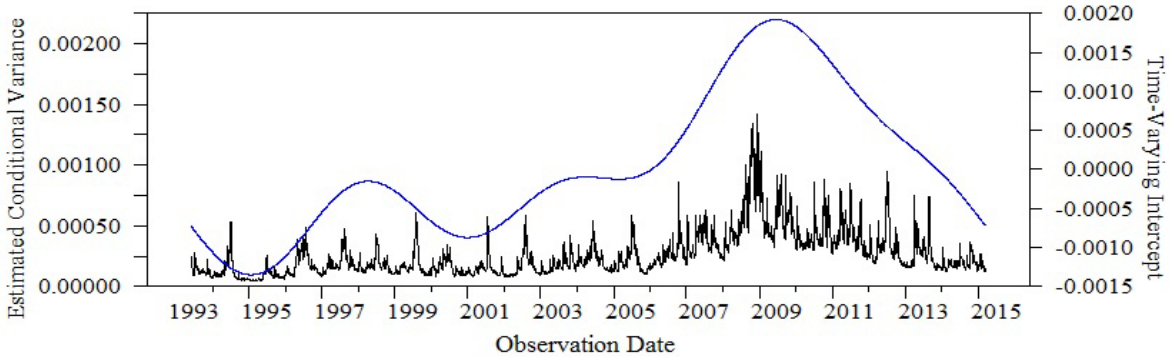
Figure 2.2. Estimates of Conditional Variance: Short-Term Futures.

Panels (a) through (c) present the estimates of crude oil variance, corn variance, and correlation series for our sample period. The variance estimates are the predicted values from equation (2.9). The correlation estimate is obtained by scaling the covariance estimate by the variance estimates. The time-varying intercept from each equation in equation (2.9) is plotted on the second (right) axis. The evolution of the intercept mimics the evolution of the long-run mean of each series.

(a) Crude Oil Variance



(b) Corn Variance



(c) Correlation Coefficient

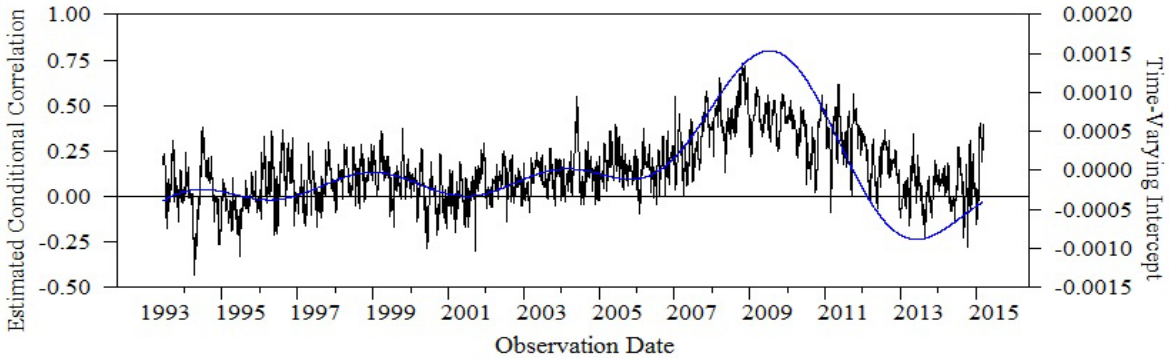
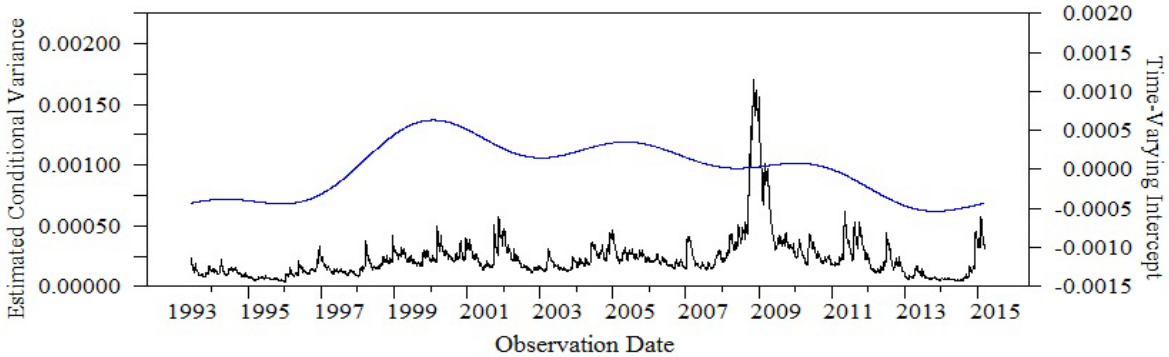


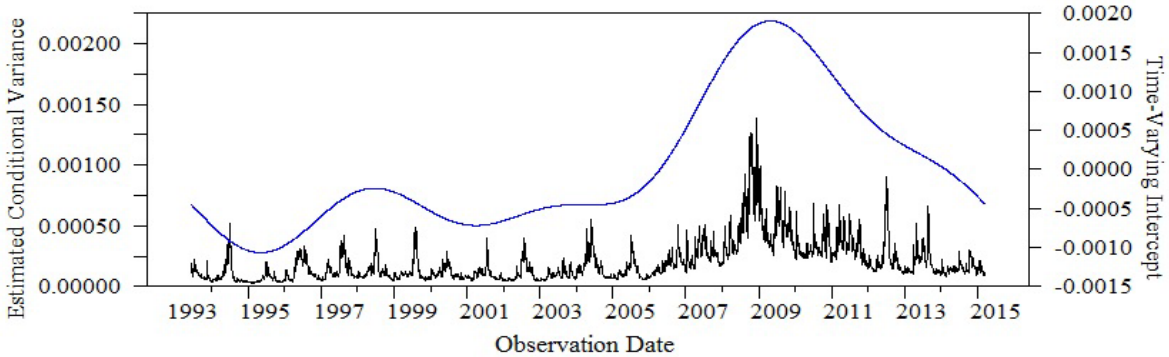
Figure 2.3. Estimates of Conditional Variance: Long-Term Futures.

Panels (a) through (c) present the estimates of crude oil variance, corn variance, and correlation series for our sample period. The variance estimates are the predicted values from equation (2.9). The correlation estimate is obtained by scaling the covariance estimate by the variance estimates. The time-varying intercept from each equation in equation (2.9) is plotted on the second (right) axis. The evolution of the intercept mimics the evolution of the long-run mean of each series.

(a) Crude Oil Variance



(b) Corn Variance



(c) Correlation Coefficient

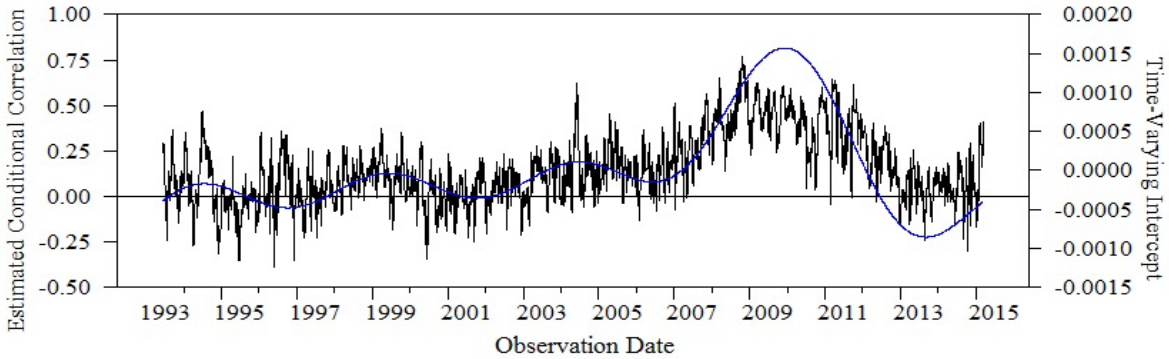


Figure 2.4. Variance Impulse Responses: Short-Term Futures.

Panels (a) through (e) present the variance impulse responses to the shock of September 29, 2008. Responses in Panels (a), (c), and (e) use the model that includes four Fourier frequencies in the variance equations, whereas responses in the other panels use the model without Fourier terms in the variance equations.

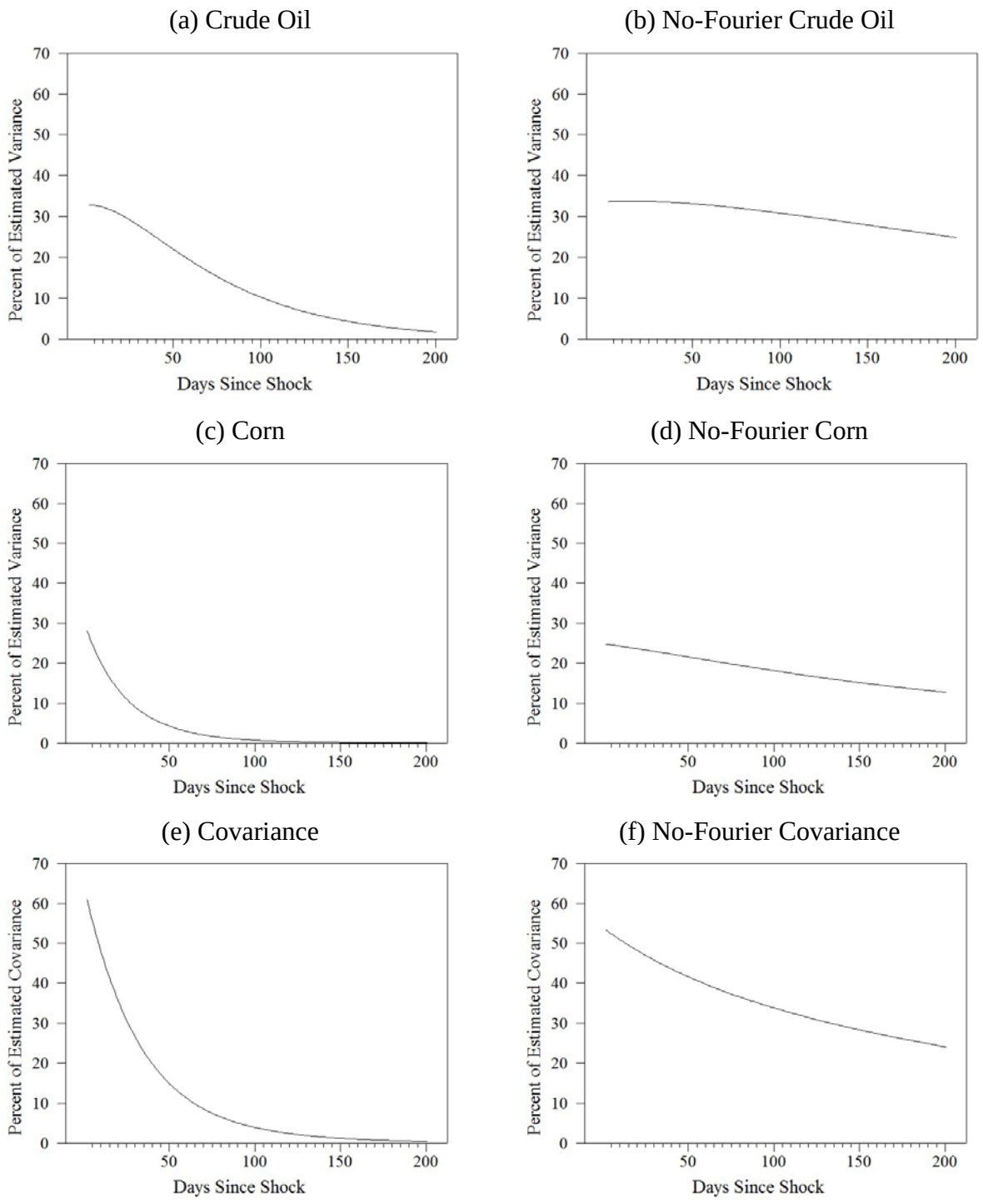
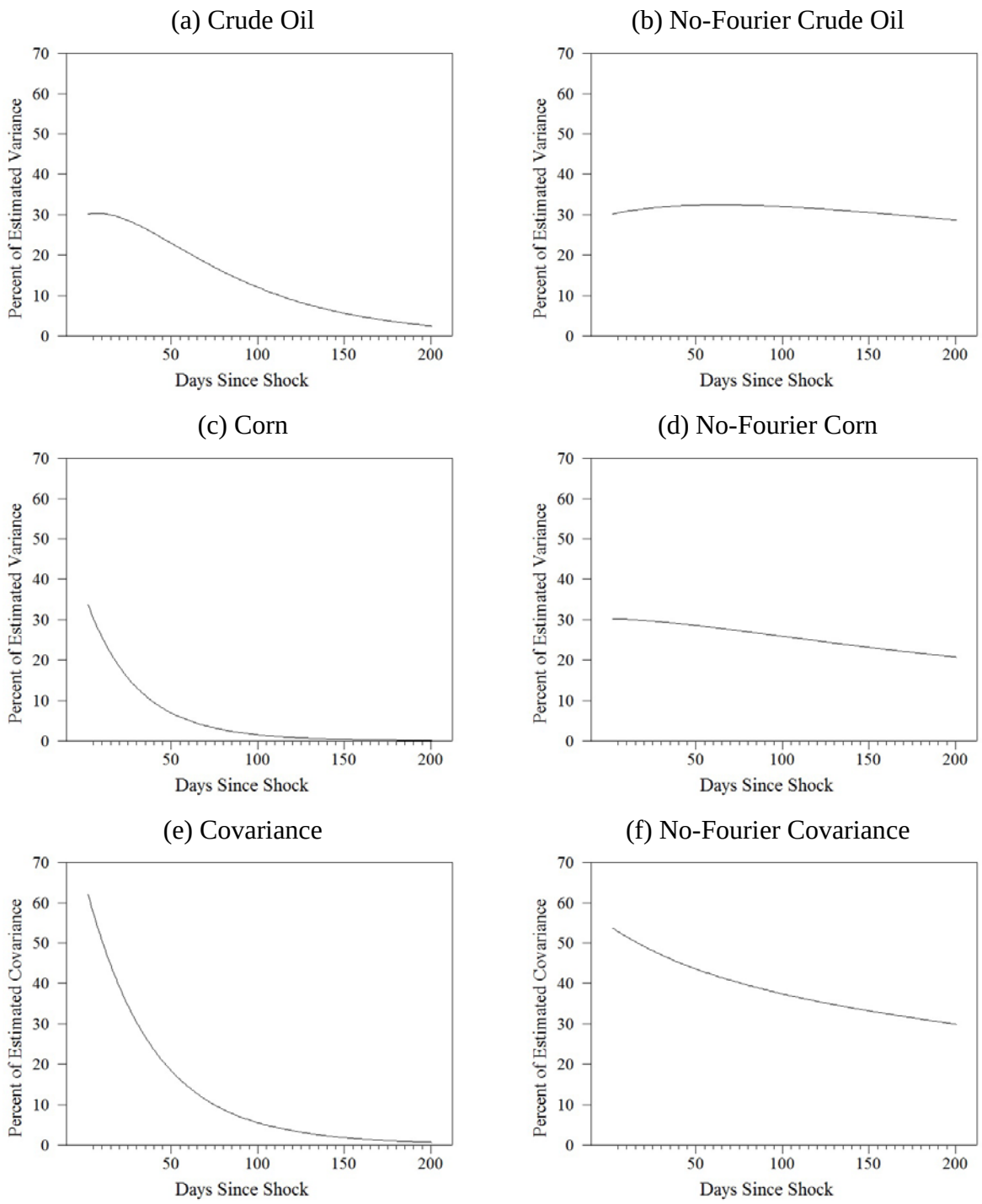


Figure 2.5. Variance Impulse Responses: Long-Term Futures.

Panels (a) through (e) present the variance impulse responses to the shock of September 29, 2008. Responses in Panels (a), (c), and (e) use the model that includes four Fourier frequencies in the variance equations, whereas responses in the other panels use the model without Fourier terms in the variance equations.



CHAPTER 3: THE INFORMATION IN GLOBAL INTEREST RATE FUTURES CONTRACTS

3.1. Introduction

Studying cross-country differences in the information content of the interest rate term structure is important to policymakers and entities involved in the international trade and finance since differences in the yield curve are linked to exchange rate movements and excess currency returns (Chen and Tsang, 2013). Interest rate futures contracts are tied to the average of select interest rates based on the loans funded between two entities. Although these contracts reflect market expectations of future rates, they also contain other information, such as anticipated default and differing term premiums.

Estrella and Hardouvelis (1991) show that the U.S. term structure reflects monetary-policy-independent factors that predict real economic activity. Consequently, the term structure provides useful information to both private investors and policy makers. Estrella and Mishkin (1997) likewise find that the inference of real economic activity persists for European economies. Evidence also suggests that the domestic term structure of one country predicts future real growth of the economy of another country (Plosser and Geert Rouwenhorst, 1994).

Just as the ability of the term structure to forecast real economic activity and growth in different countries is important to investors and policy makers, so is the ability of current forward rates to predict future rate changes and holding period returns in different countries. However, most of the existing literature on the estimation of term premiums and the information

about future rate changes and holding period returns uses data only from a single country, most often the United States (Wright, 2011).

Studies that do examine the term structure across countries find that there exist global yield factors that explain significant fractions of a country's yield curve dynamics (Diebold, Li, and Yue, 2008). The studies also find that the term premium component of forward rates in the ten major industrialized countries with independent monetary policies has trended down for the last 20 years, a phenomenon best explained by lower inflation uncertainty resulting from changes in monetary policy (Wright, 2011). Consistent with this evidence, Dahlquist and Hasseltoft (2013) find that international bond returns are predicted not only by local factors, but also by a global factor closely linked to U.S. bond risk premiums and international business cycles.[17] These drive risk premiums and expected short-term interest rates in opposite directions. They also observe increased correlations between international bond risk premiums over time and suggest an increase in the integration of markets as a possible explanation.

The goal of this study is to examine the association between the informational content of the term structure across economies. Evidence suggesting convergence of the informational content across countries would be consistent with the literature on global yield factors and global financial cycle. Alternatively, evidence suggesting that the term structures of these markets contain distinct information would suggest that markets participants in difference economies behave in different ways, perhaps due to difference in macroeconomic conditions or monetary policy.

[17] Existence of a global risk factor and its dependence on macroeconomic conditions in the center country are the two features echoed by the emerging literature on the global financial cycle (Rey, 2015; Miranda-Agrippino and Rey, 2015).

We focus our analysis of the term structure on global interest rate futures contracts. There are two major reasons why the information content of global interest rate futures may vary from the information content of domestic interest rates. First, the observed rate is based on the futures market rather than the spot market. Thus, we expect differences between the spot rates and implied futures rates because informed traders are more likely to trade futures contracts rather than make interbank transactions. Second, the information content could differ from currency to currency due to the influence of macroeconomic conditions and government policies. This prediction is in line with the literature linking macroeconomic indicators and monetary policy to the term structure. See, for instance, Rudebusch (1995) and Rudebusch and Wu (2008). [18]

Rather than impose a factor structure on the yield curve, we investigate time-series variation in the information content of the term structure by employing simple forecasting regressions involving forward rates. In this regard, we extend the work of Brooks, Cline, and Enders (BCE, 2015) by applying their methodology to global interest rate futures contracts. BCE (2015) explore the informational differences between constant maturity treasury (CMT) yields and London Interbank Offered Rate (Libor) in the U.S. They extend the work of Brooks, Cline, and Enders (BCE, 2012), which examines the informational content in Libor spot rates. BCE (2012) document that during recent periods more information exists in Libor spot rates concerning future interest rates than expected holding period returns. In their extension, BCE (2015) document significant differences in the informational content between Libor and CMT. They also observe that the information content changed significantly as the financial crisis began and that these changes were related to credit default swap rates and tenor swap rates.

[18] Despite its influence, monetary policy does not completely determine the term structure. In fact, the term structure contains useful information beyond what can be explained by monetary policy and macroeconomic indicators (Estrella and Hardouvelis, 1991).

Overall, we examine three-month interbank rates in four currencies—United States Dollar, Euro, Great Britain Pound, and Swiss Franc—and empirically document five unique results. First, the information contained in implied USD futures rates is significantly different from the information contained in USD spot rates previously explored by BCE (2015). Intuitively, implied forward rates derived from Eurodollar futures contracts incorporate information that differs from information in spot Libor because futures contracts are tied solely to three-month Libor, whereas USD spot interbank rates address various maturities.

Our second major finding suggests that the four rate-based futures contracts contain similar information, particularly USD-GBP and GBP-EUR. Moreover, information content of interest rate futures in the four regions seems to be driven by a single common factor. On the one hand, differences in macroeconomic conditions and monetary policies could lead to differences in the information content of interest rate futures. Continued integration of global financial markets, however, could lessen information differences. Our evidence suggests that the latter effect tends to dominate.

Third, we show that implied futures rates contain more information regarding rate changes rather than return premiums. In this respect our findings are similar to BCE (2015); however, the result is anticipated as the underlying instrument for rate futures is a three-month interbank rate.

Fourth, information shifts appear highly correlated with macroeconomic conditions and central bank policies. Our analysis separates implied government policies from the information content of rate-based futures contracts. The evidence suggests that larger economies contribute more to information shifts than smaller economies.

Finally, we document that significant information shifts occurred during the 2013-2015 time frame. Interestingly, these shifts are more pronounced than those during the great recessionary period of 2008-2009. By comparison, macroeconomic variables experienced more widespread structural changes during the financial crisis compared to the 2013-2015 window. This evidence suggests that information changes during the 2013-2015 period are most likely explained by either new information generated in rate futures markets, or by the joint diffusive dynamics between information in these markets and macroeconomic variables. To a smaller degree, these information changes could be related to structural changes that affected both the futures markets and the macroeconomies.

The contribution of our findings to the existing literature is in providing distinct evidence that rate-based futures from four industrialized nations contain similar information. This evidence is consistent with the findings in Diebold, Li, and Yue (2008), Wright (2011), and Dahlquist and Hasseltoft (2013). The convergence of the information content, as well as the finding that larger economies contribute more to information shifts, is also consistent with the nascent research on the global financial cycle (Rey, 2015). We also uncover a previously undocumented and surprising information content shift of 2013 – 2015. The shift affected all four markets and was largely unrelated to macroeconomic fundamentals and monetary policy indicators, a finding that is consistent with idea that interest rate term structure incorporates additional information beyond expectations of macroeconomic conditions and the direction of the monetary policy.

3.2. Data and Theoretical Framework

3.2.1. Data

Our examination uses rate-based futures price data provided by Commodity Systems Incorporated (CSI). We collect all futures contracts that are Eurodollar futures (contract symbol ED), Euribor futures (contract symbol I), Sterling futures (contract symbol L), and Euroswiss futures (contract symbol S). A curve-fitting method based on the Nelson and Siegel (1987) and Svensson (1995) (discussed in detail below) is then used to construct a complete database of implied monthly discount factors. We use the monthly observations from July 1994 to October 2016 for all analysis.

The four futures markets are similar in that they all trade on the Intercontinental Exchange (ICE) and are cash settled based on the three-month interbank rate in their respective currencies: USD for Eurodollar futures, EUR for Euribor futures, GBP for Sterling futures, and CHF for Euroswiss futures.[19] From this point forward we refer to a given contract by its currency rather than its symbol.

The on-cycle contract expiry months in all four currencies are March, June, September, and December. With the exception of CHF, contract expiry months also include two to six of the nearest consecutive calendar months. In all four currencies, contracts expirations extend four to six years into the future. Trading in a contract with a given expiry month ceases either on the third Wednesday of that month (GBP), or two London business days prior (USD, EUR, CHF). The prices of all contracts are quoted as 100 minus the rate of interest, and the contract size is

[19] Full contract specifications can be found on the Intercontinental Exchange website.
USD: https://www.theice.com/products/31500928/Eurodollar-Futures;
EUR: https://www.theice.com/products/38527986/Three-Month-Euribor-Futures;
GBP: https://www.theice.com/products/37650330/Three-Month-Sterling-Short-Sterling-Future;
CHF: https://www.theice.com/products/37650324/Three-Month-Euro-Swiss-Franc-Euroswiss-Futures.

1,000,000 in the contract's currency with the exception of Sterling futures, where the notional amount is GBP 500,000.

Final settlement of Eurodollar, Sterling, and Euroswiss futures occurs at 11:00 a.m. London time on the last trading day of the contract, at which point the contracts are settled based on ICE Benchmark Administration (IBA) survey of three-month London Interbank Offered Rate (ICE Libor) in the contracts' currency. IBA maintains a panel of 11 to 17 contributor banks, and each ICE Libor rate is calculated using a trimmed arithmetic mean, where the top and bottom quartiles of contributors' quotes are excluded from averaging.[20]

Final settlement of Euribor futures occurs at 10:00 a.m. London time on the last day of trading. Euriobor futures are settled based on three-month European Money Markets Institute Euribor Rate (EMMI Euribor). EMMI maintains a panel of 20 contributor banks, whose quotes are averaged, excluding the top and bottom three quotes.[21]

Among the four contracts, Eurodollar futures are the most liquid, followed by Euribor, Sterling, and Euroswiss contracts. In our sample period, average daily volume of trading in the nearest expiry month is approximately 131 thousand contracts for Eurodollar futures, 75 thousand contracts for Euribor futures, 32 thousand contracts for Sterling futures, and 6,700 contracts for Euroswiss futures. The corresponding notional amounts are USD 131 billion, EUR 75 billion, GBP 16 billion, and CHF 6.7 billion (USD-equivalent amounts are 91 billion for EUR, 26 billion for GBP, and 5.7 billion for CHF). In all currencies, liquidity monotonically declines beginning with the fourth nearest expiry month; even so, trading in the more distant futures contracts remains active with average daily volume in the eighth nearest expiry month still exceeding USD 77 billion, EUR 21 billion, GBP 7.9 billion, and CHF 261.4 million in

[20] Visit https://www.theice.com/iba/libor for additional details on ICE Libor rates.
[21] Visit https://www.emmi-benchmarks.eu/euribor-org/about-euribor.html for additional details on EMMI Euribor.

notional amount (USD-equivalent amounts are 25.5 billion for EUR, 12.8 billion for GBP, and 220.7 million for CHF).

3.2.2. Theoretical framework

Closely following BCE (2012, 2015), we examine monthly horizons.[22] Based on Nelson and Siegel (1987), Svensson (1995) develops an approach for determining estimates of level, slope, and multiple curvature terms.[23] BCE call this approach the LSC model and express it as

$$r(\tau_j : t_i) = \sum_{n=0}^{N} b_{n,t_i} C_{j,n}(\tau_j; s_n)$$

where

$$C_{j,0}(\tau_j; s_0) = 1$$

$$C_{j,1}(\tau_j; s_1) = \frac{s_1}{\tau_j}\left[1 - \exp\left(-\frac{\tau_j}{s_1}\right)\right]$$

$$C_{j,n}(\tau_j; s_n) = \frac{s_n}{\tau_j}\left[1 - \exp\left(-\frac{\tau_j}{s_n}\right)\right] - \exp\left(-\frac{\tau_j}{s_n}\right) \text{ for } n > 1$$

and where $r(\tau_j : t_i)$ denotes the spot interest rate observed at calendar time t_i expressed in years, with maturity τ_j, measured in years from t_i, and b_{n,t_i} denotes the fitted parameters for level, slope and curvatures. The scalar s_n is deterministic and we require $s_1 = s_2$. The five-parameter version with four fixed scalars $s_1 = s_2 = 2.0$, $s_3 = 1.0$, and $s_4 = 0.5$ is applied.[24]

[22] Although the underlying rates all have three-month tenors, with the LSC model we can examine any tenor. For consistency with prior research, we examine one-month tenors.
[23] This method is widely supported in the literature. See, for example, Steeley (2008) who examines a variety of term structure estimation methods and finds that this approach is very robust.
[24] Since the intercept counts as one parameter, we only need four scalars for a five-parameter model. Several different sets of scalars are examined and have similar results. For the vast majority of our sample, the term structure is relatively smooth and a five-factor model is more than adequate to achieve an accurate fit.

The information in the term structure of interest rates can be explored in a variety of ways. Fama (1984a, 1984b, and 2006) shows the forward-spot differential can be decomposed in the following way

$$f\left(\tau_j, \tau_{j-1}: t_i\right) - r(t_i) = \mathbb{E}_{\mathrm{t_i}}[\tilde{r}(t_i + (j-1)\Delta\tau)] - r(t_i) + \mathbb{E}_{\mathrm{t_i}}\left[\widetilde{RP}\left(\tau_j: t_i + \Delta\tau\right)\right]$$
$$+ \sum_{k=2}^{j-1} \mathbb{E}_{\mathrm{t_i}}\left[\widetilde{RP}\left(\tau_{j-k+1}: t_i + k\Delta\tau\right) - \widetilde{RP}\left(\tau_{j-k+1}: t_i + (k-1)\Delta\tau\right)\right]$$

for all forward rates j, and all time t_i, $\mathbb{E}_{\mathrm{t}_i}[\cdot]$ is the conditional expectation operator over time t_i information, $f\left(\tau_j, \tau_{j-1}: t_i\right)$ denotes the forward rate between two points in maturity time (τ_j and τ_{j-1}) observed at t_i, $r(t_i)$ denotes the one period spot yield to maturity, and $\widetilde{RP}\left(\tau_j: t_i\right)$ denotes the return premium defined as the excess holding period rate of return ($\tilde{h}(\tau_k, \tau_{k-1}: t_i + \Delta\tau)$) over the current spot rate. BCE (2015) note that the return premium in this context is the profits on a portfolio of forward contracts ($\sum_{k=2}^{j} \widetilde{\Pi}_{Long}(\tau_k, \tau_{k-1}: t_i + \Delta\tau)$):

$$\widetilde{RP}\left(\tau_j: t_i\right) = \tilde{h}(\tau_k, \tau_{k-1}: t_i + \Delta\tau) - r(t_i) = \sum_{k=2}^{j} \widetilde{\Pi}_{Long}(\tau_k, \tau_{k-1}: t_i + \Delta\tau)$$
$$= \sum_{k=2}^{j} \left[f(\tau_k, \tau_{k-1}: t_i) - \tilde{f}(\tau_{k-1}, \tau_{k-2}: t_i + \Delta\tau)\right]$$

An advantage to using this expression is that it allows the forward-spot differential to be viewed as a combination of information related to the expected change in spot rates and the information related to the expected change in the return premium. For a given forward-spot differential, if the expected change in the spot rate increases, then the expected change in the return premium must decrease. One important implication of global futures contracts is that the forward rates can be traded directly, without any need for complex trades based on implied forward rates. Thus, the existence of a significant return premium would imply profitable trading

opportunities with very low transaction costs or trading restrictions (for example, short selling bans). BCE (2012) provide an overview of the extant literature. Here, we explore the informational content of global interest rate futures contracts.

3.2.3. Preliminary analysis

Abrantes-Metz and Metz (2012), Abrantes-Metz and Verstein (2013), and Abrantes-Metz, Judge, and Villas-Boas (2011) document that at the beginning of the 2008-2009 financial crisis, Libor displayed patters that differed quite dramatically from the other interest rates. By the end of 2012, several large-scale investigations were underway investigating the alleged fraudulent manipulation of Libor settings.[25] As the scandal unfolded, rate rigging was alleged in all four markets covered in this paper. This Libor scandal has resulted in some regulators calling for the termination of Libor calculations altogether resulting in the loss of the valuable information context discussed in this paper. Based on the scandal, there could be differential effects of the scandal in each market.

Figure 3.1 illustrates the behavior of the implied one-month rate in each market. Three-month GBP Libor has the highest average at 3.8%, followed by USD Libor, at 2.9%. The EUR Libor averaged 2.5% and CHF Libor averaged 1.2%. Not surprisingly, EUR and CHF are the most highly correlated at 0.93 whereas GBP and CHF are the least correlated at 0.80.[26] Although the rates in each market are distinct, the four markets tend to move together. For example, during the financial crisis all rates fell dramatically. Over the last seven years, however, the rates have been less correlated. Specifically, the correlations among the currency pairs are much lower,

[25] See "Libor Scandal," at http://en.wikipedia.org/wiki/Libor_scandal and sources cited therein. Accessed on January 17, 2017.
[26] Other correlations: USD, EUR = 0.83; USD, GBP = 0.91; USD, CHF = 0.81, and EUR, GBP = 0.90.

except for EUR-GBP, after the end of the Great Recession in June 2009.[27] This provides at least some anecdotal evidence suggesting the informational content can vary between the markets in some environments and yet be quite similar in other environments.

3.3. Empirical Methods

The purpose of our investigation is to understand the information contained in the term structure of interest rates as represented in the interest rate futures market. There are several reasons why the different country's rates may result in informational differences, including differing default risk, differing regulatory environments, differing monetary policies, and differing fiscal policies. Accordingly, we begin with forecasting regressions estimated over a rolling window to assess long-run changes in the predictive ability of forward rates across countries and then augment this analysis with formal tests for structural breaks. We also estimate the degree of co-movement in the predictive ability of forward rates across country pairs using a bivariate GARCH model. We associate changes in macroeconomic conditions and monetary policies with future changes in the information content of interest rates by regressing the coefficients from the forecasting regressions on lagged macroeconomic indicators. Lastly, we employ principal components analysis to determine whether information content of interest rates across countries is driven by common factors.

3.3.1. Fama regressions

The following time-series regressions are estimated over a rolling window to assess the predictive ability of forward rates:[28]

$$RP\left(\tau_j : t_i + \Delta\tau\right) = \alpha_1 + \beta_1\left[f\left(\tau_j, \tau_{j-1} : t_i\right) - r(t_i)\right] + \varepsilon_{t+1} \qquad \text{(Fama Regression 1)}$$

[27] Correlations before (after) June 2009 are as follows: USD, EUR = 0.55 (-0.25); USD, GBP = 0.79 (0.09); USD, CHF = 0.62 (-0.43); EUR, GBP = 0.58 (0.79); EUR, CHF = 0.92 (0.70); GBP, CHF = 0.54 (0.42).
[28] We follow the BCE's (2012, 2015) approach that is based on Fama (1984a).

$$r(t_i + (j-1)\Delta\tau) - r(t_i) = \alpha_2 + \beta_2\left[f\left(\tau_j, \tau_{j-1}: t_i\right) - r(t_i)\right]$$

$$+\eta_{t+\tau-1} \qquad \text{(Fama Regression 2)}$$

Fama Regression 1 addresses the ability of the current forward-spot differential, $f\left(\tau_j, \tau_{j-1}: t_i\right) - r(t_i)$, to predict the return premium $RP\left(\tau_j: t_i + \Delta\tau\right)$, whereas Fama Regression 2 addresses the ability to predict the future change in the one period spot rate $r(t_i + (j-1)\Delta\tau) - r(t_i)$. The two slope coefficients are interrelated based on the covariance between the expected return premium and the expected change in rates. When this covariance is zero and the current expected changes in return premiums is zero, then β_1 and β_2 sum to one. Often these two slope coefficients do not sum to one, but they are close and hence are negatively correlated.

Under the unbiased expectations hypothesis, forward rates contain no information about return premiums, they contain information solely about expected rate changes. Thus, the slope coefficient in Fama Regression 1 would be 0.0 and the slope coefficient in Fama Regression 2 would be 1.0. When return premiums do exist and forward rates contain future expected spot rate information, both slope coefficients may be greater than 0.0.

Overlapping observations exist in the dependent variable of Fama Regression 2 and individual contracts could bias the parameter estimated in the longer maturity contracts. Hence, Fama (1984a) supplements Fama Regressions 1 and 2 with the following regressions:

$$\Pi_{Long}\left(\tau_j, \tau_{j-1}: t_i + \Delta\tau\right) = \alpha_3 + \beta_3\left[f\left(\tau_j, \tau_{j-1}: t_i\right) - f\left(\tau_{j-1}, \tau_{j-2}: t_i\right)\right]$$

$$+\varepsilon_{t+1} \qquad \text{(Fama Regression 3)}$$

$$r(t_i + (j-1)\Delta\tau) - r(t_i + (j-2)\Delta\tau) = \alpha_4 + \beta_4\left[f\left(\tau_j, \tau_{j-1}: t_i\right) - f\left(\tau_{j-1}, \tau_{j-2}: t_i\right)\right]$$

$$+\eta_{t+\tau-1} \qquad \text{(Fama Regression 4)}$$

Fama Regression 3 complements Fama Regression 1 by examining the power of forward rates to predict holding period returns on adjacent maturities. Fama Regression 4 complements

Fama Regression 2 by examining the forecasting power of forward rates on the specific one period change in the spot rate.

Based on these four regressions, we seek to determine empirically if implied forward rates contain information about return premiums, $RP(\tau_j : t_i + \Delta\tau)$, or the future change in the one period spot rate, $r(t_i + (j-1)\Delta\tau) - r(t_i)$. Further, we also seek to determine whether the corresponding values of the β_i display statistically significant breaks across the distinct markets. For example, evidence that the similar markets suddenly behave very differently in the period of the fraud may be evidence that certain markets were subject to manipulation. Following prior research, we employ three different methodologies – rolling window analysis, formal tests for structural breaks suggested by Bai and Perron (1998), and analysis of conditional correlations obtained from multivariate GARCH models – to determine if there are changes in the behavior of the β_i or the behavior of the cross-market differences between the β_i.

3.3.2. Rolling window analysis

BCE (2015) argue that a five-year window of monthly observations readily captures any shifts in the coefficients and retains sufficient power to conduct inferences on the coefficients. We therefore estimate Fama Regressions 1 through 4 for each interest rate futures market using 60-month rolling windows. For a given estimation window, we obtain the point estimate of the slope coefficient as well as the ±2 Newey-West standard error confidence interval. In each iteration, we move the estimation window one month forward by discarding the earliest observation and updating the most recent observation by one month.

In order to test whether there are statistical differences in the corresponding slope coefficients across interest rate futures market pairs, we allow for cross-equation correlation of the residuals by modifying the rolling window analysis similar to BCE (2015). First, we estimate

each Fama Regression $i = 1, \ldots, 4$ as seemingly unrelated regressions (SUR) for each of the following futures market pairs: USD-EUR, USD-GBP, USD-CHF, GBP-EUR, GBP-CHF, and EUR-CHF. Second, we let $\beta_i^x(t)$ and $\beta_i^y(t)$ be the SUR estimates of the slope coefficient for each Fama Regression i in a given futures market pair, using observations $t - 60$ to t. Third, we form the difference $d_i^{xy}(t) = \beta_i^x(t) - \beta_i^y(t)$ and the corresponding ±2 standard error confidence interval. Moving the estimation window forward by one month in each iteration, we trace the path followed by $d_i^{xy}(t)$ and infer any statistically significant jumps in the difference of the estimated slope coefficients between any two contracts. Such jumps indicate a shift in the relative information content in a given interest rate futures market pair.

3.3.3. Multiple structural breaks

Rolling window analysis serves as a general diagnostic of structural shifts in the information content of the futures markets; however, it does not allow for the detection of exact break dates and the corresponding break sizes, nor does it allow for the estimation of confidence intervals around each break date. We therefore augment the rolling window analysis with a more formal procedure for detecting structural shifts suggested by Bai and Perron (1998). It should also be noted that the Bai and Perron approach has two important limitations compared to the rolling window analysis: breaks are assumed to be fully revealed within a single period and the variance of the error process is assumed to be constant across regression segments.

To implement the Bai and Perron procedure, we closely follow BCE (2015), who provide the technical details; we simply note here that the procedure essentially searches through all possible break dates and selects the set of break dates that provides the best possible fit. As standard in the literature, we allow for a maximum of five breaks, impose the restriction that breaks cannot be closer than 12 months apart, and test the null hypothesis of no breaks against

the alternative hypothesis of five breaks using Bai and Perron's supremum F-test. The critical values of the test at the 90% and 95% significance levels are 8.50 and 9.12, respectively. If the null hypothesis of no structural breaks is rejected, we select the appropriate set of breaks using the Bayesian information criterion (BIC).

We apply the Bai and Perron procedure directly to Fama Regressions 1 through 4 for each interest rate futures market. We use a modified procedure when testing whether the set of breaks in one futures market differs from the set of breaks in another. Specifically, for each Fama Regression i and each futures market pair, we obtain a series of estimates $d_i^{xy}(t) = \beta_i^x(t) - \beta_i^y(t)$ from the SUR rolling window analysis and then apply the Bai and Perron procedure to this series. Essentially, we test for breaks in the long-run mean of the $d_i^{xy}(t)$ series, which allows us to determine statistically significant breaks in the relative information content between any two futures markets.

3.3.4. Time-varying correlations

An alternative method of determining the relative information content changes between any two futures markets is to calculate time-varying correlation coefficients between the innovations in each market for each Fama Regression i. As in BCE (2015), let us consider the multivariate GARCH model for the USD-EUR futures market pair and Fama Regression i:

$$u_{USD,t} = \alpha_{USD} + \beta_{USD} v_{USD,t} + \varepsilon_{USD,t}$$

$$u_{EUR,t} = \alpha_{EUR} + \beta_{EUR} v_{EUR,t} + \varepsilon_{EUR,t}$$

where $u_{USD,t}$ and $v_{USD,t}$ are the dependent and independent variables in the USD market, and $u_{EUR,t}$ and $v_{EUR,t}$ are the respective variables in the EUR market.

The multivariate GARCH specification allows the variance-covariance matrix of the innovations $\varepsilon_{USD,t}$ and $\varepsilon_{EUR,t}$ to be time-varying:

$$\begin{bmatrix} \mathrm{var}(\varepsilon_{USD,t}) & \mathrm{cov}(\varepsilon_{USD,t}, \varepsilon_{EUR,t}) \\ \mathrm{cov}(\varepsilon_{USD,t}, \varepsilon_{EUR,t}) & \mathrm{var}(\varepsilon_{EUR,t}) \end{bmatrix} = \begin{bmatrix} \sigma_{11}(t) & \sigma_{12}(t) \\ \sigma_{12}(t) & \sigma_{22}(t) \end{bmatrix}$$

We can, therefore, specify a time-varying correlation coefficient as

$$\rho(t) = \frac{\sigma_{12}(t)}{\sqrt{\sigma_{11}(t)\sigma_{22}(t)}}$$

By estimating a multivariate GARCH model for each Fama Regression i across all futures market pairs, we obtain a time-varying correlation coefficient for the corresponding pair. For our results to be consistent between the futures market pairs, we use the same specification for each set of Fama Regressions. Specifically, we use a standard BEKK(1,1) specification as in Enders (2010, pp. 178 – 179). If two futures markets are closely related in terms of their information content, we expect the estimated correlation coefficient between the innovations to be close to unity. On the other hand, if the estimated values of $\rho(t)$ deviate from unity, we conclude that the two markets do not move together with respect to the information content.

3.4. Empirical Results

3.4.1. Individual interest rate futures results

Table 3.1 reports estimates of the number of structural breaks and their corresponding dates for all four futures markets based on the Bai-Perron procedure. Using the 90% critical value of the supremum *F*-test (8.50), we infer no structural breaks for any market in Fama Regression 4 and no breaks for CHF in Fama Regressions 1 and 3. The remaining markets all had at least one break during the financial crisis period in each Fama Regression.

Although there were the maximum number of breaks reported for Fama Regression 2 for all countries, there were no breaks found for Fama Regression 4. Further, more breaks were found for Fama Regression 3 when compared with Fama Regression 1. Specifically, Fama Regression 3 breaks were found in the 2003-2005 range—a period absent in Fama Regression 1.

Thus, the dominant break information is in Fama Regression 2, but there are interesting results related to return premiums, particularly incremental return premiums.

Figures 3.2 through 3.5 plot the point estimates and ±2 standard error confidence bands from rolling window estimation of Fama Regressions 1 through 4, respectively. Each figure contains four panels representing the four individual rate-based futures markets. We make four key observations from these four figures.

First, the plots in Panel (a) of Figures 3.2 through 3.5 indicate that USD-based implied rates contain information significantly different from that presented in BCE (2015). This difference is driven by the fact that futures contracts are tied solely to three-month Libor whereas spot USD interbank rates address various maturities. Therefore, implied forward rates derived from Eurodollar futures contracts contain significantly different information when compared to spot Libor. Eurodollar futures only reflects three-month Libor, no other tenor is available for all of these markets.[29]

Second, although each currency has unique characteristics, the general patterns are similar across USD, EUR, GBP, and CHF. For example, in Figure 3.2 there is a significant downward shift in the Fama Regression 1 slope coefficient during the financial crisis as well as a significant upward move over the 2013-2015 period. Across all panels, a similar but opposite pattern occurs in Figure 3.3. Combined, this evidence implies that the information content across USD, EUR, GBP, and CHF implied futures rates is generally consistent, and is in line with the literature on global yield factors and global financial cycle.

Third, the generally positive and significant slope coefficients observed in Figure 3.3 and Figure 3.5 indicate that implied futures rates contain more information regarding rate changes

[29] In the U.S., there is an active one-month Libor contract.

than return premiums. This outcome is intuitive since these futures markets addresses only three-month rates rather than the rates of various maturities, where maturity-based return premium should be most pronounced.

Fourth, although a profound shift was expected during the financial crisis, the significant shift in the 2013-2015 time frame was not. Whatever the driver, it impacted all four Fama Regressions significantly. For example, Figure 3.2 shows a sharp rise in the slope coefficients whereas Figure 3.3 shows a sharp fall in the slope coefficients.

3.4.2. Differential beta results

Table 3.2 reports estimates of the number and the timing of structural breaks in the differential beta based on the Bai-Perron procedure. Interestingly, every market pair has the maximum allowable number of structural breaks in the differential beta except for GBP-CHF in Fama Regression 3.

For most pairs, there is a structural break during the great recessionary period. A few pairs, however, do not have a break between late 2007 and 2009; for example, EUR-CHF in Fama Regression 1 as well as USD-GBP and USD-CHF in Fama Regression 4. There also appears to be a significant shift in the differential information content between each of the futures market pairs during the 2013-2015 period. This shift was more widespread than the information shift associated with the great recession because each pair experienced a break in each Fama Regression.

Table 3.3 contains additional information about the differential beta breaks. For each break, we report the break date and the associated 90% confidence interval, as well as the differential beta corresponding to the period preceding a given break date. For instance, the reported $d_i(t) = 0.373$ for the USD-EUR in Fama Regression 1 is the average differential beta

during the period before the first break occurred in December 2000. After the break, the average differential beta shifts to $d_i(t) = -0.592$ until the next break occurs in August 2006, corresponding to the break size of -0.965 (-0.592 minus 0.373). The December 2000 break also appears to be relatively accurately determined as the confidence interval is narrow (four months between 2000:10 and 2001:01) compared to some of the other identified breaks, for instance, the last break in Fama Regression 1 for USD-CHF (between 2009:07 and 2015:04).

We use the estimated break sizes to further investigate the difference between the shift associated with the financial crisis and the shift during the 2013-2015 time frame. For each futures market pair and each Fama Regression, we identify the first break that occurred during either the 2007-2009 period, or the 2013-2015 period, and then calculate the average of the magnitudes of these breaks. The first breaks that occurred during the financial crisis have an average magnitude of 0.534, whereas the first breaks that occurred during the 2013-2015 period have an average magnitude of 0.737. Thus, the 2013-2015 information shift appears to be both more widespread and more pronounced than the information shift during the financial crisis. Both shifts appear to be very close in terms timing uncertainty – the average length of the confidence interval is approximately 9 months for the financial crisis breaks and 8 months for the 2013-2015 breaks.

Figures 3.6 through 3.9 illustrate the point estimates and ±2 standard error confidence bands for the differential betas for Fama Regressions 1 through 4, respectively. Each figure contains six panels representing the six pairs of rate-based futures market comparisons. We make four key observations.

First, overall the differential betas for all four Fama Regressions across the six currency pairs are rarely significantly different from zero. Thus, whatever information is contained in one

futures market, it is generally reflected in the other futures markets. This result is surprising as the markets represent different countries.

Second, the two pairs most tightly aligned are USD-GBP and GBP-EUR. The evidence is the tight two standard deviation confidence intervals along with the overall closeness to zero in Panels (b) and (d) of Figures 3.6 through 3.9. For example, in Figure 3.6 the two standard deviation confidence intervals are visibly wider for USD-EUR, USD-CHF, GBP-CHF (later half), and EUR-CHF (later half) when compared to USD-GBP and GBP-EUR.

Third, often during the financial crisis the differential beta experienced a sharp change in value. For example, in Figure 3.7 Panel (b) the USD-GBP differential beta drops sharply and is no longer statistically different from zero.

Fourth, a profound shift during the financial crisis is expected, but we did not anticipate significant shifts in the 2013-2015 time frame. Whatever the cause, it impacted all six differential betas significantly across all four Fama Regressions. For example, Figure 3.6 Panel (c) shows a sharp drop and then a sharp rise in the USD-CHF differential beta in this time frame. This similar pattern is seen for the GBP-CHF and EUR-CHF differential betas in Panels (e) and (f).

The results for the multivariate GARCH analysis are presented in Figures 3.10 through 3.13. Conditional correlation plots are quite noisy for certain combinations of futures market pairs and Fama Regressions. Therefore, we follow BCE (2015) and plot the time-series of the conditional correlation coefficients after smoothing them with a ±3 months window.

The most profound results documented in these figures are the positive correlations for all four Fama Regressions. For most our sample period – and for all futures market pairs – the conditional correlation coefficients across all four Fama Regressions are positive. The exceptions tend to be after 2009 and involve primarily CHF. For example, in Figure 3.10 Panel (c), the

USD-CHF Fama Regression 1 correlation is positive except for a brief period in the late 1990s and a significant period starting in 2009. A somewhat similar pattern is observed for GBP-CHF in Figure 3.10 Panel (e). In Figure 3.11 Panel (c), the results are similar for Fama Regression 2. Interestingly, the pattern is not the same for USD-GBP in Figure 3.11 Panel (b). The lack of correlation is particularly pronounced in the later periods. Thus, innovations in USD and GBP for Fama Regression 2 were not as strongly linked in these latter periods.

3.4.3. Interpreting the results

Our findings suggest that the estimated Fama regression betas from the four different economies move together. To explore this co-movement, we seek to identify the key factors. We consider four categories of explanatory variables: interest rate risk premiums, central bank monetary policy targets, macroeconomic conditions, and business cycle and uncertainty indicators.

In money markets, the interest rate risk premium variables include measures of the default premium, term premium, and the liquidity premium. In the wake of the Great Recession, and the following European debt crisis, there were significant concerns about possible bank defaults in many European countries. This casted doubt on the Euro as well as Euro-denominated debt securities. Under these circumstances, the varying default risks across economies are likely to contribute significantly to variation in beta estimates. We therefore include credit spreads as a measure of default premium.

Since all futures contracts in our study have the same maturity and the same tenor of the underlying, we do not explore various term premium measures. In addition, rate-based futures contracts tend to be very actively traded, so we do not examine liquidity premium variables. We

therefore contend that the time-varying default premiums should contain the most explanatory power with respect to the three risk premium determinants.

One important property of the rate-based futures contracts is that these contracts are cash settled based on the three-month interbank rate, a rate closely affected by central banks. For instance, according to the Swiss National Bank (SNB), its monetary policy is implemented by fixing a target range for the reference interest rate, which is the Libor for three-month interbank loans in Swiss Francs.[30] Clearly, the rate-based futures are heavily affected by the conduct of government monetary policy. To measure the effect of monetary policy, we consider the central bank target rate and the month-on-month growth of M1 and include it in the regressions.

Macroeconomic indicators reflecting government monetary policy are also expected to provide significant explanatory power for our information measures.[31] We therefore include the inflation rate, unemployment rate, and the nominal effective exchange rate (NEER).

Macroeconomic activity or business cycle factors affect not only the risk premium, but are important determinants of macroeconomic variables such as inflation and unemployment. Thus, macroeconomic or financial business cycle indicators may be good candidates for forecasting excess returns on interest rate futures contracts. We therefore include the Purchasing Managers' index (PMI) and stock market implied volatility (VIX) to capture the effect of the business cycle and uncertainty.

Table 3.4 reports how the individual betas from the Fama Regressions relate to credit spreads, government monetary policy, and macroeconomic conditions. To avoid endogeneity

[30] More detailed discussion of Swiss monetary policy implementation can be found on its website through the following link: https://www.snb.ch/en/iabout/monpol

[31]For example, Switzerland, as a small open economy relying heavily on imports, chose to maintain the minimum exchange rate (no further appreciation of CHF) of CHF 1.20 per euro from September 2011 to January 2015.

concerns, the explanatory variables are lagged by one month.[32] Panels (a) through (d) examine the univariate betas from Fama Regression 1 through 4, respectively. The Fama Regression betas are significantly correlated to most macroeconomic factors, including inflation, central bank target rate, M1 growth rate, unemployment rate, PMI, VIX, and nominal effective exchange rate. The R^2 for EUR, GBP, CHF, and USD are approximately 0.5, 0.8, 0.4, and 0.6, respectively, suggesting a significant portion in the variation in betas is explained by our model. Noticeably, UK's model explains 80% of the variation, suggesting effective communication between the market and UK policymakers. In contrast, the relatively lower R^2 from the Swiss Franc market is likely due to the fact that the SNB has a history of surprising the market relative to other countries.[33] Overall, both betas from return premium and rate changes regressions are highly correlated with macroeconomic conditions and central bank policy goals and targets. From this perspective, the markets are highly aware of the macroeconomic conditions and central bank targets, and thus make adjustments accordingly.

Our key finding is that Fama Regression betas follow a similar pattern in all four markets. Since the markets' expectations are highly correlated with macroeconomic conditions and central bank reactions, the common pattern may be due to the fact that the four economies experience similar macroeconomic shocks and implement monetary policies in a similar manner. To test this claim, we use two different approaches relying on individual and differential betas, respectively.

[32] We are aware of the fact that lagging macroeconomic indicators by one month may not be sufficient because Fama Regression betas are estimated over the prior 60 months. We perform two robustness checks. First, Fama Regression betas are estimated with a 12-month centered rolling window and regressed on 6-month lagged macroeconomic variables. Second, Fama Regression betas are estimated using daily data over disjoint monthly intervals (there is still one beta estimate per month) and regressed on 1-month lagged macroeconomic variables. These results are generally consistent with the baseline results.

[33] For example, the announcement of SNB to maintain the minimum exchange rate in September 2011 truly surprised the market at the time. The adoption of negative interest rate by SNB in 2015 was also less than expected.

First, if the four economies experience similar macroeconomic shocks, then these shocks are likely due to an underlying global factor (e.g. the 2007-2009 global financial crisis). To detect this potential common factor, we implement principal component analysis (PCA) on the individual betas. The goal of PCA is to identify as few components (linear combinations of individual betas) as possible to capture the sources of variation in the individual betas in the four markets.[34] As shown in Figure 3.14, one single (the largest) component explains most of the variation in the individual betas from the four Fama regressions. Table 3.5 reports the results of PCA. The largest component captures a larger share of the total variation in the individual betas in regressions involving return premiums (91.54% and 93.70% in Fama Regressions 1 and 3, respectively) than in regressions involving future rate changes (86.17% and 85.66% in Fama Regressions 2 and 4, respectively). The roughly equal component loadings suggest that the largest component is a roughly equally weighted linear combination of the four individual betas. This component therefore represents the average information content of the global market and is thus a global component, consistent with the literature on global yield factors and global financial cycle.

Second, we use differential betas to test our claim that the four economies experience similar macroeconomic shocks and implement monetary policies in a similar manner. Table 3.6 examines how macroeconomic variables impact differential betas across the six economy pairs: USD-EUR, USD-GBP, USD-CHF, GBP-CHF, GBP-EUR, and EUR-CHF. For each pair, we regress the differential beta on the relevant economies' macroeconomic variables. For example, for the USD-EUR pair, we consider macroeconomic variables in the US and Euro area. To avoid

[34] Because we have four markets, a group of four components can fully explain the variation in the individual betas.

multicollinearity, we use the US and Euro area macroeconomic variables in separate regressions. To save space, only the R^2 is reported.

The results in Table 3.6 suggest that, although each relevant economy does contribute to differential betas, the contribution is not equal. In particular, the Eurozone contributes more than the US to USD-EUR beta differential (e.g., Fama Regression 1 $R^2$of 0.795 compared to 0.462); the UK contributes more than the US to USD-GBP beta differential; the US contributes more than the Switzerland to USD-CHF beta differential; the UK contributes more than the Switzerland to GBP-CHF beta differential; the UK contributes more than the Eurozone to GBP-EUR beta differential; the Euro area contributes more than the Switzerland to EUR-CHF beta differential. Overall, as expected, larger economies contribute more to the differential betas with the exception of USD-GBP and GBP-EUR pairs. One reason for the dominance of the UK could be the fact that the contracts are based on a rate fixing occurring in London.

Collectively, the Fama Regression betas are highly correlated with macroeconomic conditions as well as central bank policy targets. This finding highlights the fact that financial markets reflect economic fundamentals and communicate effectively with policymakers. During crises, however, there is increased uncertainty regarding economy activity and government action. Thus, financial market participants have more difficulty forming consistent expectations, reflecting wider confidence intervals for the Fama Regression betas.

Up to this point we have shown that the time-series behavior of the univariate and differential Fama Regression betas is significantly related to key macroeconomic and monetary policy indicators. Both the joint diffusive dynamics and simultaneous structural breaks could be the drivers of the observed linkage between the information content of interest rate futures (Fama Regression betas) and macroeconomic indicators. We, therefore, employ the Bai-Perron

methodology to determine whether information content changes are consistent with the structural shifts in the macroeconomic variables and report the results in Table 3.7. We address non-stationarity of certain macroeconomic variables and allow for a maximum of five breaks except for the cases where the sample period was limited due to the availability of the data (three breaks for Eurozone PMI and Switzerland VIX, four breaks for United Kingdom PMI).

Table 3.7 contains the break dates and related information for inflation, policy rate, M1 growth rate, unemployment rate, PMI, VIX, credit spread, and NEER in each of the four markets. At least some of the economic indicators in each market experienced a structural shift during the financial crisis, which is consistent with the structural changes in the information content of interest rate futures during this period. Only a few of the macroeconomic variables had a structural shift during or near the 2013-2015 window, which is a time when significant shifts occurred in the interest rate futures markets. These variables include United States inflation, Eurozone VIX, and United Kingdom inflation, M1 growth rate, and NEER. Thus, coincidence of structural breaks in interest rate futures and macroeconomic indicators is less pronounced during the 2013-2015 period than during the financial crisis.

There are three potential explanations of the 2013-2015 phenomenon. First, information changes in the interest rate futures markets during this time could be due to the arrival of new information unrelated to the macroeconomic variables that we have considered. Second, information changes could be due to the joined diffusive dynamics (common shocks to differential betas and macroeconomic indicators) of macroeconomic indicators and information content of the rate-based futures. Third, information changes could be due to structural breaks that have affected both the interest rate futures markets and the macroeconomies, although our results indicate that this is the less likely explanation.

3.5. Conclusion

We examine global interest rate futures contracts with a focus on information content as revealed by the Fama regressions. We examine differential betas, structural breaks, and time-varying correlations and empirically document five unique results. First, implied USD futures rates contain information that significantly differs from previously documented information in the spot rates. Second, the four rate-based futures contracts contain similar information, particularly USD-GBP and GBP-EUR, as anticipated based on geographic location and economy size. Third, given that the underlying is always a three-month rate on interbank deposits, the implied futures rates contain more information regarding rate changes rather than return premiums. Fourth, information shifts appear highly correlated with macroeconomic conditions and central bank policies. Finally, significant information shifts occurred during the 2013-2015 time frame, even greater than during the great recessionary period of 2008-2009.

Collectively, our results indicate that the rate-based futures from four industrialized nations contain similar information. This evidence is consistent with the findings in Diebold, Li, and Yue (2008), Wright (2011), and Dahlquist and Hasseltoft (2013). The convergence of the information content, as well as the finding that larger economies contribute more to information shifts, is also consistent with the nascent research on the global financial cycle (Rey, 2015).

3.6. References

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Table 3.1. Estimated Number of Breaks and Break Dates for Individual Rates.

For each market, *F*(5) is the supremum *F*-value for the null hypothesis of 5 versus no breaks, Breaks is the estimated number of breaks, Dates are the estimated break dates, *BIC*(0) is the sample BIC value for the model with no breaks, and *BIC*(b) is the sample BIC value for the model with the optimal number of breaks. If the *F*-test indicates no breaks, the BIC is not reported. The smaller the BIC, the better the fit of the model.

Market	*F*(5)	Breaks	Dates	*BIC*(0) / *BIC*(b)
			Fama Regression 1 **(**Return Premiums)	
USD	11.88	4	2000:11 2001:11 2007:12 2008:12	-15.40/-15.58
EUR	11.81	4	1995:06 2007:07 2008:09 2009:09	-15.73/-15.91
GBP	15.00	3	1997:02 2008:09 2009:09	-15.36/-15.61
CHF	5.52	0		
			Fama Regression 2 (Rate Changes)	
USD	22.80	5	2000:10 2001:10 2004:02 2007:10 2008:12	-16.28/-16.71
EUR	24.56	5	1995:07 2001:09 2005:06 2008:07 2009:07	-16.58/-17.05
GBP	23.61	5	1998:10 1999:12 2002:08 2008:07 2009:07	-16.16/-16.60
CHF	11.97	5	1996:08 2002:01 2003:04 2008:03 2009:03	-16.33/-16.51
			Fama Regression 3 (Incremental Return Premiums)	
USD	13.92	5	2000:11 2002:03 2004:03 2007:12 2008:12	-17.44/-17.67
EUR	15.27	5	1995:07 2001:11 2005:08 2008:09 2009:09	-17.91/-18.17
GBP	13.65	4	1998:06 2003:02 2008:09 2009:09	-17.43/-17.66
CHF	6.57	0		
			Fama Regression 4 (Incremental Rate Changes)	
USD	7.28	0		
EUR	6.16	0		
GBP	5.56	0		
CHF	4.85	0		

Table 3.2. Estimated Number of Breaks and Break Dates for Rate Pairs.

For each market pair, *F*(5) is the supremum *F*-value for the null hypothesis of 5 versus no breaks, Breaks is the estimated number of breaks, Dates are the estimated break dates, *BIC*(0) is the sample BIC value for the model with no breaks, and *BIC*(b) is the sample BIC value for the model with the optimal number of breaks. If the *F*-test indicates no breaks, the BIC is not reported. The smaller the BIC, the better the fit of the model.

Markets	*F*(5)	Breaks	Dates	*BIC*(0) / *BIC*(b)
			Fama Regression 1 **(**Return Premiums)	
USD-EUR	199.91	5	2000:12 2006:08 2007:12 2008:12 2013:09	-1.50/-3.15
USD-GBP	281.57	5	2000:12 2004:08 2006:03 2008:09 2015:09	-1.76/-3.70
USD-CHF	65.65	5	2000:12 2006:03 2007:10 2008:10 2013:10	-2.05/-2.89
GBP-EUR	431.12	5	2004:07 2005:07 2007:11 2011:03 2013:11	-2.14/-4.46
GBP-CHF	56.89	5	2004:06 2007:11 2012:07 2013:10 2014:12	-2.73/-3.48
EUR-CHF	300.95	5	2001:04 2005:04 2012:07 2013:10 2014:12	-1.97/-3.98
			Fama Regression 2 (Rate Changes)	
USD-EUR	236.27	5	2001:01 2006:09 2007:11 2008:11 2013:07	-1.58/-3.38
USD-GBP	299.98	5	2000:12 2003:11 2006:04 2008:09 2015:09	-1.88/-3.88
USD-CHF	115.94	5	2000:12 2006:08 2007:10 2008:10 2015:09	-2.31/-3.53
GBP-EUR	310.85	5	2005:06 2006:09 2007:10 2008:12 2013:10	-2.64/-4.68
GBP-CHF	84.00	5	2001:03 2006:09 2007:10 2014:09 2015:09	-3.26/-4.26
EUR-CHF	412.14	5	2001:03 2005:04 2008:12 2013:10 2015:09	-2.18/-4.46
			Fama Regression 3 (Incremental Return Premiums)	
USD-EUR	166.33	5	2000:12 2006:03 2007:10 2008:10 2013:09	-0.99/-2.49
USD-GBP	173.29	5	2000:12 2003:11 2006:03 2008:09 2015:09	-1.46/-3.00
USD-CHF	48.87	5	2000:12 2006:03 2007:10 2008:10 2015:09	-1.62/-2.28
GBP-EUR	488.98	5	2003:07 2005:04 2007:11 2011:03 2013:11	-1.48/-3.93
GBP-CHF	30.62	4	2007:11 2012:10 2013:10 2014:12	-2.38/-2.82
EUR-CHF	352.13	5	2001:03 2006:08 2007:08 2013:10 2014:12	-1.36/-3.51
			Fama Regression 4 (Incremental Rate Changes)	
USD-EUR	288.34	5	2001:01 2003:12 2008:10 2013:09 2015:05	-0.79/-2.76
USD-GBP	240.43	5	2000:11 2003:11 2006:06 2013:09 2015:05	-1.47/-3.28
USD-CHF	80.06	5	2001:01 2003:11 2012:08 2013:09 2015:09	-1.65/-2.62
GBP-EUR	124.34	5	2005:04 2007:09 2008:10 2012:09 2014:02	-2.33/-3.61
GBP-CHF	209.61	5	2000:12 2007:09 2012:09 2013:09 2015:09	-1.60/-3.30
EUR-CHF	319.36	5	2000:12 2008:10 2012:01 2013:02 2015:09	-1.30/-3.35

Table 3.3. Estimated Breaks and Break Sizes.

For each market pair and each break *n**, Date is the estimate date of the break, Lower and Upper are the lower and upper bounds of the 90% confidence interval around the break date, d_i(t)is the estimated intercept of the differential beta in the period preceding the break, and StErr is the standard error of d_i(t). NA indicates that the bounds could not be reliably estimated because either the lower or the upper bound is outside the sample period.

Markets	*n**	Date	Lower	Upper	d_i(t)	StErr
	Fama Regression 1 (Return Premiums)					
USD-EUR					0.373	0.045
	1	2000:12	2000:10	2001:01	-0.592	0.024
	2	2006:08	2006:06	2007:02	-0.054	0.049
	3	2007:12	2007:07	2008:01	-0.888	0.056
	4	2008:12	2008:09	2009:09	-0.264	0.026
	5	2013:09	2013:06	2013:12	0.441	0.032
USD-GBP					0.413	0.034
	1	2000:12	2000:11	2001:01	-0.391	0.022
	2	2004:08	2004:06	2004:11	-0.798	0.034
	3	2006:03	2005:10	2006:04	-0.238	0.027
	4	2008:09	2008:06	2009:02	0.290	0.016
	5	2015:09	2015:06	2016:02	-0.096	0.043
USD-CHF					0.071	0.051
	1	2000:12	2000:10	2001:02	-0.659	0.028
	2	2006:03	2006:01	2006:06	-0.110	0.051
	3	2007:10	2007:03	2007:12	-0.699	0.064
	4	2008:10	2008:06	2009:04	-0.084	0.029
	5	2013:10	2009:07	2015:04	-0.354	0.037
GBP-EUR					-0.144	0.013
	1	2004:07	2004:01	2004:10	0.064	0.029
	2	2005:07	2004:05	2006:03	-0.098	0.019
	3	2007:11	2007:09	2008:03	-0.447	0.016
	4	2011:03	2010:10	2011:12	-0.295	0.018
	5	2013:11	2013:10	2013:12	0.574	0.017
GBP-CHF					-0.294	0.021
	1	2004:06	2004:04	2004:10	-0.026	0.026
	2	2007:11	2007:06	2008:01	-0.346	0.022
	3	2012:07	2012:03	2012:09	0.110	0.042
	4	2013:10	2013:09	2013:12	-0.716	0.044
	5	2014:12	2012:12	2015:01	-0.213	0.036
EUR-CHF					-0.259	0.027
	1	2001:04	2001:03	2001:08	-0.030	0.019
	2	2005:04	NA	2005:08	0.040	0.014
	3	2012:07	2011:01	2013:08	0.279	0.033
	4	2013:10	2013:09	2013:11	-1.121	0.034
	5	2014:12	2014:05	2015:01	-0.631	0.028

Table 3.3 (cont.)

Markets	*n**	Date	Lower	Upper	di(t)	StErr
	Fama Regression 2 (Rate Changes)					
USD-EUR					-0.492	0.039
	1	2001:01	2000:10	2001:02	0.480	0.021
	2	2006:09	2006:08	2008:01	0.110	0.046
	3	2007:11	2007:09	2007:12	0.851	0.050
	4	2008:11	2008:09	2009:01	0.250	0.023
	5	2013:07	2013:03	2013:09	-0.444	0.028
USD-GBP					-0.408	0.031
	1	2000:12	2000:11	2001:01	0.338	0.023
	2	2003:11	2003:08	2004:01	0.802	0.025
	3	2006:04	2005:05	2006:08	0.461	0.025
	4	2008:09	2008:05	2009:01	-0.096	0.015
	5	2015:09	2015:08	NA	0.199	0.039
USD-CHF					-0.088	0.037
	1	2000:12	2000:08	2001:02	0.606	0.019
	2	2006:08	2006:07	2007:04	0.151	0.043
	3	2007:10	2007:07	2007:11	0.659	0.046
	4	2008:10	2008:05	2009:01	0.187	0.018
	5	2015:09	2015:07	2015:12	0.851	0.046
GBP-EUR					-0.108	0.011
	1	2005:06	2005:05	2006:01	0.073	0.023
	2	2006:09	2006:06	2006:10	-0.149	0.025
	3	2007:10	2007:07	2007:11	0.377	0.024
	4	2008:12	2008:07	2010:01	0.162	0.012
	5	2013:10	2013:08	2013:11	-0.498	0.015
GBP-CHF					0.210	0.024
	1	2001:03	2000:10	2001:07	0.038	0.014
	2	2006:09	2006:05	2007:03	-0.117	0.031
	3	2007:10	2007:06	2007:11	0.285	0.012
	4	2014:09	2011:08	NA	0.173	0.032
	5	2015:09	2014:08	2015:12	0.570	0.032
EUR-CHF					0.359	0.022
	1	2001:03	2001:02	2001:06	0.108	0.014
	2	2005:04	2003:06	2005:05	-0.084	0.015
	3	2008:12	2008:09	2010:02	0.162	0.013
	4	2013:10	2013:09	2013:11	0.779	0.021
	5	2015:09	2014:03	2016:01	1.065	0.029

Table 3.3 (cont.)

Markets	n*	Date	Lower	Upper	$d_i(t)$	StErr
	Fama Regression 3 (Incremental Return Premiums)					
USD-EUR					0.566	0.062
	1	2000:12	2000:10	2001:01	-0.578	0.034
	2	2006:03	2006:01	2006:10	0.018	0.062
	3	2007:10	2007:05	2007:11	-1.113	0.078
	4	2008:10	2008:08	2009:08	-0.361	0.035
	5	2013:09	2013:04	2013:10	0.690	0.045
USD-GBP					0.486	0.048
	1	2000:12	2000:11	2001:02	-0.423	0.035
	2	2003:11	2003:08	2004:03	-0.849	0.040
	3	2006:03	2005:04	2006:04	-0.307	0.038
	4	2008:09	2008:04	2009:07	0.247	0.023
	5	2015:09	2015:06	2016:02	-0.359	0.061
USD-CHF					0.112	0.069
	1	2000:12	2000:09	2001:03	-0.821	0.038
	2	2006:03	2006:02	2007:02	-0.336	0.069
	3	2007:10	2007:01	2007:11	-0.976	0.087
	4	2008:10	2008:03	2009:05	-0.274	0.033
	5	2015:09	2014:01	2016:08	-0.797	0.087
GBP-EUR					0.002	0.019
	1	2003:07	2002:09	2004:09	0.212	0.029
	2	2005:04	2003:08	2006:09	0.048	0.024
	3	2007:11	2007:10	2008:01	-0.533	0.021
	4	2011:03	2010:11	2011:11	-0.343	0.023
	5	2013:11	2013:10	2013:12	0.883	0.023
GBP-CHF					-0.227	0.023
	1	2007:11	2007:08	2009:01	-0.517	0.030
	2	2012:10	2012:01	2012:12	-0.145	0.067
	3	2013:10	2013:06	2013:12	-0.898	0.062
	4	2014:12	2011:08	2015:04	-0.377	0.051
	5					
EUR-CHF					-0.431	0.035
	1	2001:03	2001:01	2001:09	-0.137	0.020
	2	2006:08	2005:12	2006:10	-0.427	0.047
	3	2007:08	2007:01	2007:12	-0.060	0.019
	4	2013:10	2013:09	2013:11	-1.652	0.043
	5	2014:12	2013:07	2015:01	-1.150	0.035

Table 3.3 (cont.)

Markets	n^*	Date	Lower	Upper	$d_i(t)$	StErr
	Fama Regression 4 (Incremental Rate Changes)					
USD-EUR					-0.880	0.053
	1	2001:01	2000:12	2001:03	0.134	0.040
	2	2003:12	2001:07	2004:01	0.565	0.031
	3	2008:10	2008:05	2010:08	0.067	0.031
	4	2013:09	2013:08	2013:10	-1.378	0.053
	5	2015:05	2014:12	2015:08	-0.748	0.059
USD-GBP					-0.568	0.043
	1	2000:11	2000:10	2000:12	0.285	0.030
	2	2003:11	2003:09	2003:12	0.972	0.033
	3	2006:06	2006:01	2006:08	0.343	0.020
	4	2013:09	2013:06	2013:12	-0.483	0.041
	5	2015:05	2015:03	2015:10	0.178	0.046
USD-CHF					-0.204	0.057
	1	2001:01	2000:12	2001:06	0.212	0.044
	2	2003:11	1999:12	2003:12	0.465	0.025
	3	2012:08	2011:11	2013:09	0.951	0.070
	4	2013:09	2013:06	2013:11	-0.167	0.052
	5	2015:09	2015:07	2015:11	1.085	0.073
GBP-EUR					-0.462	0.018
	1	2005:04	2003:10	2006:06	-0.224	0.029
	2	2007:09	2007:04	2008:02	0.238	0.043
	3	2008:10	2008:09	2009:04	-0.189	0.023
	4	2012:09	2012:01	2012:10	-0.402	0.037
	5	2014:02	2013:09	2014:04	-0.855	0.028
GBP-CHF					-0.063	0.041
	1	2000:12	2000:05	2001:11	-0.360	0.020
	2	2007:09	2007:07	2007:11	0.368	0.023
	3	2012:09	2012:02	2013:01	0.789	0.052
	4	2013:09	2013:07	2014:02	0.290	0.037
	5	2015:09	2014:12	2015:10	0.794	0.052
EUR-CHF					0.581	0.040
	1	2000:12	2000:08	2001:01	0.036	0.018
	2	2008:10	2008:09	2009:04	0.501	0.028
	3	2012:01	2011:10	2012:02	0.824	0.049
	4	2013:02	2012:06	2013:05	1.099	0.032
	5	2015:09	2014:05	2015:10	1.673	0.051

Table 3.4. Univariate Betas and Macroeconomic Conditions.

Each panel contains linear regression estimates, where the dependent variables in Panels (a) through (d) are each market's univariate betas from Fama Regressions 1 through 4, respectively. All independent variables are lagged by one month. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Panel (a): Fama Regression 1 (Return Premiums)				
	EUR	GBP	CHF	USD
Credit Spread	-0.163	-0.0606	0.0121	-0.288**
	(0.119)	(0.0569)	(0.249)	(0.129)
Policy Rate	0.0358	-0.237***	0.698***	0.000533
	(0.0720)	(0.0399)	(0.191)	(0.0207)
M1 Growth Rate	-0.0202*	0.0228***	-0.0316***	0.00107
	(0.0117)	(0.00741)	(0.00584)	(0.00748)
Inflation	-0.176***	0.102***	-0.108*	-0.220***
	(0.0501)	(0.0351)	(0.0626)	(0.0254)
Unemployment	-0.251***	-0.558***	0.790***	-0.334***
	(0.0534)	(0.0459)	(0.248)	(0.0318)
NEER	-0.0237**	0.0262***	0.0413***	-0.0149***
	(0.00944)	(0.00714)	(0.0114)	(0.00376)
PMI	-0.00752	0.0127	-0.0278**	0.0159*
	(0.00989)	(0.00969)	(0.0111)	(0.00931)
VIX	-0.0257***	-0.00633**	-0.0178	0.0146***
	(0.00547)	(0.00318)	(0.0114)	(0.00443)
Constant	6.026***	-0.336	-5.668***	2.888***
	(1.365)	(0.927)	(2.143)	(0.969)
Observations	140	166	125	191
R^2	0.586	0.817	0.336	0.626

Table 3.4 (cont.)

	Panel (b): Fama Regression 2 (Rate Changes)			
	EUR	GBP	CHF	USD
Credit Spread	0.0595	-0.0140	-0.0713	0.383***
	(0.0839)	(0.0443)	(0.182)	(0.105)
Policy Rate	-0.0286	0.203***	-0.431***	-0.00306
	(0.0565)	(0.0305)	(0.130)	(0.0191)
M1 Growth Rate	0.00353	-0.0224***	0.0303***	-0.0117*
	(0.00854)	(0.00557)	(0.00481)	(0.00610)
Inflation	0.0558	-0.0890***	0.129***	0.191***
	(0.0372)	(0.0249)	(0.0479)	(0.0231)
Unemployment	0.149***	0.399***	-0.611***	0.254***
	(0.0435)	(0.0341)	(0.168)	(0.0254)
NEER	0.0159**	-0.0245***	-0.0301***	0.0140***
	(0.00617)	(0.00566)	(0.00842)	(0.00311)
PMI	0.00662	-0.0140*	0.0195**	-0.0112
	(0.00718)	(0.00753)	(0.00891)	(0.00747)
VIX	0.0186***	0.00920***	0.0124	-0.0145***
	(0.00379)	(0.00239)	(0.00810)	(0.00370)
Constant	-2.743**	2.032***	5.112***	-1.612**
	(1.050)	(0.701)	(1.534)	(0.749)
Observations	140	166	125	191
R^2	0.549	0.833	0.426	0.574

Table 3.4 (cont.)

Panel (c): Fama Regression 3 (Incremental Return Premiums)				
	EUR	GBP	CHF	USD
Credit Spread	-0.181	-0.0577	0.0741	-0.270
	(0.150)	(0.0814)	(0.322)	(0.201)
Policy Rate	0.0263	-0.359***	0.745***	-0.0350
	(0.0921)	(0.0549)	(0.246)	(0.0297)
M1 Growth Rate	-0.0396***	0.0379***	-0.0476***	-0.00697
	(0.0143)	(0.0113)	(0.00789)	(0.0107)
Inflation	-0.211***	0.196***	-0.171**	-0.294***
	(0.0614)	(0.0481)	(0.0835)	(0.0362)
Unemployment	-0.316***	-0.765***	0.896***	-0.458***
	(0.0698)	(0.0610)	(0.319)	(0.0439)
NEER	-0.0246**	0.0373***	0.0408***	-0.0256***
	(0.0117)	(0.00986)	(0.0149)	(0.00583)
PMI	-0.00868	0.0242*	-0.0359**	0.0320**
	(0.0124)	(0.0138)	(0.0160)	(0.0143)
VIX	-0.0326***	-0.00989**	-0.0288**	0.0161***
	(0.00677)	(0.00437)	(0.0132)	(0.00610)
Constant	7.166***	-0.859	-5.059*	4.187***
	(1.713)	(1.260)	(2.754)	(1.556)
Observations	140	166	125	191
R^2	0.561	0.804	0.349	0.548

Table 3.4 (cont.)

Panel (d): Fama Regression 4 (Incremental Rate Changes)				
	EUR	GBP	CHF	USD
Credit Spread	0.0758	-0.134*	0.0393	0.393***
	(0.110)	(0.0681)	(0.193)	(0.142)
Policy Rate	-0.128	0.288***	-0.272**	0.0356
	(0.0813)	(0.0434)	(0.128)	(0.0252)
M1 Growth Rate	-0.0143	-0.0407***	0.0377***	-0.0159**
	(0.0115)	(0.00779)	(0.00514)	(0.00742)
Inflation	0.0409	-0.154***	0.229***	0.229***
	(0.0436)	(0.0334)	(0.0542)	(0.0336)
Unemployment	0.115	0.442***	-0.432***	0.302***
	(0.0694)	(0.0455)	(0.157)	(0.0317)
NEER	0.0235***	-0.0357***	-0.0193**	0.0254***
	(0.00676)	(0.00830)	(0.00943)	(0.00445)
PMI	0.00848	-0.0359***	0.0231**	-0.0256**
	(0.00994)	(0.0106)	(0.0101)	(0.0104)
VIX	0.0277***	0.0164***	0.00750	-0.0162***
	(0.00457)	(0.00343)	(0.00886)	(0.00467)
Constant	-3.093**	4.135***	2.746*	-2.666**
	(1.549)	(0.986)	(1.600)	(1.096)
Observations	140	166	125	191
R^2	0.611	0.814	0.509	0.450

Table 3.5. Results of Principal Component Analysis of the Individual Fama Regressions Betas.

We consider both the covariance matrix and correlation matrix when implementing principal component analysis. Only the largest component is reported here. "Standard deviation" is the standard deviation of the component. "Proportion of Variance" is the proportion of variation in the individual betas across the four markets that can be explained by the largest component. "Loadings" are parameters of the linear combination of four betas for constructing the largest component.

	Regression 1	Regression 2	Regression 3	Regression4
	Using Sample Correlation Matrix			
Standard Deviation	0.984	0.655	1.171	0.800
Proportion of Variance	91.54%	86.17%	93.70%	85.66%
Loadings	-0.425	-0.283	-0.395	-0.511
	-0.451	-0.441	-0.418	-0.383
	-0.662	-0.691	-0.715	-0.747
	-0.423	-0.498	-0.397	-0.184
	Using Sample Covariance Matrix			
Standard Deviation	1.141	0.817	1.502	0.977
Proportion of Variance	88.88%	82.53%	89.21%	72.26%
Loadings	-0.354	-0.276	-0.316	0.317
	-0.523	-0.551	-0.525	0.557
	-0.608	-0.625	-0.604	0.623
	-0.481	-0.480	-0.510	0.449

Table 3.6. Differential Betas and Macroeconomic Conditions.

Each number corresponds to the R^2 from a linear regression of the differential betas in the corresponding column on a set of macroeconomic indicators in the corresponding row. The sets of macroeconomic indicators appear as explanatory variables only for the relevant differential betas. All macroeconomic indicators, which include inflation, policy rate, M1 growth rate, unemployment rate, PMI, VIX, credit spread, and NEER, are lagged by one month.

	USD-EUR	USD-GBP	USD-CHF	GBP-CHF	GBP-EUR	EUR-CHF
			Fama Regression 1 (Return Premiums)			
Eurozone	0.795				0.664	0.611
UK		0.724		0.251	0.707	
Switzerland			0.328	0.179		0.323
US	0.462	0.489	0.372			
			Fama Regression 2 (Rate Changes)			
Eurozone	0.874				0.743	0.771
UK		0.691		0.674	0.765	
Switzerland			0.316	0.509		0.666
US	0.499	0.417	0.467			
			Fama Regression 3 (Incremental Return Premiums)			
Eurozone	0.738				0.633	0.653
UK		0.650		0.305	0.793	
Switzerland			0.300	0.134		0.393
US	0.448	0.477	0.322			
			Fama Regression 4 (Incremental Rate Changes)			
Eurozone	0.861				0.647	0.732
UK		0.493		0.709	0.675	
Switzerland			0.061	0.558		0.747
US	0.463	0.319	0.281			

Table 3.7. Estimated Number of Breaks and Break Dates for Macroeconomic Indicators.

For each macro variable, *F*(5) is the supremum *F*-value for the null hypothesis of 5 versus no breaks, Breaks is the estimated number of breaks, Dates are the estimated break dates, *BIC*(0) is the sample BIC value for the model with no breaks, and *BIC*(b) is the sample BIC value for the model with the optimal number of breaks. If the *F*-test indicates no breaks, the BIC is not reported. The smaller the BIC, the better the fit of the model.

Macro Variable	*F*(5)	Breaks	Dates	*BIC*(0)/ *BIC*(b)
			USD	
Inflation	95.48	5	2001:09 2004:04 2008:10 2009:10 2014:11	0.59/-0.49
Policy Rate	36.71	5	2000:12 2001:12 2004:05 2007:08 2008:12	-3.19/-3.71
M1 Growth Rate	7.20	0		
Unemployment	4.44	0		
PMI	6.14	0		
VIX	82.07	5	2003:06 2007:07 2008:08 2009:08 2012:01	4.26/3.28
Credit Spread	111.53	5	2001:11 2003:09 2007:07 2008:07 2009:07	-1.58/-2.78
NEER	8.23	0		
			EUR	
Inflation	13.98	4	2007:07 2008:07 2009:07 2011:04	-2.79/-2.96
Policy Rate	20.35	4	2000:10 2003:06 2008:07 2009:07	-3.76/-4.05
M1 Growth Rate	13.54	5	2001:03 2003:03 2008:08 2009:08 2011:05	-0.47/-0.63
Unemployment	6.83	0		
PMI	21.00	3	2008:02 2009:02 2010:04	0.48/0.23
VIX	67.34	5	2002:05 2003:05 2008:08 2009:08 2012:08	4.39/3.54
Credit Spread	111.53	5	2001:11 2003:09 2007:07 2008:07 2009:07	-1.58/-2.78
NEER	5.30	0		
			GBP	
Inflation	12.85	5	2007:09 2008:09 2009:09 2011:09 2012:09	-2.51/-2.65
Policy Rate	23.34	4	2000:11 2001:11 2008:03 2009:03	-3.50/-3.84
M1 Growth Rate	76.81	5	2001:12 2003:12 2008:12 2012:05 2013:05	3.08/2.14
Unemployment	12.89	4	2000:06 2003:03 2008:03 2009:03	-3.85/-4.00
PMI	4.09	0		
VIX	57.35	5	2002:05 2003:05 2007:06 2008:08 2009:08	4.13/3.36
Credit Spread	111.53	5	2001:11 2003:09 2007:07 2008:07 2009:07	-1.58/-2.78
NEER	9.08	3	2007:08 2009:01 2015:08	1.12/1.02

Table 3.7 (cont.).

Macro Variable	*F*(5)	Breaks	Dates	*BIC*(0)/ *BIC*(b)
			CHF	
Inflation	6.18	0		
Policy Rate	11.00	4	2000:06 2003:03 2008:03 2009:03	-3.01/-3.13
M1 Growth Rate	17.80	5	2003:10 2004:10 2008:07 2009:07 2010:07	1.92/1.68
Unemployment	12.15	5	2001:09 2003:02 2008:09 2010:01 2011:06	-4.08/-4.21
PMI	8.59	5	2000:06 2001:11 2008:02 2009:03 2010:03	1.77/1.71
VIX	54.26	3	2007:06 2008:08 2009:08	4.00/3.31
Credit Spread	111.53	5	2001:11 2003:09 2007:07 2008:07 2009:07	-1.58/-2.78
NEER	7.69	0		

Figure 3.1. Estimated One Month Spot Rates.

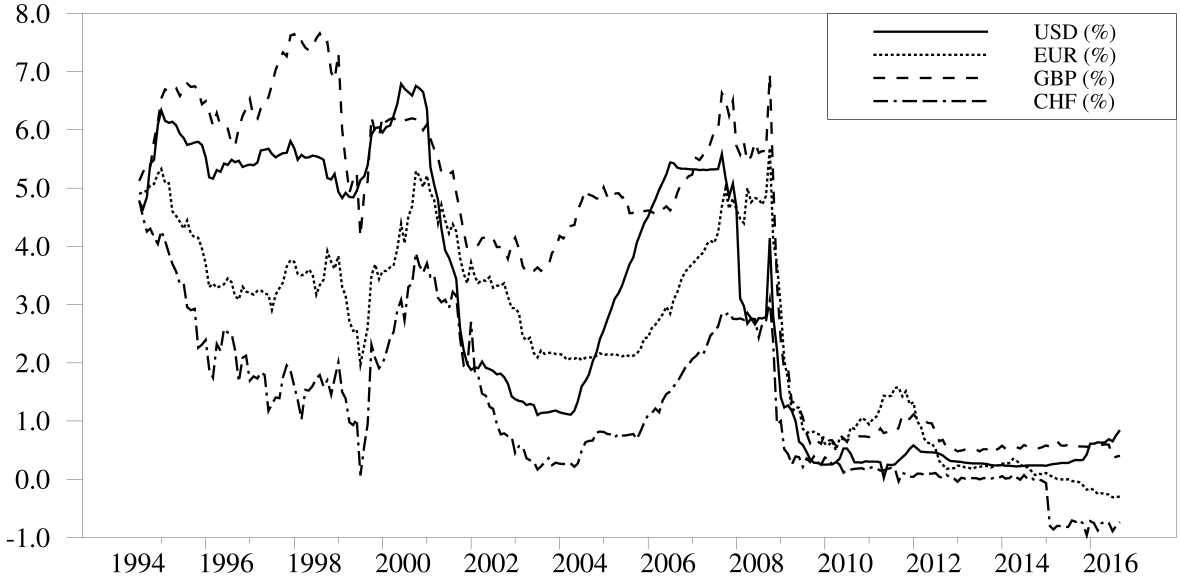


Figure 3.2. Slope Coefficients and Two Standard Deviation Confidence Intervals: Fama Regression 1 (Return Premiums).

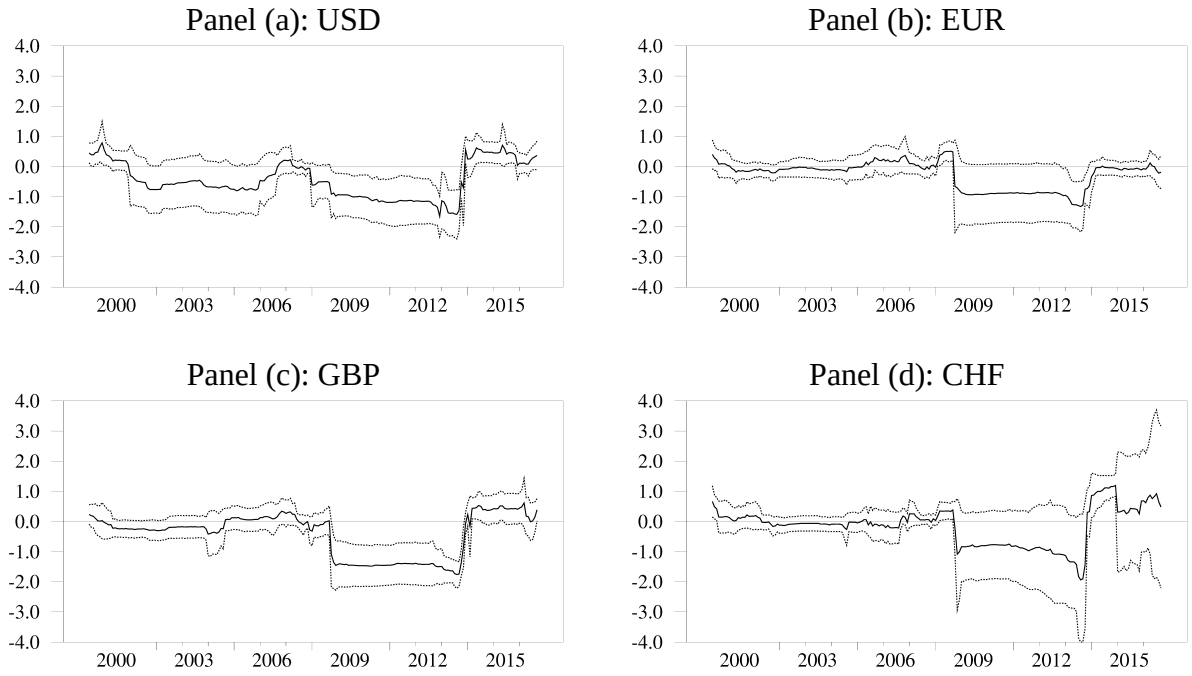


Figure 3.3. Slope Coefficients and Two Standard Deviation Confidence Intervals: Fama Regression 2 (Rate Changes).

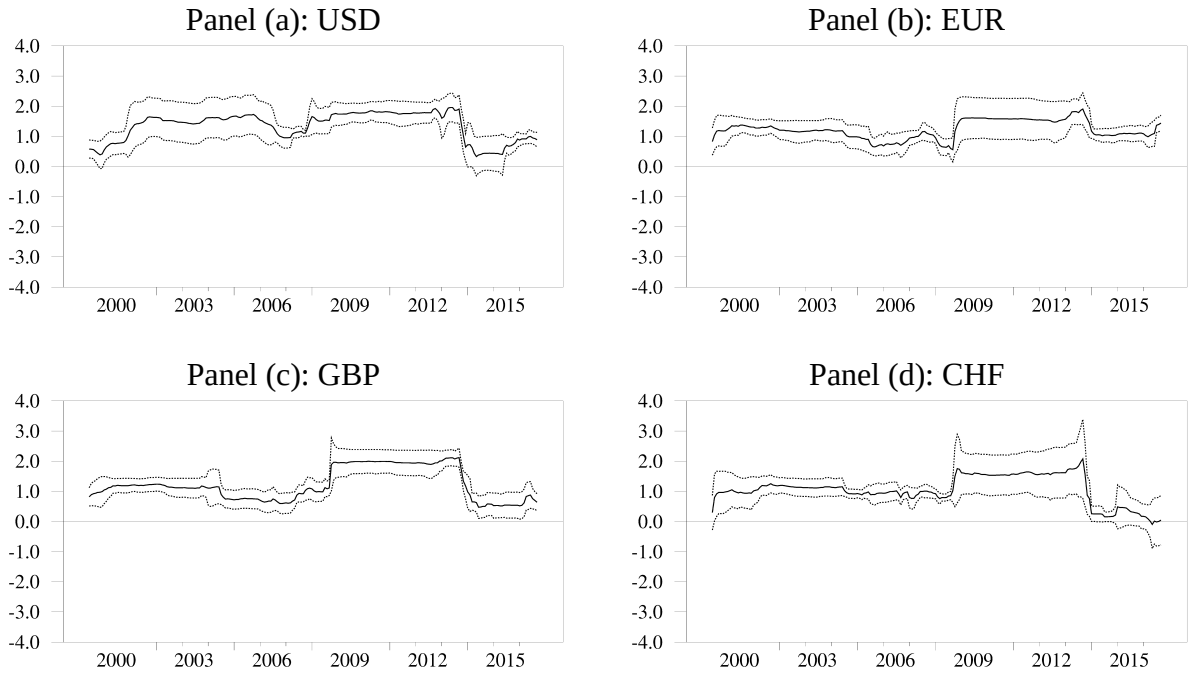


Figure 3.4. Slope Coefficients and Two Standard Deviation Confidence Intervals: Fama Regression 3 (Incremental Return Premiums).

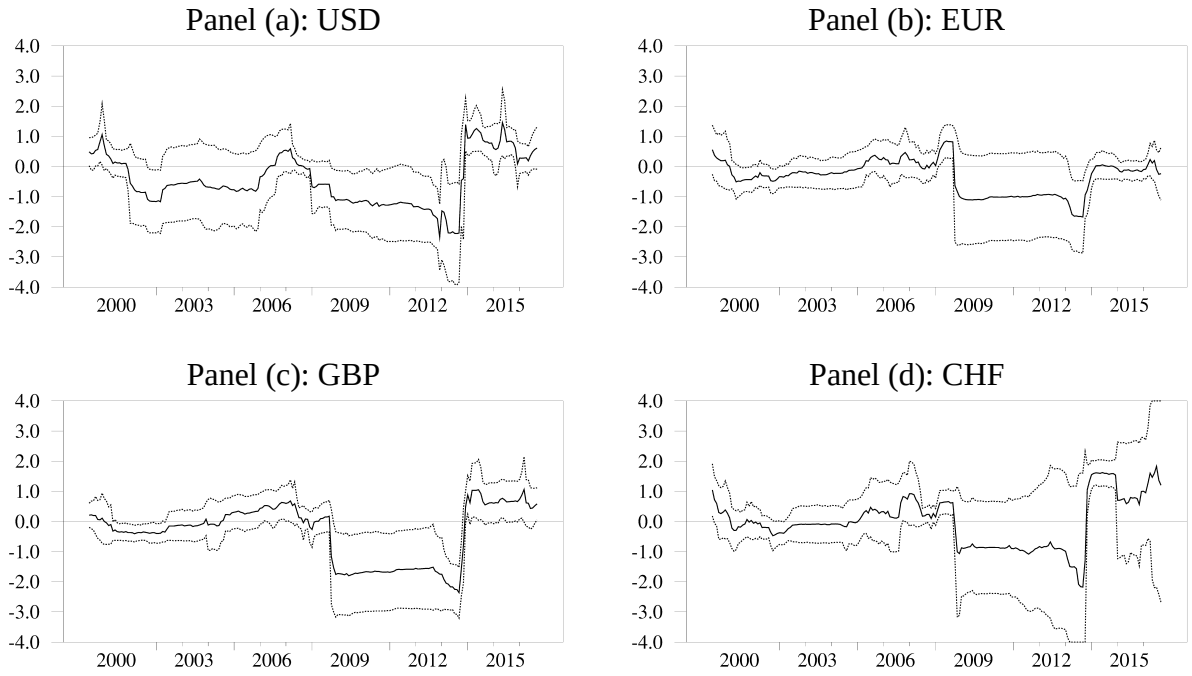


Figure 3.5. Slope Coefficients and Two Standard Deviation Confidence Intervals: Fama Regression 4 (Incremental Rate Changes).

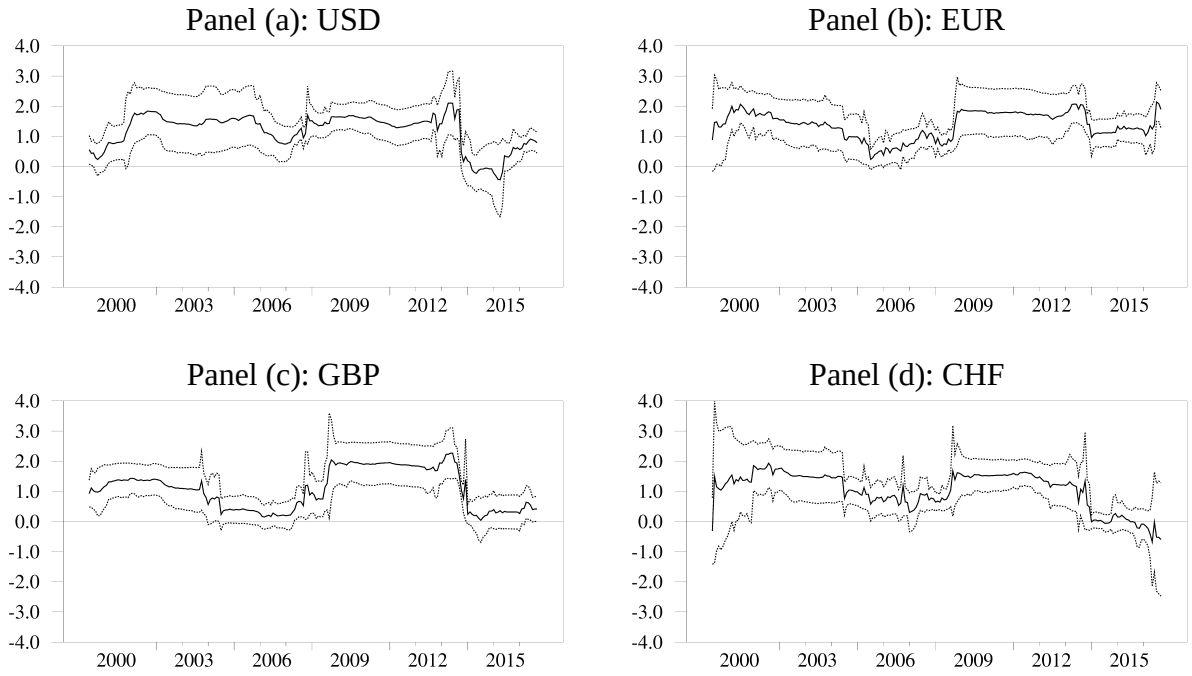


Figure 3.6. Differential Betas and Two Standard Deviation Confidence Intervals: Fama Regression 1 (Return Premiums).

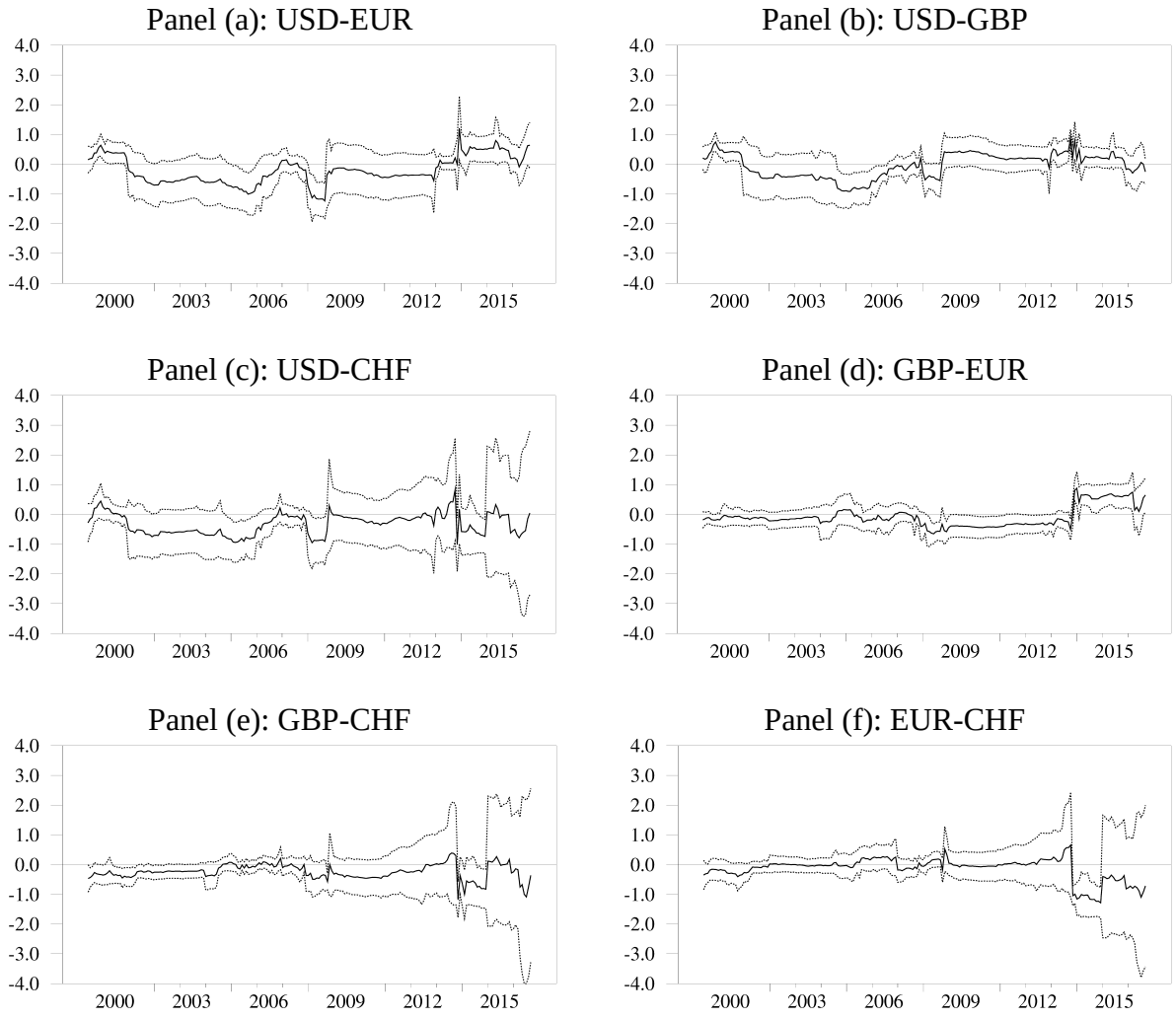


Figure 3.7. Differential Betas and Two Standard Deviation Confidence Intervals: Fama Regression 2 (Rate Changes).

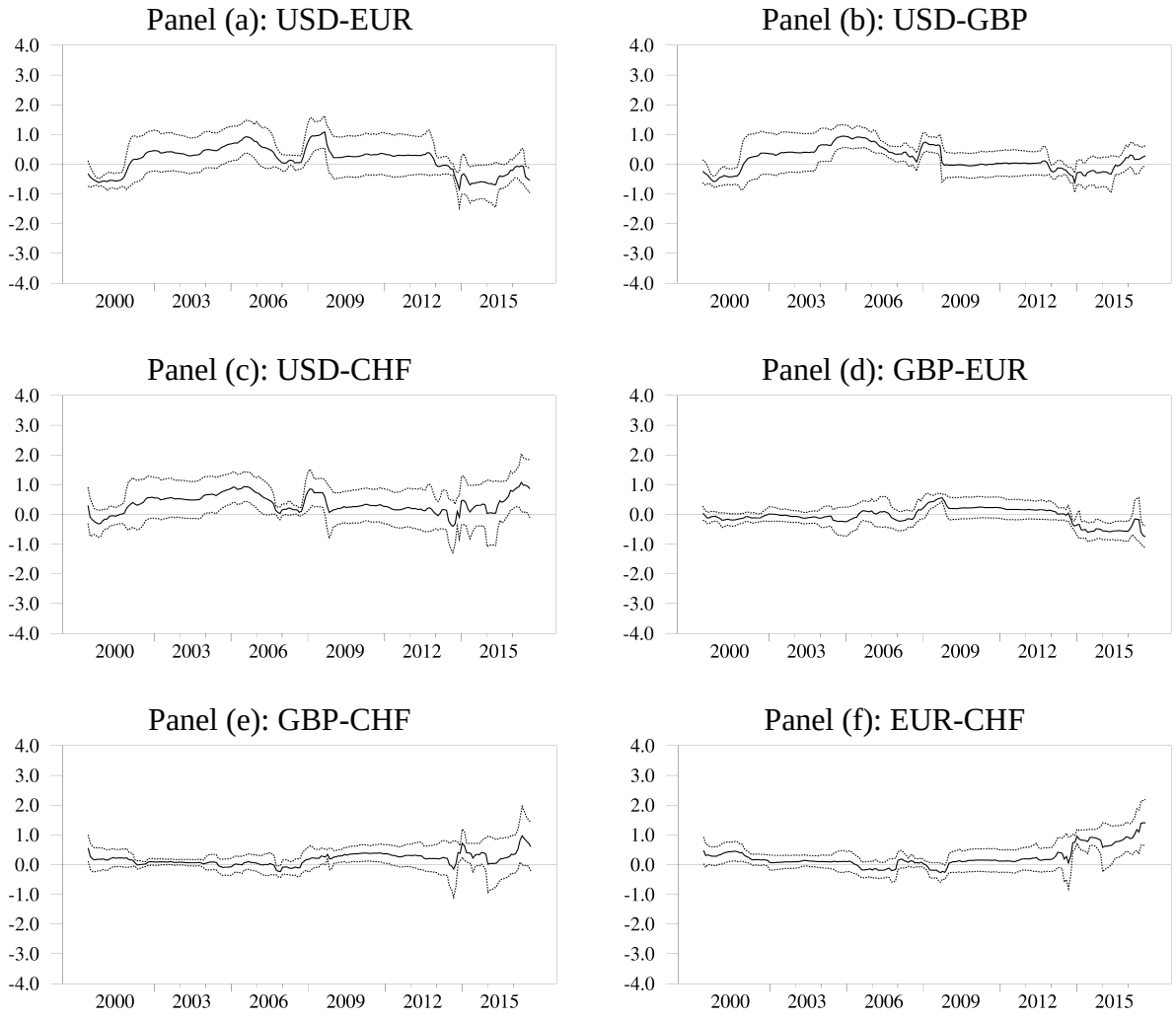


Figure 3.8. Differential Betas and Two Standard Deviation Confidence Intervals: Fama Regression 3 (Incremental Return Premiums).

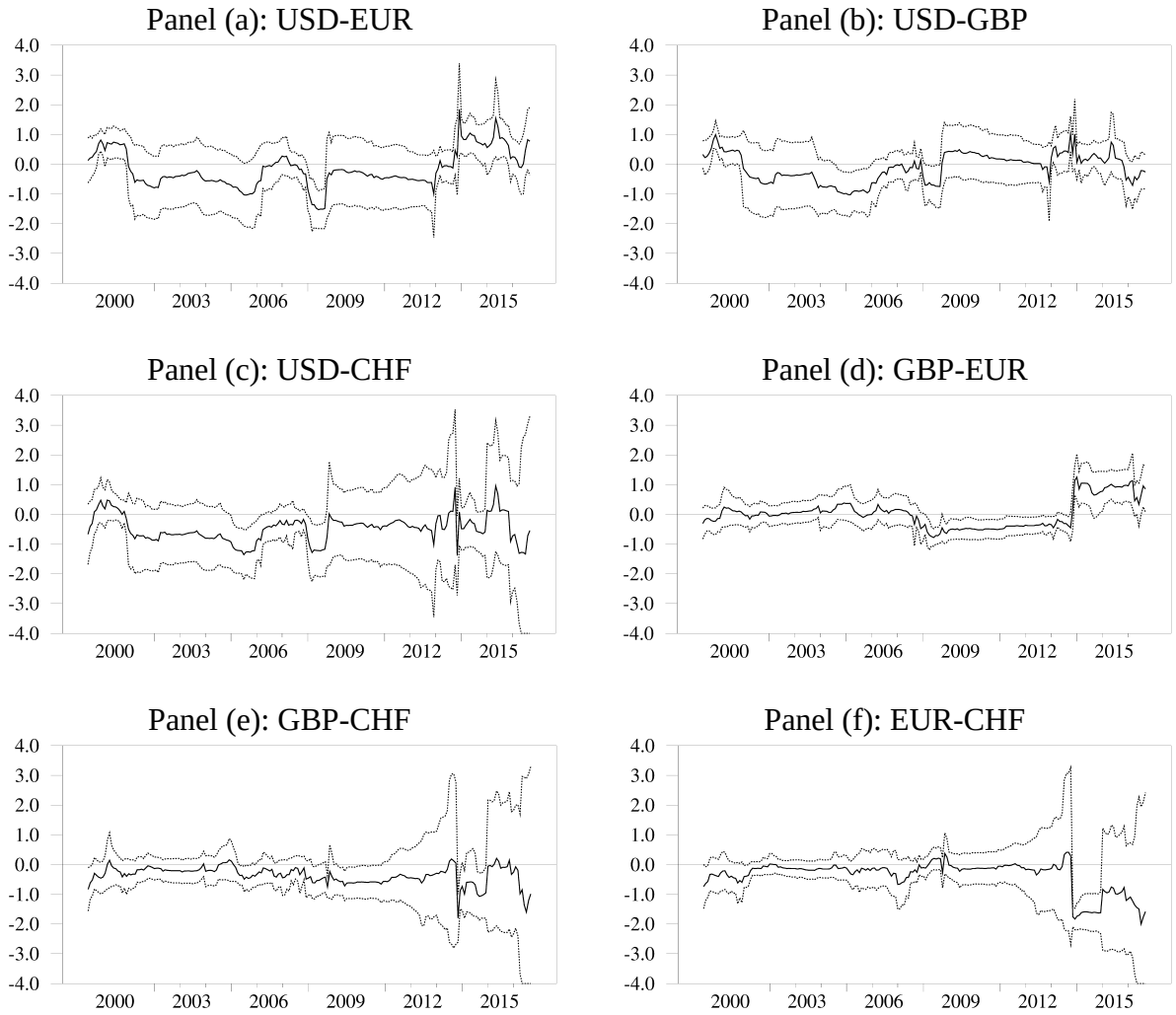


Figure 3.9. Differential Betas and Two Standard Deviation Confidence Intervals: Fama Regression 4 (Incremental Rate Changes).

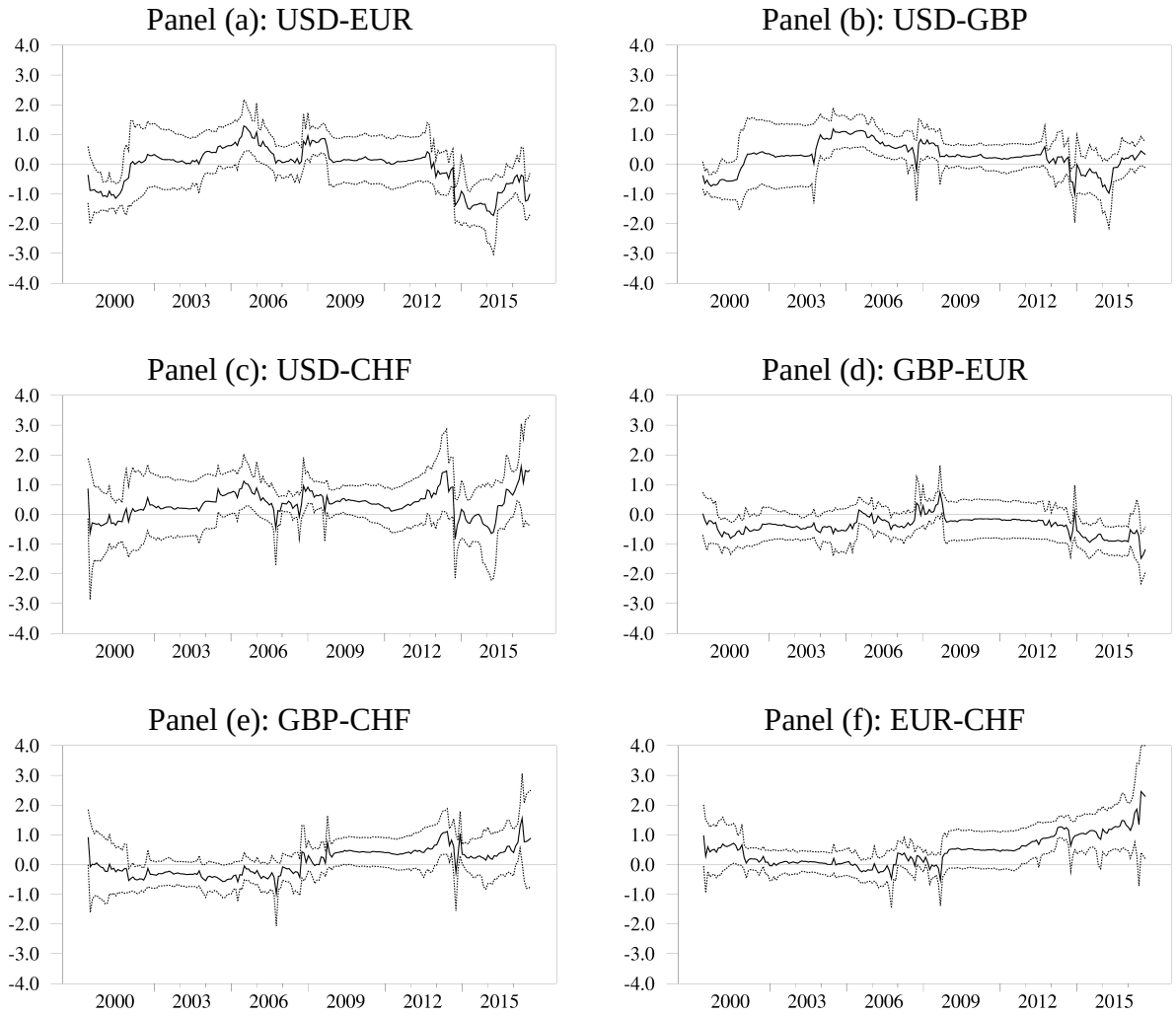


Figure 3.10. Time-Varying Correlations: Fama Regression 1 (Return Premiums).

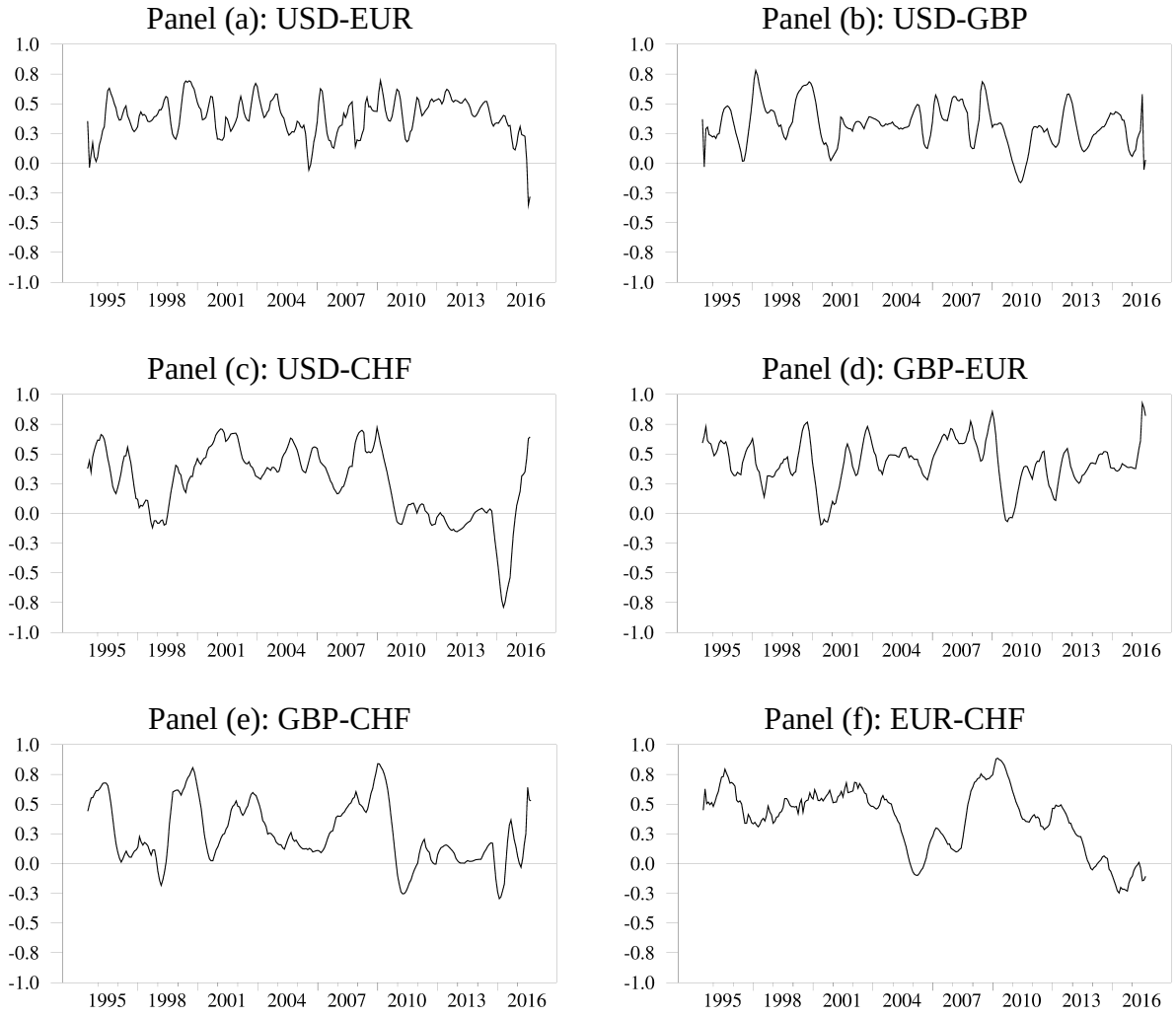


Figure 3.11. Time-Varying Correlations: Fama Regression 2 (Rate Changes)

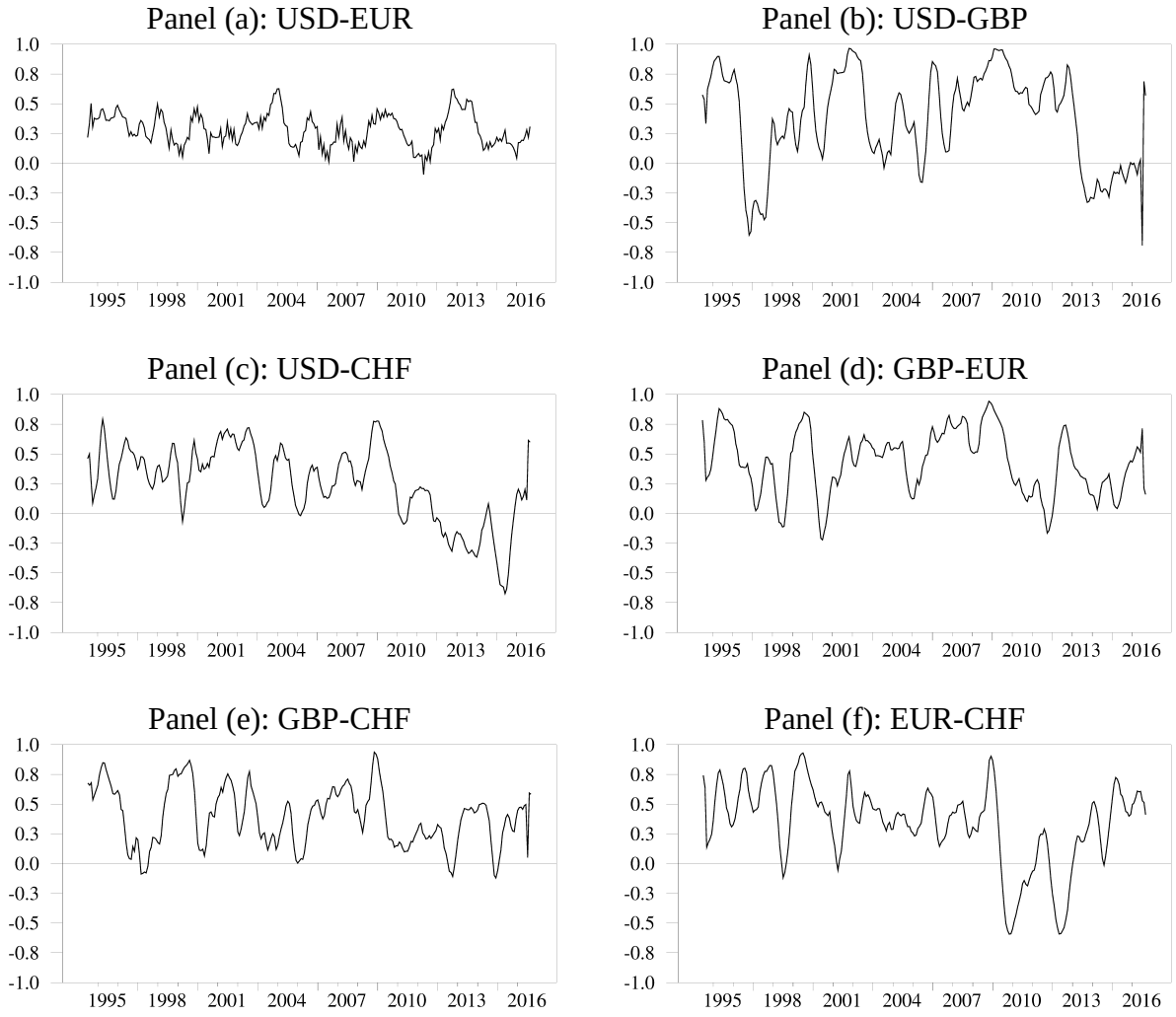


Figure 3.12. Time-Varying Correlations: Fama Regression 3 (Incremental Return Premiums).

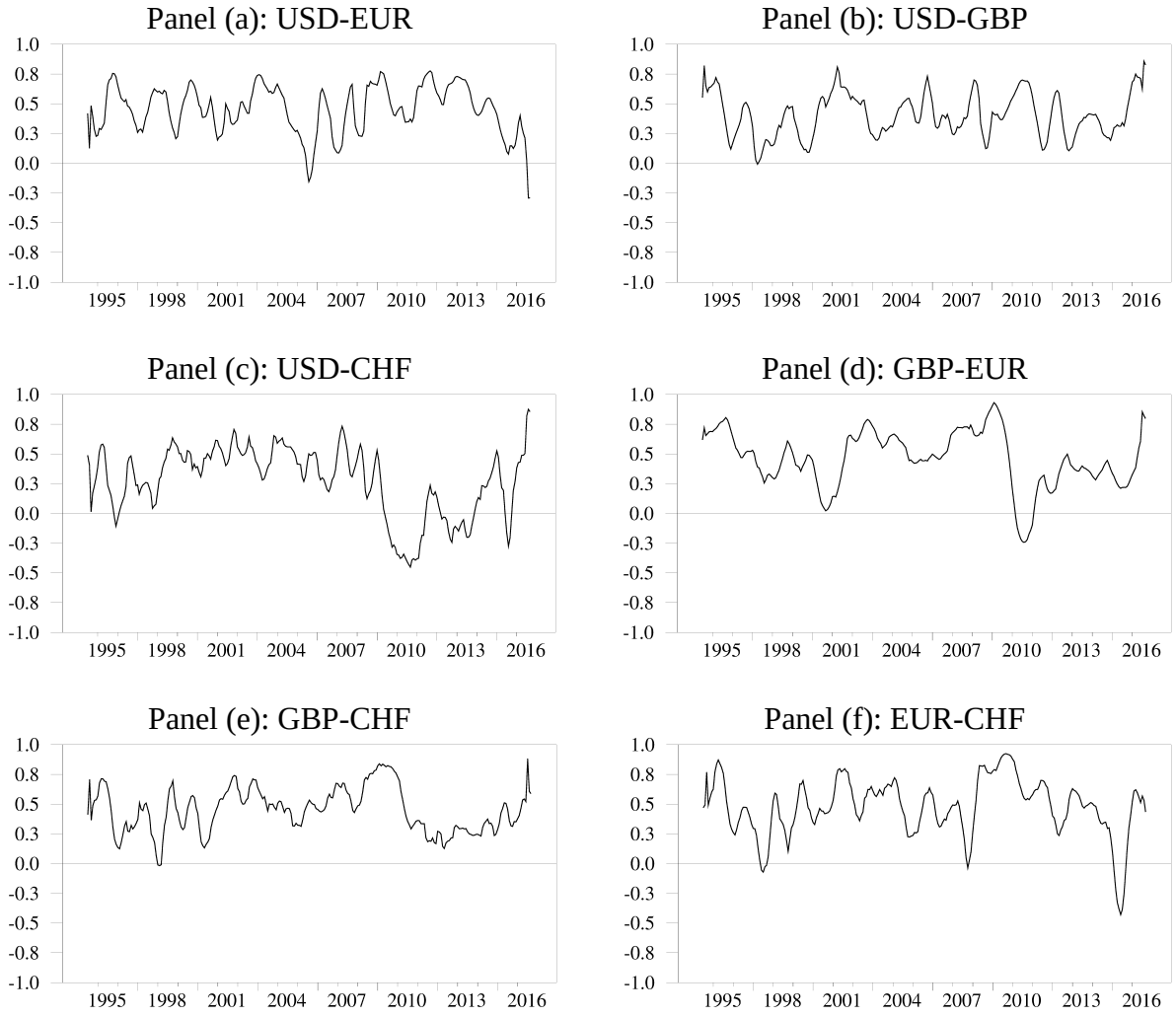


Figure 3.13. Time-Varying Correlations: Fama Regression 4 (Incremental Rate Changes).

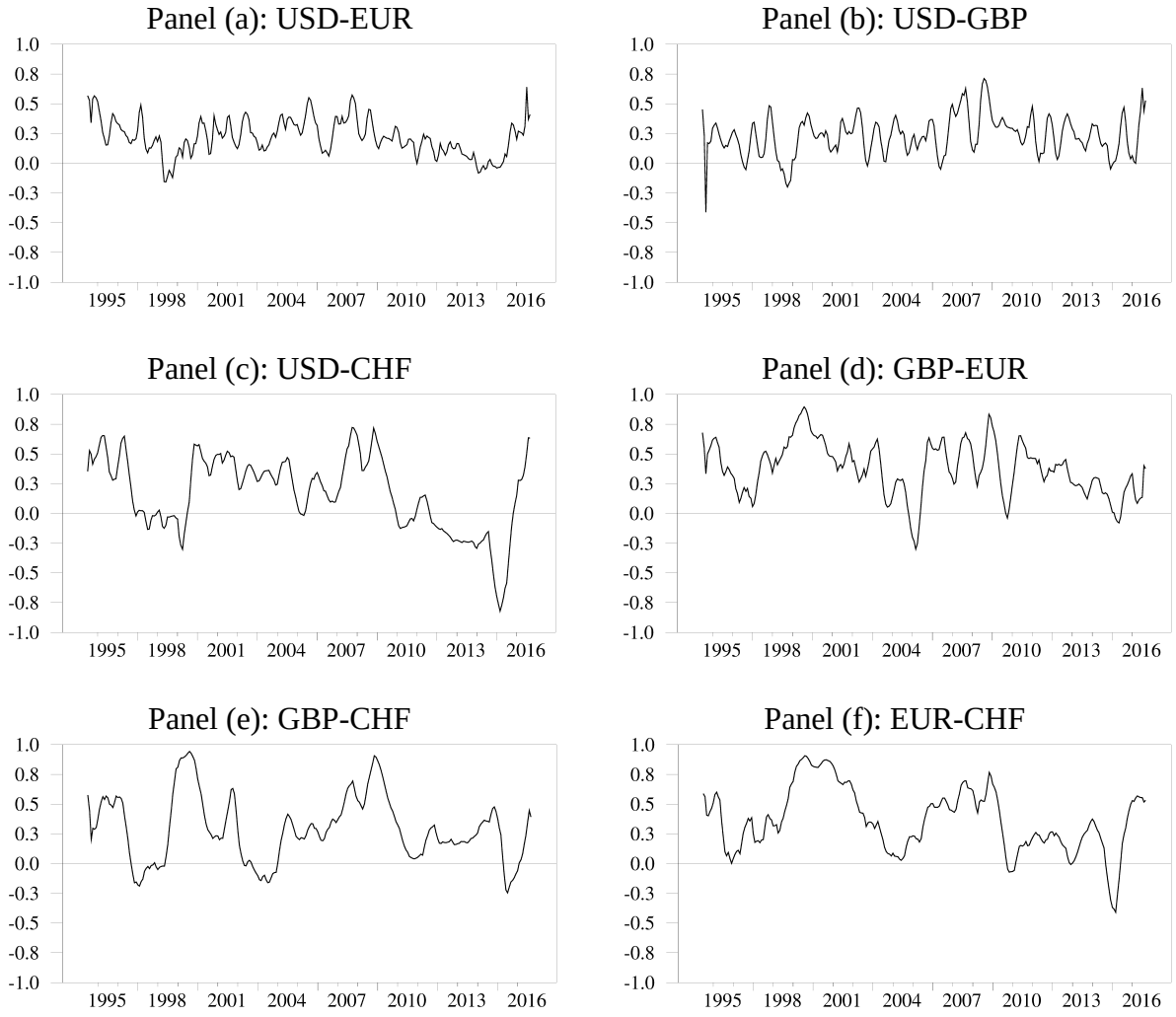
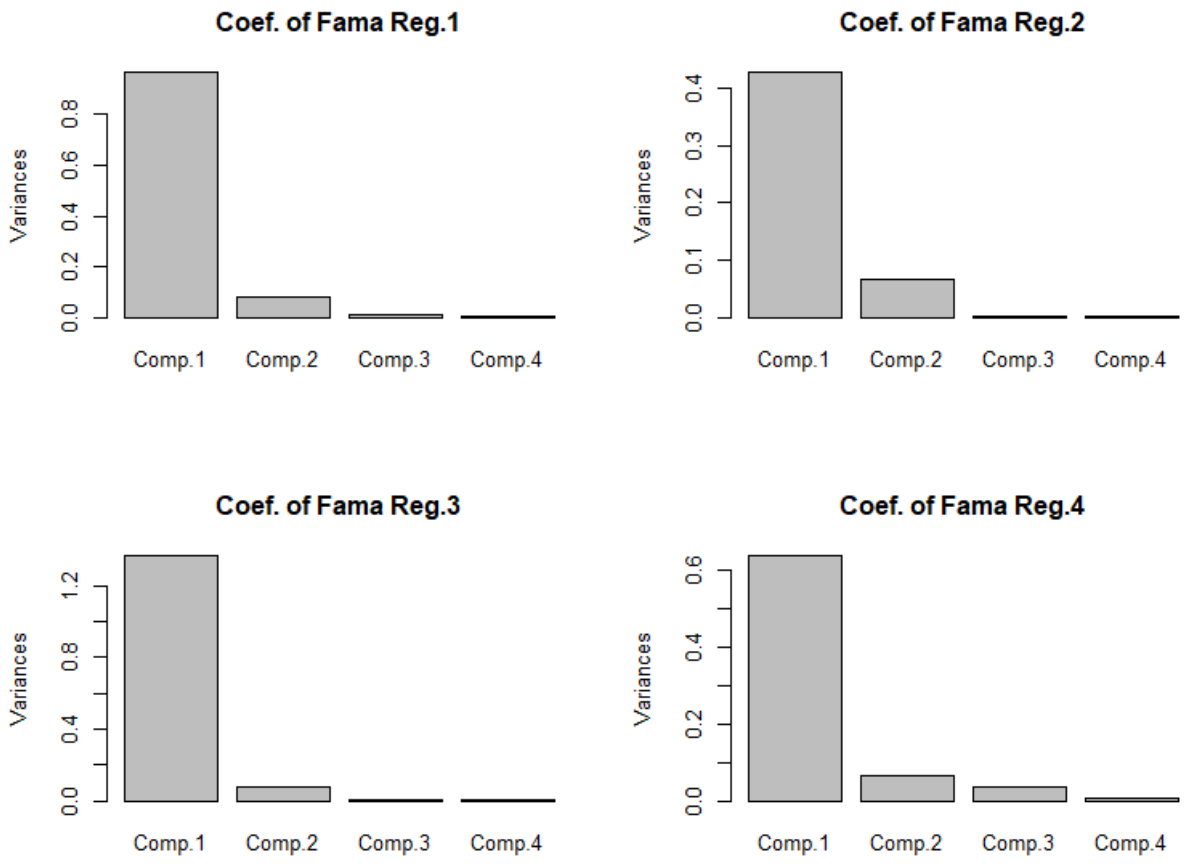


Figure 3.14. Results of Principal Component Analysis of the Individual Fama Regression Betas.



CHAPTER 4: SAMUELSON HYPOTHESIS, ARBITRAGE ACTIVITY, AND FUTURES RISK PREMIUMS

4.1. Introduction

The prediction that futures volatility increases as the expiration date approaches has become known as the Samuelson hypothesis after Samuelson (1965) used it as an illustration of his theoretical model. The inverse relationship between futures volatility and time to maturity is also referred to as simply the maturity effect in some of the literature.

Studying futures volatility term structure is important for several reasons. First, the term structure of volatility influences the selection of the number of futures contracts and the specific contract used for hedging in a futures-based hedging strategy. Second, the volatility term structure determines the value of futures options, related derivatives, and the corresponding implied risk parameters. Third, a better understanding of the futures volatility term structure can improve the process of setting futures margin requirements, leading to a safer and more efficient trading environment. Fourth, the volatility term structure affects the equilibrium risk premium in futures markets (Hirshleifer, 1988) and, therefore, the cost of hedging.

Our focus is on the slope of the futures volatility term structure. The negative slope of the futures volatility term structure is often interpreted as an implication of the hypothesis that futures volatility increases as the time to maturity nears. Our approach is to capture the information in the volatility term structure with three factors that are related to the level, slope, and curvature of the term structure. This design allows us to study the evolution of the Samuelson hypothesis in each market over time because the three factors can be seen as driving

the dynamics of the volatility term structure, so that time-series variation in the slope factor is a measure of the time-series variation in the strength of the maturity effect. In addition, our design allows us to directly relate the slope of the volatility term structure to the level of inventories and to the futures term premiums.

We study the volatility term structure in ten futures markets comprising three categories: agriculture, energy, and metals. We show that there is significant time-series variation in the strength of the maturity effect in each market. We also show that the slope of the volatility term structure is more negative when inventories are low and that the threshold for high/low inventory is specific to each market. Our explanation of the relationship between the Samuelson hypothesis and inventory levels is rooted in the cost-of-carry model. The empirically observed threshold behavior is indicative of carry arbitrage being feasible only when inventories are sufficiently high. Our hypothesis that presence of carry arbitrage is the driving force behind the absence of the maturity effect is further corroborated by tests showing that futures term premiums vanish when the slope factor approaches zero.

Existing literature on the Samuelson hypothesis can largely be subdivided into mostly theoretical and mostly empirical with a few exceptions (Bessembinder, Coughenour, Seguin, & Smoller, 1996; Brooks, 2012) that contribute both theoretically and empirically. Theoretical papers focus on establishing a set of conditions that lead to the existence of the maturity effect in futures markets.

Rutledge (1976) shows that the maturity effect is supported by the Samuelson's model only when the spot price follows a stationary autoregressive process and does not hold when the spot price process is random walk. Anderson and Danthine (1983) introduce a multi-period model of hedging in which futures prices are volatile in times when much uncertainty is resolved

and are stable when little uncertainty is resolved; the maturity effect can then be interpreted as a special case of the Anderson-Danthine state-variable framework whereby progressively more information is revealed as the maturity date approaches. Bessembinder et al. (1996) establish a framework that identifies the conditions under which the Samuelson hypothesis is expected to hold; specifically, they show that the hypothesis will generally be supported in markets where the spot prices and convenience yields are positively correlated, whereas clustering of information near the delivery dates is not a necessary condition for the hypothesis to hold.

Routledge, Seppi, and Spatt (2000) introduce a model of joint dynamics of spot prices and inventories and prove that within their model the Samuelson hypothesis need not hold conditionally. Specifically, they show that when inventory is sufficiently high it is possible for the opposite of the Samuelson hypothesis to hold: forward price volatility is an increasing function of time to maturity. Brooks (2012) develops a futures market representation showing that the Samuelson hypothesis cannot hold in fully arbitraged markets; moreover, the inverse link between the hypothesis and carry arbitrage appears to be continuous in the sense that the maturity effect is stronger (weaker) when carry arbitrage forces are weaker (stronger).

Because the Samuelson hypothesis is an empirical proposition, there is a large empirical literature. Most studies that test the hypothesis across a variety of markets find mixed results. Rutledge (1976) finds support for the hypothesis in silver and cocoa futures, but not in wheat and soybean futures. Castelino and Francis (1982) study the volatility of changes in the basis and find support for the Samuelson hypothesis in wheat, soybeans, soybean oil, and soybean meal futures.

Anderson (1985) finds that various forms of seasonality are a stronger determinant of futures volatility than the maturity effect; nonetheless, the maturity effect is still present in oats, soybean oil, live cattle, and cocoa futures, while it is absent in wheat, corn, soybeans, and silver

futures. Milonas (1986) extends the work of Anderson and shows that the maturity effect is present in 10 out of 11 markets (not present in corn futures), including Treasury bond futures and industrial and precious metals, even after accounting for the contract month effect.

Barnhill, Jordan, and Seale (1987) control for the effect of quarterly refunding on the volatility of Treasure bond futures and still find support for the Samuelson hypothesis, which is stronger of the two effects. Kenyon et al. (1987) identify and control for several economic factors that affect futures volatility from year to year and still reach the conclusion that the maturity effect is present in corn, soybeans, and wheat futures. Khoury and Yourougou (1993) provide international evidence in support of the maturity effect by showing that six agricultural commodity futures traded on the Winnipeg exchange are driven by the same five determinants (month and year seasonality, trading session effect, contract month effect, and maturity effect) that drive the corresponding U.S. futures markets.

Based on the theory of storage (Working, 1949; Brennan, 1958; Telser, 1958), Fama and French (1988) predict that the maturity effect should (not) hold when inventories are low (high) and, using a proxy for inventory levels, find empirical support for this refinement of the Samuelson hypothesis in the futures markets for industrial metals. In the most extensive study of the Samuelson hypothesis at the time of publication, Galloway and Kolb (1996) study the term structure of volatility in 45 markets, including agricultural and energy commodity futures, precious and industrial metal futures, and stock index, currency, and interest rate futures. Their findings provide support for the maturity effect in agricultural and energy commodities, but not in precious metals and financials. Galloway and Kolb conclude that the maturity effect is present in commodities that exhibit seasonal supply and demand patterns, but is virtually nonexistent in the markets where the cost-of-carry model works well.

Bessembinder et al. (1996) find that the Samuelson effect holds in agricultural and crude oil futures and less strongly in metal futures, while it does not hold in financial futures. Their conclusion is that empirical evidence is consistent with their prediction that the presence of a mean reverting component in the spot price process (negative correlation between the spot price and the slope of the futures price term structure) governs the presence of the maturity effect.

Duong and Kalev (2008) use intraday data from 20 futures markets to construct a measure of futures volatility as a sum of squared intraday returns and find that the Samuelson hypothesis holds in agricultures futures, but does not hold in other futures. They also show that their findings are consistent with the negative covariance explanation of Bessembinder et al. (1996). Kalev and Duong (2008) also use intraday data, but measure futures volatility as the realized intraday range and find that among 14 futures markets there is strong support for the Samuelson hypothesis in agricultural futures and no support in any of metal and financial futures.

Gurrola & Herrerías (2011) study the maturity effect in the Mexican interest rate futures using panel data techniques and find that the inverse of the Samuelson hypothesis prevails: volatility increases with time to expiration. To reconcile the findings with the negative covariance theory of Bessembinder et al. (1996), the study describes additional criteria that must be met in order for the maturity effect to hold. Liu (2016) uses stochastic volatility as a measure of futures volatility and examines the maturity effect using stochastic dominance tests. While there is mild support for the Samuelson hypothesis in energy futures in terms of the first two degrees of stochastic dominance, the hypothesis is more likely to hold at low stochastic volatility levels. Jaeck and Lautier (2016) find support for the Samuelson hypothesis in electricity markets

and show that shocks propagate from the spot to the futures contracts with intensity decreasing as time to expiration increases.

We contribute to the literature on the futures markets and specifically their volatility term structure in several ways. First, we point out a common technical issue that plagues time-series studies of futures prices and propose a method of overcoming it with a well-known interpolation. A common approach is to construct time-series of futures prices on a nearby basis; however, the time to expiration varies even within a given nearby time-series, introducing noise into the volatility-maturity relationship. We overcome the maturity drift problem by interpolating futures prices with a Nelson and Siegel (1987) curve and then using a point on the curve corresponding to an exact maturity. The result is a vector of futures price time-series with each time-series corresponding to an exact maturity on every trading day.

Second, borrowing from the literature on modeling the term structure of interest rates, we impose a factor model on the futures volatility term structure to parsimoniously explain the changes in the shape of term structure as being driven by just three factors. We fit the Nelson and Siegel model to the observed volatility term structure and, following Diebold and Li (2006), interpret model estimates as dynamic factors whose time-series behavior determines changes in the shape of the volatility term structure. This interpretation allows us to study the time-series variation in the strength of the Samuelson effect as represented by the variation in the slope factor. We show that in most markets the slope factor is strongly negative in certain periods and only weakly or not at all negative in other periods, reflecting varying strength of the Samuelson effect.

Third, we provide new evidence in support of the ability to conduct carry arbitrage as the driving force behind the Samuelson effect. We first show that the maturity effect is weaker when

inventories are high, which could be consistent with several explanations of the Samuelson effect. Specifically, we find that high inventory levels correspond to a flatter volatility term structure in corn, wheat, crude oil, heating oil, gold, silver, and copper futures. We next show that the link between inventories and the maturity effect exhibits threshold behavior, which can be consistent with the carry arbitrage explanation, but not with other theories put forth to explain the Samuelson effect.

Fourth, we study the link between the Samuelson hypothesis and futures risk premiums. When the volatility term structure flattens, term premiums in all futures markets except for wheat move closer to zero, consistent with the explanation that arbitrageurs provide infinite supply to meet net hedging demand.

4.2. Data

We examine the most actively traded physical commodity futures in three broad categories: agriculture, energy, and metals.[35] The agriculture category includes corn futures (ticker: C), soybean futures (S), and Chicago soft red winter wheat futures (W). The energy category is comprised of crude oil futures (CL), heating oil futures (HO),[36] Henry Hub natural gas futures (NG), and reformulated blend futures (RB).[37] Copper futures (HG), gold futures (GC), and silver futures (SI) are the contracts in the metals category.

Using daily data from 6/1/1993 to 2/28/2017, we form time-series of futures prices, time to maturity, and open interest for up to twelve futures contracts nearest to expiration for each commodity. We follow the standard practice in the literature and construct a vector of continuous

[35] We only consider futures traded on U.S. exchanges, namely CME, COMEX, and NYMEX. In each of the three categories we select three to four most actively traded contracts based on open interest. See http://www.cmegroup.com/education/files/cme-group-leading-products-2017-q2.pdf.
[36] The contract currently traded under the HO ticker is the New York Harbor Ultra-Low Sulfur Diesel futures.
[37] The full contract name is RBOB (reformulated blendstock for oxygenated blending) gasoline futures.

series ordered based on closeness to expiration, from the nearest to the most distant. We choose the last day of trading of the expiring contract as the rollover date since no significant difference has been found between different choices of the rollover date (Carchano and Pardo, 2009).

The resulting time-series are ordered by maturity in the sense that on any given trading day the first nearby contract is closer to expiration than the second nearby and so forth; however, even within a given series there is a day to day variation in the time to maturity because the contracts whose prices are used in constructing the series gradually expire and are replaced by new contracts. For example, the first nearby contract in any of the energy futures ranges in maturity from 23 days to 1 day. To address the maturity drift problem that could introduce noise in the volatility-maturity relationship, we fit a Nelson and Siegel (1987) curve to the observed daily term structure of futures prices and then obtain predicted values (pseudo prices) that correspond to exact maturities of 1 through 12 months.[38] Because our goal is to simply interpolate the futures price term structure, we follow the original interpretation of the Nelson and Siegel model as an approximating function that can be used to interpolate and extrapolate data that exhibits exponential decay and curvature in the maturity dimension; we do not attempt to interpret the price term structure as determined by the factors derived from the Nelson and Siegel model (we do this for the volatility term structure).

Because our interest is in the term structure of volatility of commodity futures, we aggregate the daily data into a monthly frequency to obtain an estimate of the futures volatility in any given month. This estimate is simply the annualized standard deviation of daily changes in the logarithm of the futures prices during the month in question. As a result of aggregation, we have a sample of 285 observations of futures volatility, as well as intra-month averages of futures

[38] The pseudo prices can be viewed as daily-rebalanced weighted average of the prices of two actual futures contracts.

returns and open interest. With pseudo prices time to maturity is fixed for each daily observation, but with raw prices we must use the average time to maturity within the month as corresponding to that month's futures volatility.

The inventory data for the underlying commodities is from Bloomberg, where it is compiled from original sources. The original source of the inventory data for agricultural commodities is the USDA World Agricultural Supply and Demand Report. The report contains monthly data on U.S. total ending stocks of corn, soybeans, and wheat. The energy inventory data originates from the Energy Information Administration (EIA). The EIA reports weekly ending stocks for various hydrocarbons. Inventory data for precious and industrial metals originates from COMEX and NYMEX. These inventories are reported on the daily basis and represent the stocks at depositories and warehouses designated for delivery under the contracts.

As a measure of crude oil inventory, we use U.S. ending stocks of crude oil excluding Strategic Petroleum Reserve. Because the underlying commodity for heating oil futures is ultra-low sulfur diesel, we use U.S. ending stocks of distillate fuel oil (containing 15 part per million sulfur or less) as our measure of heating oil inventory. U.S. natural gas inventories held in underground storage facilities serve as our measure of natural gas inventory. Reformulated blend futures specify that the underlying is reformulated regular gasoline blendstock for blending with 10% denatured fuel ethanol, but beginning in 2010 the EIA reports only the total stocks of reformulated gasoline blendstock for oxygenated blending (with either ethanol or ethers). Therefore, we use ending stocks of reformulated blendstock for oxygenated blending as our measure of reformulated blend inventory, without distinguishing blendstock intended for mixing with ethanol from blendstock intended for mixing with ethers.

Futures open interest represents the number of outstanding contracts, so we convert inventory numbers from the physical units into the hypothetical number of contracts that could be fulfilled with the available inventory, thereby facilitating comparisons with open interest.

Table 4.1 reports summary statistics for each commodity. The numbers are the exact times to expiration (measured in months) and the sample means of open interest, inventories, and futures return volatility. We also report the autoregressive coefficient from an AR(1) model of volatility dynamics as a measure of volatility persistence. Each column corresponds to the index of the futures contract, starting with contract nearest to expiration (1) and ending with the contract most distant from expiration (12). In the last column, we report the total open interest across the twelve contracts, the inventories, and the ratio of inventories to total open interest.

The more distant contracts are not always traded actively. The second nearby is generally the most actively traded contract in all commodities except for crude oil.[39] In the agriculture category, open interest in the fifth through seventh nearby contract is roughly one tenth of open interest in the second nearby and much less in the more distant contracts. In the energy category (except for reformulated blend), the more distant contracts are still actively traded with even the tenth to twelfth nearby futures having more than one tenth of the open interest in the second nearby contract. Trading in the fourth through seventh nearby contracts in the metals category generates roughly one tenth of the open interest in the second nearby with the more distant futures trading even less actively.

[39] Because the commodity futures contracts are physical settled, the hedgers must unwind their positions in the nearest contract to avoid having to take delivery under the contract, which depresses open interest in the first nearby contract in those commodities where trading is still possible during the delivery month (trading in crude oil futures ceases the month before the delivery month, so that hedgers do not need to unwind their positions until the last day of trading).

The Samuelson effect is particularly pronounced in the agriculture and energy category futures, where futures volatility declines monotonically in almost all cases as the time to expiration increases. The difference in volatility between the nearest and the most distant futures is seven to eight percentage points for corn and soybeans; 10 to 12 percentage points for wheat, crude oil, and heating oil; 14 percentage points for reformulated blend; a staggering 28 percentage points for natural gas. In the metals category, the Samuelson effect is weak in copper futures and nonexistent in gold and silver futures. A flat average term structure in the metals futures and the monotonically declining average term structure in the energy and agricultural futures are consistent with the findings in Brooks (2012). Long-term volatilities are not only lower than the short-term volatilities, they are also more persistent. Important exceptions are the gold and silver futures markets, where the persistence of volatility does not seem to increase with maturity – another observation consistent with Brooks (2012).

Sample means of the futures return volatilities coupled with the exact futures maturities can be thought of as the sample average term structure of volatility. Figure 4.1 contains plots of the average volatility term structure for each commodity. The plots reveal that not only do the volatility term structures of agricultural and energy futures slope downward, but that they are also convex. This convexity is strongest in energy futures, while agricultural futures seem to have a more linear volatility term structure at longer maturities.

4.3. Estimation of the Volatility Term Structure

The main prediction of the Samuelson hypothesis is that the volatility term structure is downward sloping. One way to empirically measure the slope of the term structure is to take the difference between the volatility of the most distant futures contract and the contract nearest to expiration. However, this approach ignores the information contained in the volatility of the

intermediate contracts. Therefore, to capture this information we estimate the slope of the volatility term structure by fitting a curve to the observed volatilities of contracts with different maturities. The slope of this curve can be thought of as a measure of the slope of the volatility term structure.

To estimate the slope of the volatility term structure we use the Nelson and Siegel (1987) functional form, which is a three factor approximation that imposes an exponential structure on the factor loadings. Christensen, Diebold, and Rudebusch (2009) note that the Nelson and Siegel framework fits the cross-section of bond yields in many countries remarkably well and has been widely used by financial market participants and central banks. Diebold and Li (2006) estimate the Nelson and Siegel yield curve period by period and show that the three time-varying parameters of the model can be interpreted as factors corresponding to level, slope, and curvature, and that their time-series behavior can be efficiently estimated with autoregressive models. The alternative to the Diebold and Li approach is to cast the model in a state-space representation with latent factor loadings taking the Nelson and Siegel exponential form (Diebold, Li, and Yue, 2008).

We follow Diebold and Li (2006) and fit the time-series of futures volatility term structures period by period rather than cast the model in a state-space representation. We use the following factorization of the Nelson and Siegel model:

$$\sigma_t(\tau) = \beta_{1t} + \beta_{2t}\left(\frac{1 - e^{-\lambda_t \tau}}{\lambda_t \tau}\right) + \beta_{3t}\left(\frac{1 - e^{-\lambda_t \tau}}{\lambda_t \tau} - e^{e^{-\lambda_t \tau}}\right) \tag{4.1}$$

where $\sigma_t(\tau)$ is the time t volatility of the futures contract with maturity τ (measured in months), and $\theta_t = \{\beta_{1t}, \beta_{2t}, \beta_{3t}, \lambda_t\}$ are estimated parameters that govern the shape of the volatility term structure. We can interpret β_{1t} as the factor that governs the level of the volatility term structure because $\lim_{\tau \to \infty} \sigma_t(\tau) = \beta_{1t}$. If we define the slope of the volatility term structure as $\sigma_t(\infty) -$

$\sigma_t(0)$, then β_{2t} can be interpreted as the factor that governs the slope of the volatility term structure because $\lim_{\tau\to\infty} \sigma_t(\tau) - \lim_{\tau\to 0} \sigma_t(\tau) = -\beta_{2t}$. Even if we define the slope as $\sigma_t(12) - \sigma_t(0)$, then $-\beta_{2t}$ is still closely related to the slope of the volatility term structure because[40] $\sigma_t(12) - \lim_{\tau\to 0} \sigma_t(\tau) = -0.977\beta_{2t} + 0.023\beta_{3t}$. Lastly, β_{3t} can be interpreted as the factor that governs the curvature of the term structure because an increase in β_{3t} will most significantly affect medium-term volatilities, but have little effect on the short-term and long-term volatilities, leading to an increase in the curvature of the term structure. Because of our interpretation, we refer to β_{1t}, $-\beta_{2t}$, and β_{3t} as the level, slope, and curvature factors.

The parameter λ_t governs the exponential decay rate and controls where the loading on β_{3t} achieves its maximum. We could estimate the parameters $\theta_t = \{\beta_{1t}, \beta_{2t}, \beta_{3t}, \lambda_t\}$ by nonlinear least squares, but instead we fix λ_t at a prespecified value, which allows us to first calculate factor loadings and then estimate the models using ordinary least squares. We set the value $\lambda_t = 3.58656$ to maximize the loading on the curvature factor at the six-month maturity. Because prior literature has not examined where the volatility term structure of commodity futures tends to achieve its maximum curvature, we choose the maturity corresponding to the maximum curvature based on the plots in Figure 4.1.[41]

While the Nelson and Siegel framework has been predominantly applied to the term structure of interest rates, we expect it to also be a good model of the dynamics of futures volatility term structure. Although it is ultimately an empirical matter, the model has the ability, in principle, to capture the following stylized facts about the volatility term structure:

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[40] Setting $\lambda_t = 3.58656$ for reasons outlined below.

[41] We examine several different values of λ_t that maximize volatility term structure curvature anywhere between four and eight months and obtain quantitatively similar results in subsequent tests.

(1) The average volatility term structure is decreasing and convex. In the Nelson and Siegel framework, the average volatility terms structure corresponds to the average values of β_{1t}, β_{2t}, and β_{3t}, and the functional form guarantees that the fitted curve can assume a decreasing and convex shape.

(2) Depending on the commodity and the time period, the volatility term structures can assume a variety of shapes, including downward sloping, upward sloping, humped, and inverted humped. The Nelson and Siegel curve can assume any of these shapes and the frequency with which it changes the shapes depends entirely on the behavior of β_{1t}, β_{2t}, and β_{3t}.

(3) Volatility dynamics are persistent, but the volatility spreads are somewhat less persistent.[42] Strong persistence of volatility dynamics can be explained by high persistence of β_{1t}, and a weaker persistence of volatility spreads can be explained by lower persistence of β_{2t}.

(4) Long-term volatilities are more persistent than the short-term volatilities. In the Nelson and Siegel framework, the long-term volatilities depend only β_{1t}, so if β_{1t} is the most persistent factor, then long-term volatilities will be more persistent than short-term.

We estimate the model in equation (4.1) for every month t by regressing futures return volatility on the factor loadings. Table 4.2 reports the sample mean, standard deviation, and the AR(1) coefficient (measure of persistence) of the level factor, the slope factor, and the empirical slope of term structure, which we calculate as $\sigma_t(12) - \sigma_t(1)$. We also report the correlation coefficient between the estimated slope factor and the empirical slope of the term structure. The last column of the table reports the sample mean of the R^2 as a measure of fit of the Nelson and Siegel model to the observed volatility term structure.

[42] Table 2 reports the autoregressive coefficient from an AR(1) model as a measure of persistence of volatility spread (see the Empirical Slope AR(1) column).

The statistics in Table 4.2 allow us to draw conclusions about the empirical validity of the Nelson and Siegel framework as an approximation of the futures volatility term structure. We find that the model's principal ability to fit a variety of possible shapes of the term structure translates into high average R^2 across most commodities. The level factor is generally more persistent than the slope factor (the two have similar persistence in heating oil, natural gas, and reformulated blend futures), explaining higher persistence of observed volatilities and lower persistence of volatility spreads. In addition, the level factor is significantly more persistent than the curvature factor[43], so that it is generally the most persistent of the three factors, which is consistent with our observation that long-term volatilities are generally more persistent than the short-term volatilities.

There are two other important observation to be made regarding Table 4.2. First, the standard deviation of the slope factor is appreciably higher than the standard deviation of the empirical slope in seven of the ten commodities, while in the other three commodities the standard deviations are almost equal. The slope factor experiences higher variability because it incorporates the information from the entire term structure rather than just two points. The incorporation of information is the theoretical reason why we work with the estimated slope factor instead of the empirical slope, but from a practical point of view the higher time-series variation of the slope factor can also help with identification. Second, in most commodities the slope factor is moderately persistent, which justifies our methodological choice of calculating futures volatility over disjoint monthly intervals rather than using rolling calculations or GARCH models, both of which would yield a larger sample, but introduce additional autocorrelations to an already persistent series.

[43] The AR(1) coefficients of the curvature factor range from 0.008 for silver to 0.385 for reformulated blend.

4.4. Results

The Nelson and Siegel estimates of the futures volatility term structure allow us to parsimoniously study the time-series evolution of the Samuelson effect in each of the futures markets. On the one hand, the summary statistics of the return volatility of futures contracts with various maturities indicate that the Samuelson effect was present (in terms of economic significance), on average, in all but two markets – gold and silver. The Nelson and Siegel estimates of the slope factor tell a similar story – the sample mean of the factor is reliably negative in the agriculture and energy categories, less negative in the copper market, and very close to zero in the gold and silver markets (based on economic significance; statistically, they are all significantly negative at the 1% level). On the other hand, we cannot rule out the possibility that there were periods of time when the Samuelson effect was weaker or stronger in each of the markets.

In order to study the time-series variation in the strength of the Samuelson effect, we construct the 60-month moving average of the slope factor and the corresponding 95% confidence bands.[44] We use the 60-month window because it is small enough to readily capture any shifts in the slope factor and large enough to allow for reliable inference. We cannot simply plot the monthly slope factor value because each monthly value is an estimate from on a regression with only 8 degrees of freedom (12 observations, 1 dependent variables, 3 factor loadings) so that the confidence interval is large.

Figure 4.2 depicts the time-series behavior of the volatility slope factor and inventories in each market. We make several key observations. First, there is significant variation in the slope

[44] To obtain the moving average we regress the slope factor on its first lag, its twelfth lag, and a constant within each window to account for the autoregressive behavior of the slope factor and potential seasonality ($Slope_t = \beta_0 + \beta_1 Slope_{t-1} + \beta_2 Slope_{t-12} + \varepsilon_t$). We then calculate the mean of the series as $\mathbb{E}(Slope_t) = \beta_0/(1 - \beta_1 - \beta_2)$.

factor in each market over time. All markets experienced periods when the maturity effect was strong, followed by periods when the effect was less pronounced, and vice versa. Even the markets that are expected to have an almost flat volatility term structure, such as gold and silver, experienced periods when the Samuelson effect was statistically detectable.

Second, almost all markets had a statistically flat volatility term structure sometime during the sample period. Specifically, corn in 2003 – 2007, soybeans in 2004 and 2009, wheat in 2003 and after 2014, crude oil in 2006 and briefly during 2015, heating oil in 2010 – 2014 and after 2016, reformulated blend prior to 2000 and in 2012 – 2016, gold prior to 2002 and after 2010, copper in 2002 – 2006 and in 2012 – 2014, and silver after 2009. The fact that the Samuelson effect was absent in corn, soybeans, wheat, crude oil, heating oil, and reformulated blend futures during certain periods is particularly remarkable because at other times the effect was very strong; in contrast, even when the Samuelson effect was present in gold, copper, and silver futures it was not very strong. The natural gas futures market never approached a statistically flat volatility term structure during the sample period; nonetheless, there has been a significant upward shift in the volatility slope around 2008 that has been sustained since.

Third, a visual inspection of the inventory time-series (these are simple moving averages over a 60-month window) gives some indication that the volatility slope is flatter when inventories are higher. There is a noticeable correspondence of inventory troughs and peaks with volatility slope troughs and peaks in corn, soybeans, wheat, heating oil, and copper futures. In other markets, the latter half of the sample tends to have higher inventories and a flatter volatility term structure.

To further explore the relationship between the slope of the futures volatility term structure and inventory levels, we relate monthly estimates of the slope factor to the monthly

inventory levels via a regression. Specifically, we estimate the following regression for each market:

$$Slope_t = \beta_0 + \beta_1 Inventory_t + \beta_2 Slope_{t-1} + \beta_3 Inventory_t \cdot Slope_{t-1} + \varepsilon_t \qquad (4.2)$$

where $Inventory_t$ is a dummy variable that is equal to 1 when the inventory level is above its median. While the coefficient of interest is β_1, we choose a model that includes the $Inventory_t \cdot Slope_{t-1}$ interaction term to allow for different autoregressive coefficients in the high and low inventory regimes. When the inventory level is above the median, the autoregressive coefficient is effectively equal to $\beta_2 + \beta_3$, while it is equal to β_2 when the inventory level is below the median.

Table 4.3 reports OLS estimates of the regression specified by equation (4.2) for each market. We find that the slope of the volatility term structure is positively and significantly related to inventory levels in corn, crude oil, heating oil, gold, and copper futures, while no significant relationship is revealed in other markets. Because the slope factor corresponds to the difference between volatilities of short-dated and long-dated contracts measured in percentage points, the coefficient estimates have the following economic interpretation. When inventories are high, the volatility term structure is 3.5 percentage points flatter in corn and crude oil futures, 4.9 percentage points flatter in heating oil futures, 0.45 percentage points flatter in gold futures, and 1.8 percentage points flatter in copper.

Instead of defining the inventory dummy variables based on a median split, we could try alternative thresholds, such as the mean or the third quartile. If arbitrage activity is the driving force behind the inventory and volatility relationship, the thresholds should not be arbitrary because inventory levels determine when arbitrage is feasible and when it is not in each market. Therefore, we perform a test of threshold behavior by estimating the model in equation (4.2)

with alternative definitions of the inventory dummy. Specifically, we throw out 15% at each tail of the inventory distribution and then consider each remaining percentile as a potential threshold in defining the inventory dummy. We choose the model with the lowest sum of squared residuals; however, because the corresponding F-statistic represents a supremum, it does not have an *F*-distribution. To get a sense of statistical significance of the threshold, we instead bootstrap the distribution of the supremum *F*-statistic with 1,000 normal draws and obtain the p-value.

We report the optimal thresholds and the corresponding p-values for each market in Panel (a) of Table 4.4. If there is an indication of threshold behavior (p-value < 0.05), then we report the estimates of the model corresponding to the optimal threshold in Panel (b). We find that when inventory dummy is redefined per the optimal threshold, then wheat futures join the group of markets that appear to display a positive relationship between inventories and the slope of the volatility term structure. When inventories are high, the term structure of wheat futures volatility is 9.3 percentage points flatter; moreover, with optimal thresholds inventories appear to be more strongly associated with the slope factor in crude oil and gold futures compared to the case when the threshold is set equal to the median.

Our analysis has so far focused on monthly estimates of the volatility terms structure slope and monthly inventory levels. While inventory levels for metals are available at a daily frequency, we need a way to estimate futures volatility and therefore the slope of the volatility term structure on a daily basis. Borrowing from the literature on high-frequency volatility estimation, we use the squared logarithmic difference between pseudo futures price from day to day as a daily proxy for variance. We then apply the Nelson and Siegel methodology to the square root of this variance proxy to produce a daily estimate of the volatility slope factor.

Using daily data, we repeat OLS regressions given by equation (4.2) and report the estimates for the three metals futures markets in Table 4.5. We find that silver futures exhibit a positive and (weakly) significant relationship between inventories and the slope of the volatility term structure. We also confirm the previously documented positive and significant relationship in gold and copper futures. Panel (a) of Table 4.6 shows that when we repeat the tests for threshold behavior, all three markets exhibit threshold behavior. Panel (b) of Table 4.6 shows that when the inventory dummies are redefined according to the optimal threshold, there is a positive and statistically significant relationship between inventories and the slope of the volatility term structure in all three metals futures.

We now examine the relationship between the futures volatility term structure and futures term premiums. We define the term premium of the i-th nearby contract as:

$$TP_i = \log\left(\frac{F_{i.t}}{F_{i.t-1}}\right) - \log\left(\frac{F_{1.t}}{F_{1.t-1}}\right) \tag{4.3}$$

where $F_{i,t}$ is the pseudo future price of contract i in period t. We also define the incremental term premium of the i-th nearby contract as:

$$ITP_i = \log\left(\frac{F_{i.t}}{F_{i.t-1}}\right) - \log\left(\frac{F_{i-1.t}}{F_{i-1.t-1}}\right) \tag{4.4}$$

Figure 4.3 plots the term risk premiums (average term premiums) in each of the futures markets as a function of maturity. The term premiums in corn, wheat, and natural gas futures are positive and are increasing with maturity, indicating that the incremental term premiums are positive. In soybean futures, the term premiums are positive and do not change with maturity, indicating that the incremental term premiums other than ITP_2 are close to zero. In reformulated blend and copper futures, the term premiums are negative and do not change with maturity, indicating that the incremental term premiums other than ITP_2 are close to zero. In heating oil,

gold, and silver futures, the term premiums are close to zero, but slightly negative; in crude oil, the term premiums are close to zero, but slightly positive.

In a fully arbitraged futures market, arbitrageurs provide infinite supply to meet net hedging demand across contract maturities, so that futures prices are determined by the cost-of-carry model and do not reflect any term premiums. To the extent that the volatility term structure (particularly its slope) reflects the degree to which a market is arbitraged, we can expect Nelson and Siegel level, slope, and curvature factors to be related to the term premiums. In order to test this prediction, we estimate the following regressions for each market and each futures maturity:

$$TP_t = \beta_0 + \beta_1 Level_t + \beta_2 Slope_t + \beta_3 Curvature_t + \varepsilon_t \tag{4.5}$$

We also estimate supplementary regressions involving incremental term premiums:

$$ITP_t = \beta_0 + \beta_1 Level_t + \beta_2 Slope_t + \beta_3 Curvature_t + \varepsilon_t \tag{4.6}$$

Tables 4.7 and 4.8 report the results for term premiums and incremental term premiums, respectively. When examining the sensitivities of term premiums to the slope factor, it is important to keep in mind that the average slope of the volatility term structure is negative in all markets except for gold and silver futures where it is essentially zero. Thus, an increase in the slope of the volatility term structure leads to a flatter term structure.

In corn, soybeans, and natural gas futures, the average term premiums are positive, so that the negative β_2 estimates in Table 4.7 indicate that flattening of the volatility term structure reduces the term premiums, driving them closer to zero. In gold and silver futures, the average term premiums are slightly negative, so that the positive β_2 estimates in Table 4.7 indicate that flattening of the volatility term structure increases the term premiums, driving them closer to zero. Since the average term premiums in crude oil and heating oil futures are close to zero, the β_2 estimates in Table 4.7 indicate that flattening of the volatility term structure does not affect

the term premiums: the β_2 estimates for crude oil are not statistically significant, while the β_2 estimates for heating oil are not economically significant even when they are statistically significant. Therefore, in corn, soybeans, crude oil, heating oil, natural gas, gold, and silver futures, the relationship between the term premiums and the slope of the volatility term structure is consistent with the carry arbitrage explanation of the Samuelson effect: arbitrage activity, as evidenced by the flatter volatility term structure, drives term premiums to zero.

In wheat, reformulated blend, and copper, the β_2 estimates in Table 4.7 indicate that flattening of the volatility term structure does not drive term premiums closer to zero – positive term premiums become more positive, and negative term premiums become more negative. We turn to Table 4.8 to determine whether this effect plagues the entire term structure of risk premiums. There is no support for the carry arbitrage explanation of the Samuelson effect in wheat futures since all incremental term premiums are positively and significantly related to the slope factor.

There is still some support for the carry arbitrage explanation of the Samuelson effect in reformulated blend and copper futures. In these markets, the incremental term premiums with shorter maturities are negatively related to the slope factor, whereas the incremental term premiums with longer maturities are positively related to the slope factor. Since the average term premiums in these markets are negative, the positive β_2 estimates in Table 4.8 indicate that flattening of the volatility term structure drives the term premiums of longer dated contracts to zero.

4.5. Conclusion

We study the Samuelson hypothesis in ten U.S. futures markets in the agriculture, energy, and metals categories. Applying the Nelson and Siegel model to the term structure of futures

volatility, we find that the strength of the Samuelson effect, as captured by the volatility slope factor, varies over time in each of the ten markets. Remarkably, the Samuelson effect was absent in corn, soybeans, wheat, crude oil, heating oil, and reformulated blend futures during certain periods. This finding lends support to the idea that these typically unarbitraged markets have experienced periods of strong arbitrage activity.

The ability to conduct arbitrage depends on the feasibility of the carry trade, which is determined by the inventory level. We find that the volatility slope factor is positively related to inventories in seven out of the ten markets. Further, arbitrageurs provide infinite supply to meet net hedging demand, reducing future term premiums to zero. We find that a flatter volatility term structure indicative of higher arbitrage activity moves futures term premiums toward zero in nine of the ten markets.

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Table 4.1. Descriptive Statistics.

This table reports summary statistics for the first twelve contracts in each futures market. N is the number of monthly observations in the sample. Maturity is the maturity of the corresponding pseudo contract measured in months. Volatility is the sample average of annualized standard deviations of daily logarithmic changes in futures pseudo prices recalculated each month. Volatility AR(1) is the autoregressive coefficient of the volatility time-series. Open Interest is the average number of outstanding contracts measured in thousands. Inventory is the average number of contracts that can be covered with existing stocks of the underlying commodity. Relative Inventory is the ratio of inventory to the sum of open interest across the first three contracts.

Futures Index	1	2	3	4	5	6	7	8	9	10	11	12	Total
						Corn							
N	285	285	285	285	285	285	285	285	285	285	285	285	
Maturity	1.00	2.00	3.00	4.00	5.00	6.00	7.00	8.00	9.00	10.00	11.00	12.00	
Volatility (%)	25.23	24.44	23.99	23.56	23.03	22.40	21.68	20.92	20.15	19.41	18.72	18.09	
Volatility AR(1)	0.44	0.57	0.61	0.62	0.62	0.62	0.63	0.64	0.65	0.66	0.67	0.68	
Open Interest	217.72	265.31	130.69	78.09	55.19	29.90	11.93	7.80	5.95	5.52	3.97	3.22	1216.10
Inventory													283.86
Relative Inventory													0.25
						Soybeans							
N	285	285	285	285	285	285	285	285	285	285	285	285	
Maturity	1.00	2.00	3.00	4.00	5.00	6.00	7.00	8.00	9.00	10.00	11.00	12.00	
Volatility (%)	22.26	21.60	21.30	21.04	20.69	20.22	19.66	19.06	18.45	17.86	17.31	16.82	
Volatility AR(1)	0.56	0.61	0.62	0.63	0.63	0.64	0.65	0.65	0.66	0.66	0.66	0.66	
Open Interest	80.23	107.56	53.11	46.90	28.35	18.12	11.49	6.92	2.40	1.76	2.61	1.82	527.88
Inventory													59.43
Relative Inventory													0.15

Table 4.1 (cont.)

Futures Index	1	2	3	4	5	6	7	8	9	10	11	12	Total
						Wheat							
N	285	285	285	285	285	285	285	285	285	285	285	285	
Maturity	1.00	2.00	3.00	4.00	5.00	6.00	7.00	8.00	9.00	10.00	11.00	12.00	
Volatility (%)	28.77	27.49	26.67	25.94	25.18	24.36	23.49	22.62	21.77	20.98	20.26	19.62	
Volatility AR(1)	0.48	0.58	0.61	0.62	0.62	0.63	0.64	0.65	0.67	0.68	0.69	0.70	
Open Interest	79.30	92.46	38.28	21.16	12.70	6.52	2.54	2.24	1.13	0.70	0.42	0.16	420.39
Inventory													134.69
Relative Inventory													0.37
						Crude Oil							
N	285	285	285	285	285	285	285	285	285	285	285	285	
Maturity	1.00	2.00	3.00	4.00	5.00	6.00	7.00	8.00	9.00	10.00	11.00	12.00	
Volatility (%)	31.29	29.46	28.06	26.93	25.99	25.19	24.50	23.92	23.43	23.01	22.67	22.39	
Volatility AR(1)	0.62	0.63	0.64	0.65	0.66	0.66	0.67	0.67	0.67	0.67	0.67	0.67	
Open Interest	169.63	160.41	83.22	58.31	46.86	39.97	34.44	31.07	27.96	26.56	23.88	21.33	723.62
Inventory													321.72
Relative Inventory													0.56
						Heating Oil							
N	285	285	285	285	285	285	285	285	285	285	285	285	
Maturity	1.00	2.00	3.00	4.00	5.00	6.00	7.00	8.00	9.00	10.00	11.00	12.00	
Volatility (%)	30.64	28.39	27.01	26.04	25.21	24.48	23.83	23.29	22.88	22.59	22.44	22.40	
Volatility AR(1)	0.59	0.61	0.62	0.62	0.62	0.63	0.63	0.63	0.62	0.62	0.61	0.60	
Open Interest	41.55	51.59	28.95	20.20	15.65	12.42	10.03	8.17	6.65	5.47	4.30	3.32	208.31
Inventory													129.08
Relative Inventory													0.69

Table 4.1 (cont.)

Futures Index	1	2	3	4	5	6	7	8	9	10	11	12	Total
						Natural Gas							
N	285	285	285	285	285	285	285	285	285	285	285	285	
Maturity	1.00	2.00	3.00	4.00	5.00	6.00	7.00	8.00	9.00	10.00	11.00	12.00	
Volatility (%)	47.22	39.51	35.04	31.94	29.43	27.26	25.41	23.97	23.02	22.63	22.79	23.37	
Volatility AR(1)	0.55	0.54	0.57	0.60	0.62	0.64	0.66	0.67	0.68	0.67	0.66	0.64	
Open Interest	74.33	95.57	64.41	46.70	38.64	32.66	28.36	25.23	22.66	20.09	17.72	15.64	482.01
Inventory													247.56
Relative Inventory													0.75
						Reformulated Blend							
N	285	285	285	285	285	285	285	285	285	285	285	285	
Maturity	1.00	2.00	3.00	4.00	5.00	6.00	7.00	8.00	9.00	10.00	11.00	12.00	
Volatility (%)	33.82	29.45	27.43	26.35	25.61	25.05	24.68	24.53	24.63	24.97	25.52	26.25	
Volatility AR(1)	0.60	0.63	0.64	0.64	0.64	0.63	0.62	0.59	0.55	0.51	0.47	0.43	
Open Interest	40.96	51.70	25.48	17.11	12.46	8.89	6.42	4.71	3.56	2.76	2.16	1.61	191.15
Inventory													96.13
Relative Inventory													0.54
						Gold							
N	285	285	285	285	285	285	285	285	285	285	285	285	
Maturity	1.00	2.00	3.00	4.00	5.00	6.00	7.00	8.00	9.00	10.00	11.00	12.00	
Volatility (%)	15.08	14.95	14.92	14.91	14.90	14.89	14.87	14.85	14.82	14.80	14.77	14.76	
Volatility AR(1)	0.60	0.61	0.61	0.60	0.60	0.60	0.61	0.61	0.61	0.61	0.61	0.61	
Open Interest	61.95	122.54	41.72	17.74	11.90	9.26	6.69	4.51	3.77	3.12	2.65	3.81	289.66
Inventory													53.11
Relative Inventory													0.16

Table 4.1 (cont.)

Futures Index	1	2	3	4	5	6	7	8	9	10	11	12	Total
						Copper							
N	285	285	285	285	285	285	285	285	285	285	285	285	
Maturity	1.00	2.00	3.00	4.00	5.00	6.00	7.00	8.00	9.00	10.00	11.00	12.00	
Volatility (%)	24.74	24.12	23.68	23.32	23.01	22.72	22.45	22.21	22.00	21.82	21.67	21.54	
Volatility AR(1)	0.60	0.61	0.61	0.62	0.63	0.64	0.64	0.64	0.65	0.65	0.65	0.65	
Open Interest	26.01	40.38	14.30	5.92	2.94	1.94	1.03	0.54	0.41	0.27	0.16	0.05	96.99
Inventory													6.67
Relative Inventory													0.09
						Silver							
N	285	285	285	285	285	285	285	285	285	285	285	285	
Maturity	1.00	2.00	3.00	4.00	5.00	6.00	7.00	8.00	9.00	10.00	11.00	12.00	
Volatility (%)	27.23	26.95	26.81	26.74	26.68	26.62	26.56	26.48	26.41	26.34	26.28	26.22	
Volatility AR(1)	0.58	0.60	0.60	0.60	0.61	0.61	0.61	0.61	0.61	0.61	0.61	0.61	
Open Interest	33.22	44.35	13.54	6.81	5.21	3.08	1.85	1.28	1.05	1.04	1.00	0.72	112.65
Inventory													27.61
Relative Inventory													0.25

Table 4.2. Summary Statistics of Volatility Term Structure Factors.

This tables reports sample averages, standard deviations, and autoregressive coefficients of the level and slope of the volatility term structure. Volatility terms structure is estimated using the Nelson and Siegel (1985) framework with three factors: level, slope, and curvature. For comparison, we report sample statistics of the empirical slope, defined as the difference between volatility of the first nearby and the twelfth nearby contracts. ρ is the correlation between the slope factor and the empirical slope. R^2 is the sample average of the Nelson and Siegel model R^2.

Futures Market	Level Factor			Slope Factor			Empirical Slope			ρ	R^2
	Mean	StDev	AR(1)	Mean	StDev	AR(1)	Mean	StDev	AR(1)		
Corn	9.65	10.76	0.53	-15.00	8.30	0.26	-7.15	6.86	-0.04	0.70	0.99
Soybeans	10.17	9.65	0.59	-11.48	8.11	0.56	-5.44	5.29	0.29	0.77	0.97
Wheat	10.82	12.52	0.50	-18.05	9.21	0.46	-9.16	7.41	0.24	0.73	0.99
Crude Oil	18.70	9.37	0.63	-14.69	9.49	0.49	-8.89	5.72	0.54	0.94	1.00
Heating Oil	20.39	10.21	0.39	-12.61	7.89	0.45	-8.24	4.78	0.56	0.81	0.99
Natural Gas	22.75	19.66	0.45	-33.43	19.32	0.42	-23.85	13.38	0.53	0.79	0.98
Reformulated Blend	33.64	23.80	0.19	-5.26	18.88	0.19	-7.57	8.76	0.23	0.85	0.96
Gold	14.64	7.09	0.62	-0.46	0.99	0.21	-0.32	0.77	0.02	0.79	0.96
Copper	19.75	10.63	0.65	-5.56	5.88	0.55	-3.20	3.57	0.61	0.94	0.99
Silver	25.77	12.49	0.58	-1.57	2.17	0.25	-1.01	2.20	-0.05	0.76	0.97

Table 4.3. Effect of Inventories on the Slope of the Volatility Term Structure.

This table reports coefficient estimates from regressions specified by $Slope_t = \beta_0 + \beta_1 Inventory_t + \beta_2 Slope_{t-1} + \beta_3 Inventory_t \cdot Slope_{t-1} + \varepsilon_t$. $Slope_t$ is the value of the slope factor in period t. $Inventory_t$ is the dummy variable that takes on a value of 1 when the inventory level in period t is above its median, and zero otherwise. Regressions are estimated using monthly data. *t*-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 level, respectively.

	Corn	Soybeans	Wheat	Crude Oil	Heating Oil	Natural Gas	Reform. Blend	Gold	Copper	Silver
Constant	-13.143***	-6.039***	-9.105***	-9.391***	-9.072***	-19.869***	-1.922	-0.612***	-3.397***	-1.143***
	(-9.262)	(-5.924)	(-6.295)	(-7.139)	(-8.835)	(-7.185)	(-1.231)	(-6.603)	(-5.985)	(-4.892)
$Inventory_t$	3.544*	1.840	-2.533	3.485*	4.894***	-1.753	-3.317	0.445***	1.791**	-0.002
	(1.779)	(1.309)	(-1.025)	(1.918)	(3.168)	(-0.401)	(-1.287)	(3.573)	(2.140)	(-0.008)
$Slope_{t-1}$	0.194**	0.535***	0.482***	0.388***	0.262***	0.363***	0.139**	0.126*	0.501***	0.347***
	(2.552)	(8.268)	(7.231)	(5.107)	(3.861)	(5.171)	(2.211)	(1.819)	(8.661)	(4.013)
$Inventory_t$* $Slope_{t-1}$	0.110	0.053	-0.159	0.186*	0.428***	0.058	0.231	0.122	0.122	-0.186
	(0.937)	(0.513)	(-1.244)	(1.789)	(4.118)	(0.515)	(1.294)	(0.942)	(1.018)	(-1.599)

Table 4.4. Threshold Behavior in the Effect of Inventories on the Slope of the Volatility Term Structure.

Panel (a) reports the results of the test for threshold behavior. Inventory threshold is the optimal threshold that produces the highest model F-statistic. Bootstrap p-Value is the p-value associated with the optimal threshold calculated using a bootstrap with 1,000 normal draws. Where the p-Value in Panel (a) is below 0.05, Panel (b) reports the estimates from regressions specified by $Slope_t = \beta_0 + \beta_1 Inventory_t + \beta_2 Slope_{t-1} + \beta_3 Inventory_t \cdot Slope_{t-1} + \varepsilon_t$. $Slope_t$. $Slope_t$ is the value of the slope factor in period t. $Inventory_t$ is the dummy variable that takes on a value of 1 when the inventory level in period t is above the optimal threshold, and zero otherwise. Regressions are estimated using monthly data. t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 level, respectively.

	Corn	Soybeans	Wheat	Crude Oil	Heating Oil	Natural Gas	Reformulated Blend	Gold	Copper	Silver
					Panel (a)					
Inventory Threshold	268.000	88.000	94.000	293.958	126.228	157.949	41.887	63.130	3.431	35.441
Bootstrap p-Value	0.179	0.445	0.039	0.028	0.005	0.060	0.001	0.010	0.155	0.006
					Panel (b)					
Constant			-18.098***	-12.002***	-9.057***		7.343***	-0.618***		-0.895***
			(-6.633)	(-7.398)	(-8.576)		(2.619)	(-6.784)		(-5.340)
$Inventory_t$			9.321***	6.531***	4.569***		-13.745***	0.468***		-1.393***
			(3.073)	(3.356)	(2.966)		(-4.427)	(3.774)		(-3.315)
$Slope_{t-1}$			0.228**	0.243***	0.259***		0.078	0.118*		0.384***
			(2.298)	(2.824)	(3.713)		(0.984)	(1.721)		(5.378)
$Inventory_t$* $Slope_{t-1}$			0.230*	0.372***	0.409***		0.084	0.140		-0.409***
			(1.858)	(3.481)	(3.947)		(0.710)	(1.060)		(-3.445)

Table 4.5. Effect of Inventories on the Slope of the Volatility Term Structure with Daily Frequency.

This table reports coefficient estimates from regressions specified by $Slope_t = \beta_0 + \beta_1 Inventory_t + \beta_2 Slope_{t-1} + \beta_3 Inventory_t \cdot Slope_{t-1} + \varepsilon_t$. $Slope_t$ is the value of the slope factor in period t. $Inventory_t$ is the dummy variable that takes on a value of 1 when the inventory level in period t is above its median, and zero otherwise. Regressions are estimated using daily data. *t*-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 level, respectively.

	Gold	Copper	Silver
Constant	-0.487***	-4.790***	-1.292***
	(-9.587)	(-18.874)	(-12.420)
Inventory	0.273***	1.803***	0.254*
	(3.818)	(4.962)	(1.742)
$Slope_{t-1}$	0.037**	0.042***	0.065***
	(2.366)	(2.978)	(3.466)
Inventory*$Slope_{t-1}$	-0.017	0.027	-0.078***
	(-0.622)	(0.846)	(-3.052)

Table 4.6. Threshold Behavior in the Effect of Inventories on the Slope of the Volatility Term Structure with Daily Frequency.

Panel (a) reports the results of the test for threshold behavior. Inventory threshold is the optimal threshold that produces the highest model *F*-statistic. Bootstrap p-Value is the p-value associated with the optimal threshold calculated using a bootstrap with 1,000 normal draws. Where the p-Value in Panel (a) is below 0.05, Panel (b) reports the estimates from regressions specified by $Slope_t = \beta_0 + \beta_1 Inventory_t + \beta_2 Slope_{t-1} + \beta_3 Inventory_t \cdot Slope_{t-1} + \varepsilon_t$. $Slope_t$. $Slope_t$ is the value of the slope factor in period t. $Inventory_t$ is the dummy variable that takes on a value of 1 when the inventory level in period t is above the optimal threshold, and zero otherwise. Regressions are estimated using daily data. *t*-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 level, respectively.

	Gold	Copper	Silver
		Panel (a)	
Inventory Threshold	76.123	3.844	24.893
Bootstrap p-Value	0.000	0.000	0.005
		Panel (b)	
Constant	-0.472***	-5.013***	-1.290***
	(-10.702)	(-18.265)	(-12.388)
Inventory	0.361***	2.019***	0.247*
	(4.802)	(5.514)	(1.695)
$Slope_{t-1}$	0.041***	0.031**	0.063***
	(2.962)	(2.130)	(3.354)
Inventory*$Slope_{t-1}$	-0.066*	0.064**	-0.074***
	(-1.954)	(2.197)	(-2.896)

Table 4.7. Futures Term Premiums and Volatility Term Structure Factors.

This table reports the estimates from regressions specified by $TP_t = \beta_0 + \beta_1 Level_t + \beta_2 Slope_t + \beta_3 Curvature_t + \varepsilon_t$. TP_t is the futures term premium in period t. $Level_t$, $Slope_t$, and $Curvature_t$ are the values of the level, slope, and curvature factors of the volatility term structure in period t. The dependent variable in column i is the term premium of the futures contract with maturity i-month maturity over the contract with 1-month maturity. Regressions are estimated using daily data. *t*-statistics are reported in parentheses.

TP Index	2	3	4	5	6	7	8	9	10	11	12
						Corn					
Constant	-10.982	-18.040	-22.483	-25.140	-26.570	-27.155	-27.165	-26.790	-26.165	-25.385	-24.518
	(-6.959)	(-6.904)	(-6.847)	(-6.778)	(-6.688)	(-6.572)	(-6.426)	(-6.250)	(-6.046)	(-5.820)	(-5.577)
Level	0.493	0.779	0.938	1.019	1.051	1.052	1.035	1.006	0.970	0.931	0.891
	(6.046)	(5.767)	(5.528)	(5.315)	(5.118)	(4.927)	(4.735)	(4.538)	(4.336)	(4.129)	(3.920)
Slope	-1.407	-2.352	-2.979	-3.381	-3.625	-3.755	-3.805	-3.800	-3.758	-3.691	-3.609
	(-24.938)	(-25.176)	(-25.375)	(-25.499)	(-25.520)	(-25.416)	(-25.175)	(-24.796)	(-24.288)	(-23.669)	(-22.963)
Curvature	-0.484	-0.810	-1.029	-1.173	-1.263	-1.315	-1.341	-1.348	-1.343	-1.328	-1.309
	(-21.238)	(-21.473)	(-21.704)	(-21.895)	(-22.018)	(-22.049)	(-21.974)	(-21.786)	(-21.489)	(-21.095)	(-20.620)
						Soybeans					
Constant	-3.368	-5.560	-6.973	-7.864	-8.405	-8.710	-8.855	-8.893	-8.859	-8.779	-8.669
	(-2.307)	(-2.280)	(-2.268)	(-2.266)	(-2.270)	(-2.274)	(-2.274)	(-2.268)	(-2.251)	(-2.225)	(-2.188)
Level	0.175	0.290	0.368	0.421	0.460	0.489	0.512	0.531	0.547	0.562	0.574
	(2.237)	(2.220)	(2.231)	(2.265)	(2.317)	(2.382)	(2.454)	(2.527)	(2.595)	(2.656)	(2.705)
Slope	-0.602	-0.992	-1.237	-1.379	-1.451	-1.473	-1.461	-1.427	-1.379	-1.322	-1.260
	(-9.849)	(-9.726)	(-9.616)	(-9.501)	(-9.365)	(-9.192)	(-8.972)	(-8.700)	(-8.377)	(-8.009)	(-7.606)
Curvature	-0.259	-0.428	-0.534	-0.596	-0.627	-0.636	-0.631	-0.616	-0.595	-0.570	-0.544
	(-10.550)	(-10.441)	(-10.335)	(-10.218)	(-10.072)	(-9.883)	(-9.643)	(-9.348)	(-8.998)	(-8.601)	(-8.170)

Table 4.7 (cont.)

TP Index	2	3	4	5	6	7	8	9	10	11	12
						Wheat					
Constant	2.405	5.179	7.882	10.344	12.519	14.415	16.063	17.495	18.746	19.843	20.812
	(1.271)	(1.649)	(1.991)	(2.303)	(2.589)	(2.850)	(3.085)	(3.294)	(3.477)	(3.635)	(3.767)
Level	-0.207	-0.385	-0.529	-0.641	-0.726	-0.790	-0.837	-0.872	-0.897	-0.915	-0.927
	(-2.400)	(-2.683)	(-2.921)	(-3.120)	(-3.284)	(-3.416)	(-3.518)	(-3.591)	(-3.640)	(-3.666)	(-3.673)
Slope	0.146	0.328	0.506	0.665	0.801	0.916	1.013	1.094	1.163	1.222	1.272
	(2.423)	(3.284)	(4.020)	(4.659)	(5.216)	(5.703)	(6.125)	(6.487)	(6.792)	(7.045)	(7.251)
Curvature	0.077	0.151	0.210	0.253	0.281	0.298	0.305	0.307	0.304	0.298	0.291
	(2.868)	(3.369)	(3.716)	(3.942)	(4.070)	(4.120)	(4.108)	(4.046)	(3.948)	(3.824)	(3.684)
						Crude Oil					
Constant	-0.665	-1.178	-1.588	-1.923	-2.201	-2.434	-2.631	-2.797	-2.939	-3.061	-3.167
	(-0.613)	(-0.634)	(-0.656)	(-0.676)	(-0.693)	(-0.707)	(-0.718)	(-0.725)	(-0.730)	(-0.732)	(-0.733)
Level	0.023	0.049	0.075	0.098	0.120	0.139	0.156	0.171	0.184	0.196	0.206
	(0.509)	(0.636)	(0.744)	(0.835)	(0.911)	(0.974)	(1.026)	(1.068)	(1.102)	(1.129)	(1.150)
Slope	-0.028	-0.040	-0.044	-0.043	-0.041	-0.037	-0.033	-0.029	-0.024	-0.020	-0.016
	(-0.769)	(-0.639)	(-0.535)	(-0.450)	(-0.378)	(-0.317)	(-0.264)	(-0.218)	(-0.177)	(-0.140)	(-0.108)
Curvature	-0.022	-0.031	-0.036	-0.039	-0.041	-0.042	-0.044	-0.045	-0.046	-0.047	-0.048
	(-0.923)	(-0.779)	(-0.688)	(-0.630)	(-0.593)	(-0.569)	(-0.553)	(-0.541)	(-0.532)	(-0.524)	(-0.518)

Table 4.7 (cont.)

TP Index	2	3	4	5	6	7	8	9	10	11	12
						Heating Oil					
Constant	-1.858	-2.758	-3.051	-2.952	-2.602	-2.093	-1.490	-0.835	-0.158	0.520	1.186
	(-1.124)	(-1.011)	(-0.899)	(-0.782)	(-0.654)	(-0.514)	(-0.362)	(-0.201)	(-0.038)	(0.123)	(0.275)
Level	-0.029	-0.052	-0.067	-0.071	-0.066	-0.056	-0.040	-0.022	-0.001	0.019	0.040
	(-0.411)	(-0.456)	(-0.467)	(-0.446)	(-0.398)	(-0.325)	(-0.232)	(-0.124)	(-0.008)	(0.109)	(0.222)
Slope	-0.171	-0.263	-0.295	-0.283	-0.241	-0.178	-0.102	-0.018	0.069	0.157	0.243
	(-3.002)	(-2.793)	(-2.520)	(-2.176)	(-1.757)	(-1.266)	(-0.716)	(-0.126)	(0.478)	(1.071)	(1.629)
Curvature	-0.090	-0.148	-0.183	-0.203	-0.210	-0.209	-0.202	-0.191	-0.177	-0.162	-0.146
	(-3.141)	(-3.126)	(-3.115)	(-3.093)	(-3.045)	(-2.960)	(-2.832)	(-2.659)	(-2.446)	(-2.204)	(-1.945)
						Natural Gas					
Constant	-12.748	-17.681	-19.326	-19.409	-18.641	-17.338	-15.657	-13.696	-11.527	-9.206	-6.782
	(-2.937)	(-2.544)	(-2.264)	(-2.052)	(-1.872)	(-1.701)	(-1.522)	(-1.326)	(-1.112)	(-0.883)	(-0.644)
Level	0.220	0.203	0.086	-0.063	-0.208	-0.338	-0.448	-0.540	-0.616	-0.678	-0.729
	(1.234)	(0.713)	(0.245)	(-0.161)	(-0.510)	(-0.808)	(-1.062)	(-1.275)	(-1.449)	(-1.586)	(-1.689)
Slope	-0.149	-0.229	-0.286	-0.331	-0.363	-0.383	-0.391	-0.389	-0.377	-0.358	-0.333
	(-1.935)	(-1.856)	(-1.888)	(-1.968)	(-2.052)	(-2.116)	(-2.141)	(-2.119)	(-2.049)	(-1.934)	(-1.780)
Curvature	-0.217	-0.342	-0.424	-0.476	-0.505	-0.516	-0.513	-0.499	-0.476	-0.446	-0.411
	(-3.829)	(-3.768)	(-3.796)	(-3.847)	(-3.881)	(-3.876)	(-3.816)	(-3.695)	(-3.511)	(-3.271)	(-2.985)

Table 4.7 (cont.)

TP Index	2	3	4	5	6	7	8	9	10	11	12
						Reformulated Blend					
Constant	-11.554	-17.954	-21.645	-23.780	-24.949	-25.475	-25.553	-25.312	-24.841	-24.209	-23.466
	(-4.137)	(-4.035)	(-4.026)	(-4.075)	(-4.149)	(-4.218)	(-4.254)	(-4.235)	(-4.149)	(-3.997)	(-3.793)
Level	0.390	0.624	0.764	0.847	0.896	0.922	0.935	0.939	0.937	0.933	0.926
	(3.862)	(3.871)	(3.924)	(4.010)	(4.114)	(4.218)	(4.299)	(4.339)	(4.324)	(4.254)	(4.135)
Slope	-0.375	-0.587	-0.711	-0.780	-0.812	-0.817	-0.802	-0.771	-0.729	-0.679	-0.624
	(-4.909)	(-4.826)	(-4.839)	(-4.894)	(-4.946)	(-4.955)	(-4.888)	(-4.724)	(-4.459)	(-4.107)	(-3.693)
Curvature	-0.017	-0.009	0.004	0.016	0.026	0.037	0.049	0.062	0.076	0.092	0.109
	(-0.468)	(-0.152)	(0.053)	(0.203)	(0.332)	(0.465)	(0.614)	(0.783)	(0.966)	(1.156)	(1.342)
						Gold					
Constant	0.917	1.578	2.049	2.379	2.606	2.760	2.861	2.924	2.961	2.979	2.986
	(3.210)	(3.336)	(3.469)	(3.607)	(3.747)	(3.889)	(4.027)	(4.160)	(4.284)	(4.397)	(4.497)
Level	-0.071	-0.123	-0.160	-0.185	-0.203	-0.215	-0.223	-0.228	-0.231	-0.233	-0.234
	(-4.097)	(-4.260)	(-4.431)	(-4.609)	(-4.792)	(-4.975)	(-5.155)	(-5.328)	(-5.490)	(-5.637)	(-5.768)
Slope	0.595	1.018	1.312	1.512	1.643	1.727	1.776	1.802	1.812	1.810	1.802
	(7.895)	(8.147)	(8.409)	(8.677)	(8.946)	(9.212)	(9.468)	(9.707)	(9.924)	(10.115)	(10.275)
Curvature	0.606	1.008	1.262	1.412	1.489	1.516	1.510	1.483	1.442	1.394	1.343
	(31.514)	(31.651)	(31.756)	(31.815)	(31.817)	(31.746)	(31.594)	(31.351)	(31.013)	(30.580)	(30.058)

Table 4.7 (cont.)

TP Index	2	3	4	5	6	7	8	9	10	11	12
						Copper					
Constant	-1.355	-2.370	-3.136	-3.720	-4.166	-4.507	-4.768	-4.968	-5.121	-5.239	-5.328
	(-1.911)	(-1.977)	(-2.036)	(-2.086)	(-2.124)	(-2.149)	(-2.162)	(-2.162)	(-2.152)	(-2.134)	(-2.109)
Level	0.042	0.077	0.109	0.136	0.161	0.183	0.203	0.221	0.237	0.252	0.265
	(1.434)	(1.570)	(1.712)	(1.855)	(1.992)	(2.120)	(2.236)	(2.336)	(2.422)	(2.492)	(2.550)
Slope	-0.208	-0.344	-0.429	-0.477	-0.499	-0.502	-0.492	-0.473	-0.449	-0.421	-0.392
	(-5.174)	(-5.071)	(-4.921)	(-4.728)	(-4.495)	(-4.230)	(-3.941)	(-3.640)	(-3.334)	(-3.032)	(-2.741)
Curvature	-0.197	-0.333	-0.428	-0.495	-0.541	-0.573	-0.594	-0.608	-0.616	-0.621	-0.622
	(-9.941)	(-9.951)	(-9.956)	(-9.938)	(-9.884)	(-9.790)	(-9.655)	(-9.482)	(-9.281)	(-9.058)	(-8.824)
						Silver					
Constant	2.749	4.681	5.985	6.822	7.322	7.587	7.689	7.684	7.609	7.490	7.348
	(5.874)	(5.966)	(6.048)	(6.119)	(6.175)	(6.214)	(6.235)	(6.235)	(6.214)	(6.174)	(6.116)
Level	-0.065	-0.109	-0.136	-0.150	-0.156	-0.157	-0.153	-0.147	-0.140	-0.133	-0.125
	(-4.057)	(-4.024)	(-3.974)	(-3.907)	(-3.823)	(-3.721)	(-3.602)	(-3.469)	(-3.324)	(-3.169)	(-3.007)
Slope	1.388	2.411	3.148	3.666	4.023	4.264	4.420	4.518	4.575	4.603	4.612
	(22.518)	(23.331)	(24.150)	(24.964)	(25.758)	(26.512)	(27.209)	(27.831)	(28.365)	(28.804)	(29.145)
Curvature	0.965	1.645	2.104	2.399	2.576	2.671	2.708	2.708	2.683	2.643	2.594
	(63.610)	(64.638)	(65.555)	(66.347)	(66.988)	(67.449)	(67.708)	(67.748)	(67.566)	(67.169)	(66.576)

Table 4.8. Incremental Futures Term Premiums and Volatility Term Structure Factors.

This table reports the estimates from regressions specified by $ITP_t = \beta_0 + \beta_1 Level_t + \beta_2 Slope_t + \beta_3 Curvature_t + \varepsilon_t$. ITP_t is the incremental futures term premium in period t. $Level_t$, $Slope_t$, and $Curvature_t$ are the values of the level, slope, and curvature factors of the volatility term structure in period t. The dependent variable in column i is the incremental term premium of the futures contract i-month maturity over the contract with $(i-1)$-month maturity. Regressions are estimated using daily data. *t*-statistics are reported in parentheses.

ITP Index	2	3	4	5	6	7	8	9	10	11	12
						Corn					
Constant	-10.982	-7.058	-4.442	-2.658	-1.430	-0.585	-0.010	0.375	0.625	0.780	0.867
	(-6.959)	(-6.758)	(-6.335)	(-5.382)	(-3.703)	(-1.707)	(-0.030)	(1.151)	(1.947)	(2.493)	(2.879)
Level	0.493	0.286	0.159	0.081	0.032	0.001	-0.018	-0.029	-0.036	-0.039	-0.040
	(6.046)	(5.293)	(4.395)	(3.168)	(1.596)	(0.071)	(-1.034)	(-1.724)	(-2.144)	(-2.410)	(-2.587)
Slope	-1.407	-0.945	-0.627	-0.403	-0.243	-0.130	-0.050	0.005	0.042	0.067	0.082
	(-24.938)	(-25.306)	(-25.006)	(-22.807)	(-17.615)	(-10.600)	(-4.260)	(0.420)	(3.680)	(5.962)	(7.601)
Curvature	-0.484	-0.326	-0.219	-0.144	-0.090	-0.052	-0.026	-0.007	0.006	0.014	0.020
	(-21.238)	(-21.633)	(-21.614)	(-20.145)	(-16.204)	(-10.604)	(-5.408)	(-1.516)	(1.217)	(3.139)	(4.520)
						Soybeans					
Constant	-3.368	-2.192	-1.413	-0.891	-0.541	-0.305	-0.145	-0.038	0.034	0.080	0.110
	(-2.307)	(-2.224)	(-2.144)	(-1.975)	(-1.577)	(-0.996)	(-0.479)	(-0.123)	(0.108)	(0.262)	(0.368)
Level	0.175	0.115	0.077	0.054	0.039	0.029	0.023	0.019	0.016	0.014	0.013
	(2.237)	(2.180)	(2.192)	(2.217)	(2.102)	(1.778)	(1.419)	(1.152)	(0.979)	(0.870)	(0.802)
Slope	-0.602	-0.391	-0.245	-0.143	-0.071	-0.022	0.012	0.034	0.048	0.057	0.062
	(-9.849)	(-9.478)	(-8.874)	(-7.551)	(-4.975)	(-1.725)	(0.913)	(2.638)	(3.731)	(4.449)	(4.945)
Curvature	-0.259	-0.169	-0.106	-0.062	-0.031	-0.009	0.005	0.015	0.021	0.025	0.027
	(-10.550)	(-10.207)	(-9.586)	(-8.161)	(-5.358)	(-1.825)	(1.030)	(2.883)	(4.042)	(4.791)	(5.297)

Table 4.8 (cont.)

ITP Index	2	3	4	5	6	7	8	9	10	11	12
						Wheat					
Constant	2.405	2.774	2.703	2.462	2.175	1.897	1.647	1.433	1.251	1.097	0.969
	(1.271)	(2.203)	(3.164)	(4.031)	(4.513)	(4.463)	(4.096)	(3.667)	(3.292)	(2.992)	(2.760)
Level	-0.207	-0.178	-0.144	-0.112	-0.085	-0.064	-0.047	-0.035	-0.025	-0.018	-0.013
	(-2.400)	(-3.087)	(-3.676)	(-4.012)	(-3.874)	(-3.293)	(-2.573)	(-1.937)	(-1.442)	(-1.069)	(-0.790)
Slope	0.146	0.182	0.178	0.159	0.137	0.115	0.097	0.081	0.069	0.059	0.051
	(2.423)	(4.550)	(6.561)	(8.202)	(8.920)	(8.533)	(7.563)	(6.546)	(5.696)	(5.037)	(4.540)
Curvature	0.077	0.074	0.059	0.043	0.028	0.017	0.008	0.001	-0.003	-0.006	-0.008
	(2.868)	(4.093)	(4.838)	(4.900)	(4.103)	(2.733)	(1.354)	(0.258)	(-0.540)	(-1.106)	(-1.507)
						Crude Oil					
Constant	-0.665	-0.513	-0.410	-0.335	-0.278	-0.233	-0.196	-0.167	-0.142	-0.122	-0.105
	(-0.613)	(-0.657)	(-0.699)	(-0.719)	(-0.707)	(-0.670)	(-0.620)	(-0.569)	(-0.523)	(-0.483)	(-0.449)
Level	0.023	0.026	0.026	0.024	0.021	0.019	0.017	0.015	0.013	0.012	0.010
	(0.509)	(0.807)	(1.056)	(1.231)	(1.317)	(1.325)	(1.286)	(1.228)	(1.168)	(1.113)	(1.065)
Slope	-0.028	-0.012	-0.004	0.001	0.003	0.004	0.004	0.004	0.004	0.004	0.004
	(-0.769)	(-0.451)	(-0.186)	(0.032)	(0.199)	(0.316)	(0.392)	(0.440)	(0.471)	(0.492)	(0.508)
Curvature	-0.022	-0.010	-0.005	-0.003	-0.002	-0.002	-0.001	-0.001	-0.001	-0.001	-0.001
	(-0.923)	(-0.571)	(-0.373)	(-0.272)	(-0.229)	(-0.215)	(-0.211)	(-0.209)	(-0.205)	(-0.198)	(-0.190)

Table 4.8 (cont.)

ITP Index	2	3	4	5	6	7	8	9	10	11	12
						Heating Oil					
Constant	-1.858	-0.900	-0.293	0.099	0.350	0.509	0.603	0.655	0.677	0.678	0.666
	(-1.124)	(-0.829)	(-0.416)	(0.204)	(0.867)	(1.258)	(1.421)	(1.491)	(1.529)	(1.555)	(1.578)
Level	-0.029	-0.024	-0.014	-0.004	0.004	0.011	0.016	0.018	0.020	0.021	0.021
	(-0.411)	(-0.521)	(-0.483)	(-0.210)	(0.255)	(0.643)	(0.871)	(1.002)	(1.083)	(1.138)	(1.179)
Slope	-0.171	-0.092	-0.032	0.012	0.042	0.063	0.076	0.084	0.087	0.088	0.086
	(-3.002)	(-2.447)	(-1.322)	(0.691)	(3.040)	(4.529)	(5.206)	(5.522)	(5.699)	(5.821)	(5.916)
Curvature	-0.090	-0.058	-0.035	-0.019	-0.008	0.001	0.007	0.011	0.014	0.015	0.016
	(-3.141)	(-3.072)	(-2.900)	(-2.289)	(-1.071)	(0.134)	(0.939)	(1.447)	(1.789)	(2.038)	(2.231)
						Natural Gas					
Constant	-12.748	-4.933	-1.645	-0.083	0.768	1.303	1.681	1.961	2.170	2.321	2.424
	(-2.937)	(-1.854)	(-0.958)	(-0.069)	(0.787)	(1.392)	(1.753)	(1.999)	(2.201)	(2.384)	(2.554)
Level	0.220	-0.016	-0.118	-0.148	-0.146	-0.130	-0.110	-0.092	-0.076	-0.062	-0.051
	(1.234)	(-0.150)	(-1.669)	(-3.028)	(-3.640)	(-3.373)	(-2.805)	(-2.286)	(-1.878)	(-1.563)	(-1.312)
Slope	-0.149	-0.080	-0.057	-0.044	-0.032	-0.020	-0.008	0.002	0.012	0.019	0.025
	(-1.935)	(-1.691)	(-1.875)	(-2.090)	(-1.867)	(-1.205)	(-0.482)	(0.140)	(0.661)	(1.104)	(1.489)
Curvature	-0.217	-0.125	-0.081	-0.052	-0.029	-0.011	0.003	0.014	0.023	0.030	0.035
	(-3.829)	(-3.597)	(-3.620)	(-3.335)	(-2.309)	(-0.922)	(0.251)	(1.128)	(1.801)	(2.345)	(2.807)

Table 4.8 (cont.)

ITP Index	2	3	4	5	6	7	8	9	10	11	12
						Reformulated Blend					
Constant	-11.554	-6.400	-3.691	-2.135	-1.168	-0.526	-0.078	0.241	0.471	0.633	0.743
	(-4.137)	(-3.820)	(-3.690)	(-3.186)	(-1.915)	(-0.794)	(-0.109)	(0.320)	(0.616)	(0.836)	(1.008)
Level	0.390	0.233	0.140	0.084	0.048	0.027	0.013	0.004	-0.001	-0.005	-0.007
	(3.862)	(3.842)	(3.869)	(3.442)	(2.193)	(1.105)	(0.487)	(0.147)	(-0.051)	(-0.172)	(-0.249)
Slope	-0.375	-0.212	-0.124	-0.070	-0.032	-0.005	0.015	0.031	0.042	0.050	0.055
	(-4.909)	(-4.633)	(-4.542)	(-3.801)	(-1.930)	(-0.273)	(0.785)	(1.489)	(2.007)	(2.415)	(2.752)
Curvature	-0.017	0.008	0.013	0.012	0.011	0.011	0.012	0.013	0.015	0.016	0.017
	(-0.468)	(0.375)	(0.964)	(1.338)	(1.335)	(1.226)	(1.223)	(1.311)	(1.447)	(1.605)	(1.768)
						Gold					
Constant	0.917	0.662	0.471	0.330	0.227	0.153	0.101	0.063	0.037	0.019	0.006
	(3.210)	(3.519)	(3.942)	(4.470)	(4.805)	(4.167)	(2.793)	(1.668)	(0.940)	(0.472)	(0.159)
Level	-0.071	-0.052	-0.037	-0.026	-0.018	-0.012	-0.008	-0.005	-0.003	-0.002	-0.001
	(-4.097)	(-4.495)	(-5.043)	(-5.730)	(-6.178)	(-5.380)	(-3.628)	(-2.186)	(-1.252)	(-0.651)	(-0.249)
Slope	0.595	0.423	0.294	0.200	0.132	0.083	0.049	0.026	0.010	-0.001	-0.008
	(7.895)	(8.510)	(9.319)	(10.244)	(10.542)	(8.572)	(5.186)	(2.569)	(0.920)	(-0.124)	(-0.817)
Curvature	0.606	0.402	0.255	0.150	0.077	0.027	-0.006	-0.027	-0.040	-0.048	-0.051
	(31.514)	(31.782)	(31.690)	(30.173)	(24.142)	(10.932)	(-2.488)	(-10.729)	(-15.294)	(-17.960)	(-19.632)

Table 4.8 (cont.)

ITP Index	2	3	4	5	6	7	8	9	10	11	12
						Copper					
Constant	-1.355	-1.014	-0.767	-0.583	-0.446	-0.341	-0.261	-0.200	-0.153	-0.117	-0.090
	(-1.911)	(-2.054)	(-2.153)	(-2.133)	(-1.954)	(-1.665)	(-1.359)	(-1.089)	(-0.871)	(-0.698)	(-0.563)
Level	0.042	0.036	0.031	0.028	0.025	0.022	0.020	0.018	0.016	0.015	0.013
	(1.434)	(1.752)	(2.121)	(2.450)	(2.628)	(2.630)	(2.523)	(2.380)	(2.241)	(2.120)	(2.018)
Slope	-0.208	-0.136	-0.085	-0.048	-0.022	-0.003	0.010	0.019	0.024	0.028	0.029
	(-5.174)	(-4.878)	(-4.218)	(-3.109)	(-1.682)	(-0.262)	(0.912)	(1.794)	(2.438)	(2.909)	(3.260)
Curvature	-0.197	-0.136	-0.095	-0.067	-0.046	-0.032	-0.021	-0.014	-0.008	-0.004	-0.001
	(-9.941)	(-9.877)	(-9.568)	(-8.726)	(-7.289)	(-5.580)	(-3.988)	(-2.690)	(-1.687)	(-0.922)	(-0.336)
						Silver					
Constant	2.749	1.932	1.304	0.837	0.501	0.264	0.103	-0.005	-0.075	-0.118	-0.143
	(5.874)	(6.082)	(6.244)	(6.180)	(5.419)	(3.593)	(1.482)	(-0.078)	(-1.075)	(-1.712)	(-2.134)
Level	-0.065	-0.043	-0.027	-0.015	-0.006	-0.000	0.003	0.006	0.007	0.008	0.008
	(-4.057)	(-3.962)	(-3.712)	(-3.127)	(-1.914)	(-0.130)	(1.437)	(2.402)	(2.944)	(3.259)	(3.454)
Slope	1.388	1.023	0.736	0.518	0.357	0.240	0.157	0.098	0.057	0.028	0.009
	(22.518)	(24.449)	(26.772)	(29.065)	(29.359)	(24.781)	(17.186)	(10.665)	(6.146)	(3.115)	(1.039)
Curvature	0.965	0.679	0.459	0.295	0.177	0.094	0.038	-0.000	-0.025	-0.040	-0.049
	(63.610)	(65.932)	(67.770)	(67.221)	(59.169)	(39.549)	(16.753)	(-0.150)	(-10.972)	(-17.889)	(-22.477)

Figure 4.1. Average Futures Volatility Term Structure.

This figure plots average futures volatility during the sample period as a function of time to expiration. Volatilities of all contracts are expressed as a percentage of the volatility of the 1-month contract. Time to expiration is measured in months.

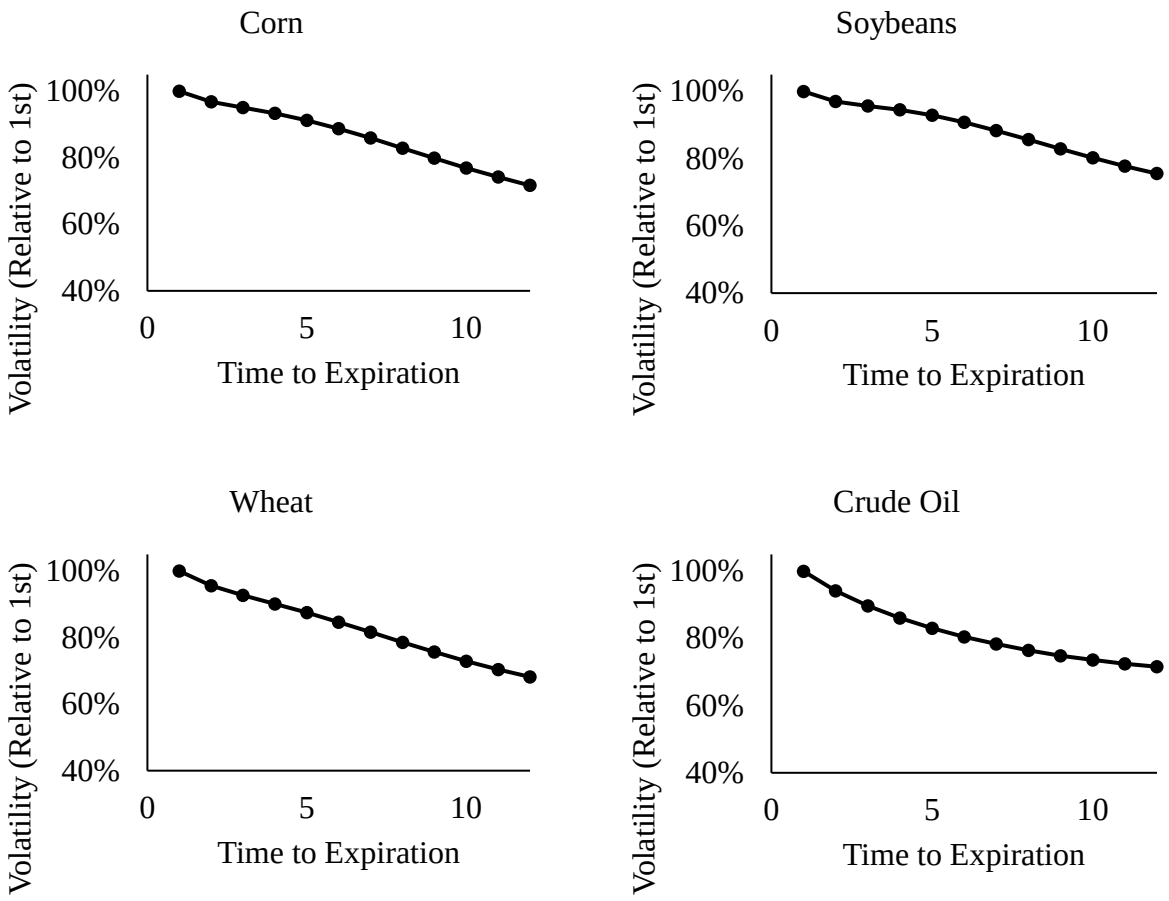


Figure 4.1 (cont.)

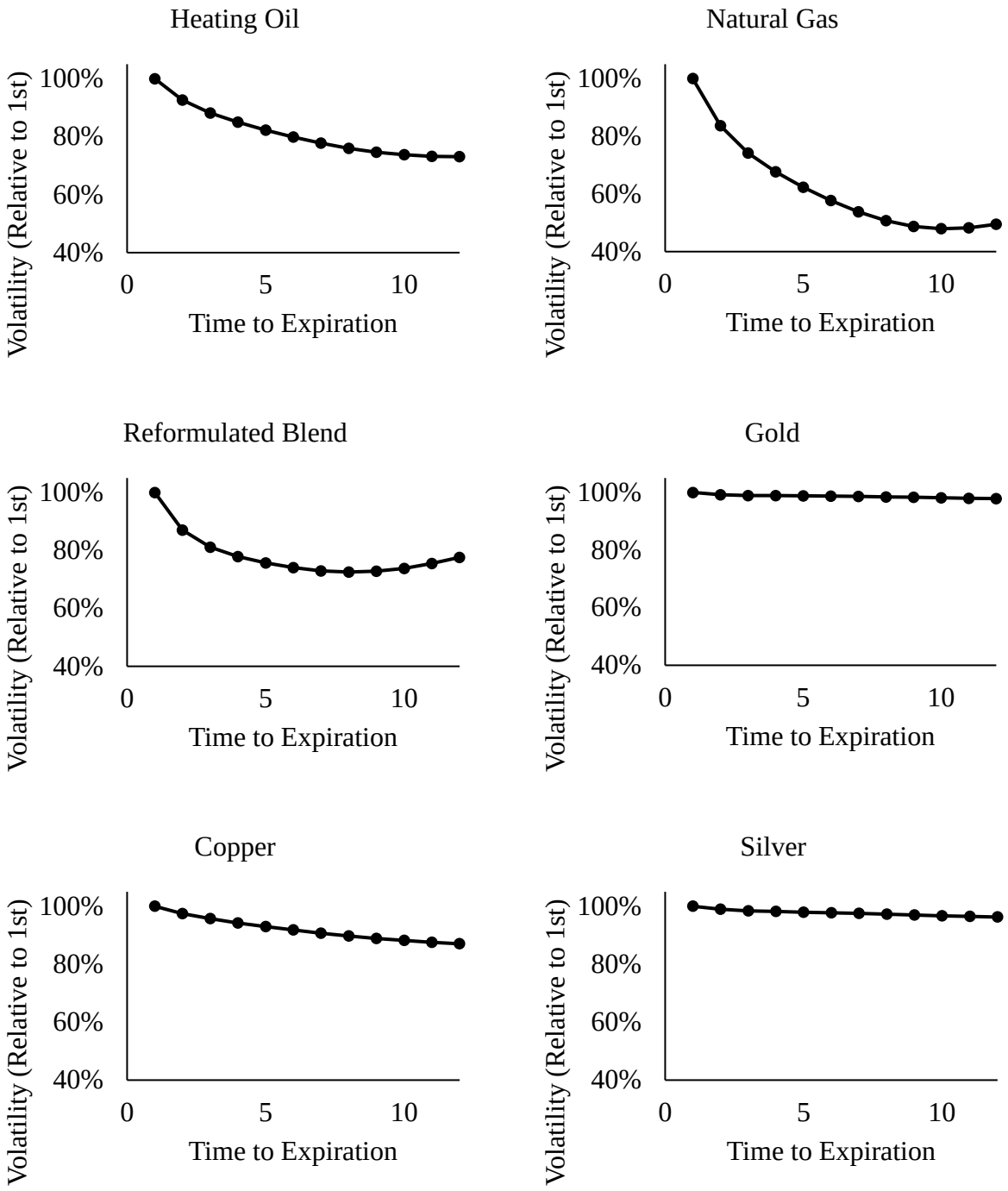


Figure 4.2. Time-Series Behavior of the Futures Volatility Slope Factor and Inventories.

This figure plots the 60-month moving average of the volatility slope factor and 95% confidence bands on the left axis. To obtain the moving average we regress the slope factor on its first lag, its twelfth lag, and a constant within each window to account for the autoregressive behavior of the slope factor and potential seasonality ($Slope_t = \beta_0 + \beta_1 Slope_{t-1} + \beta_2 Slope_{t-12} + \varepsilon_t$). We then calculate the mean of the series as $\mathbb{E}(Slope_t) = \beta_0/(1 - \beta_1 - \beta_2)$. 60-month moving average of inventory levels is plotted on the right axis.

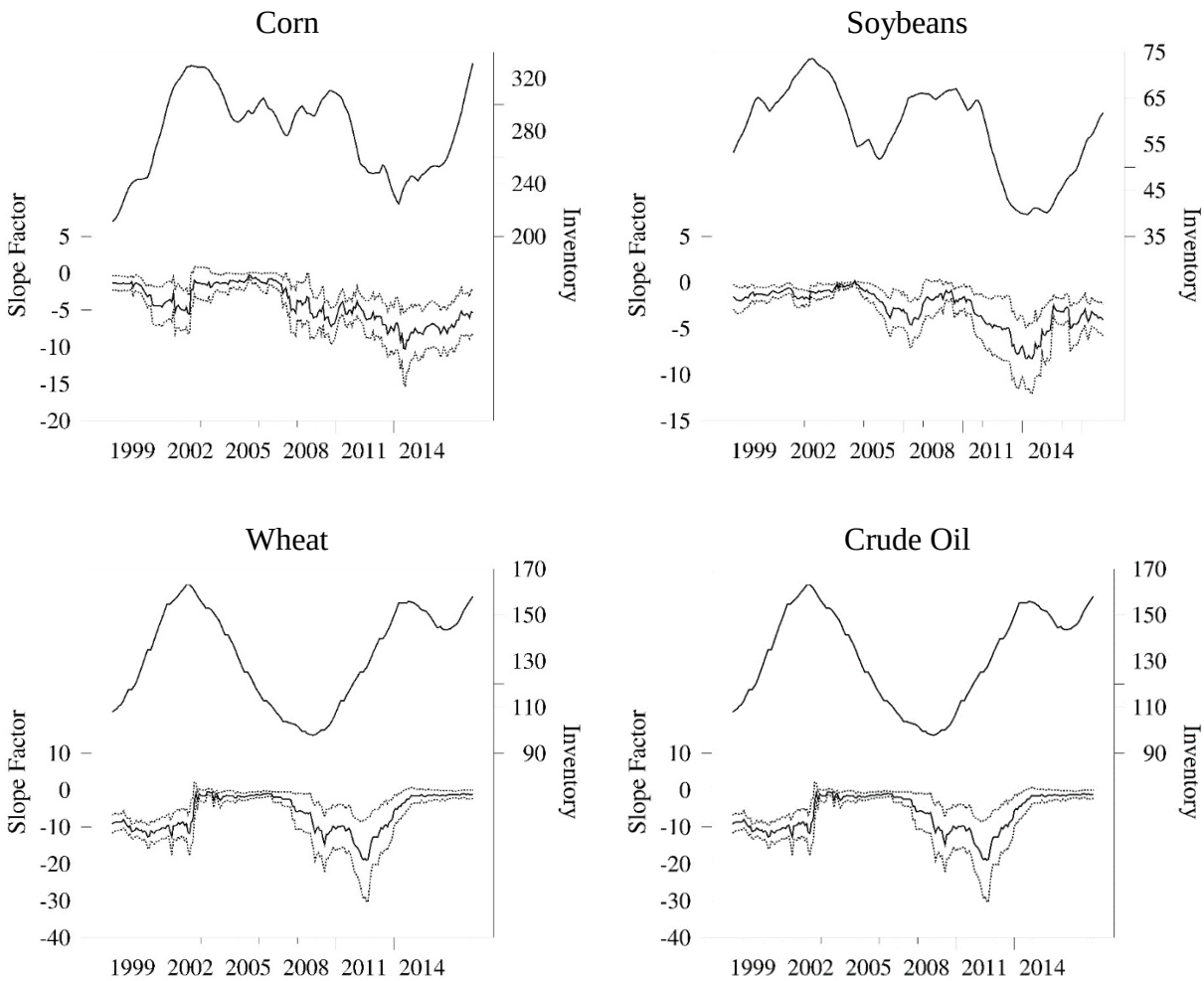


Figure 4.2 (cont.)

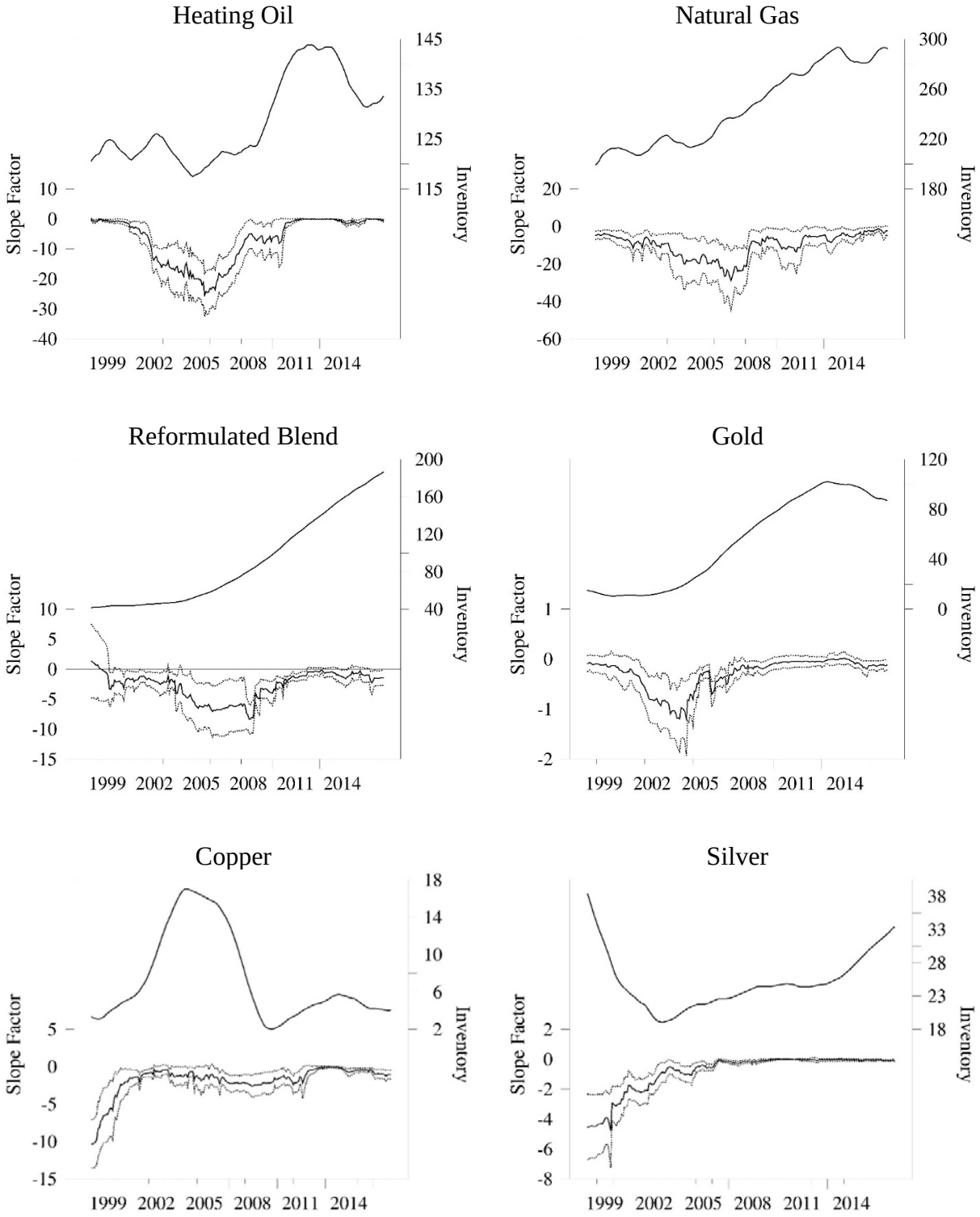


Figure 4.3. Average Futures Term Premiums.

This figure plots the futures term premiums as a function of time to expiration. Future term premium with time to expiration i is the term premium of the contract with i-month maturity over the contract with 1-month maturity.

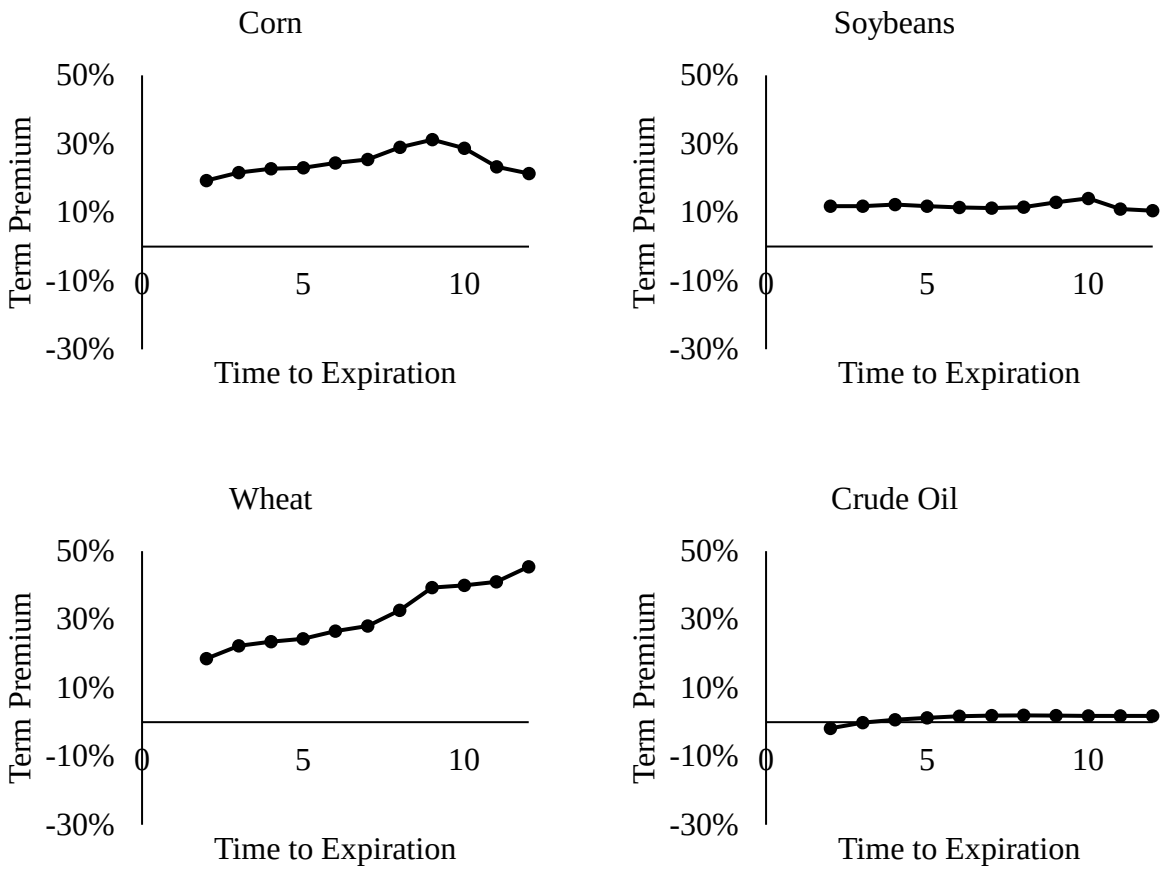
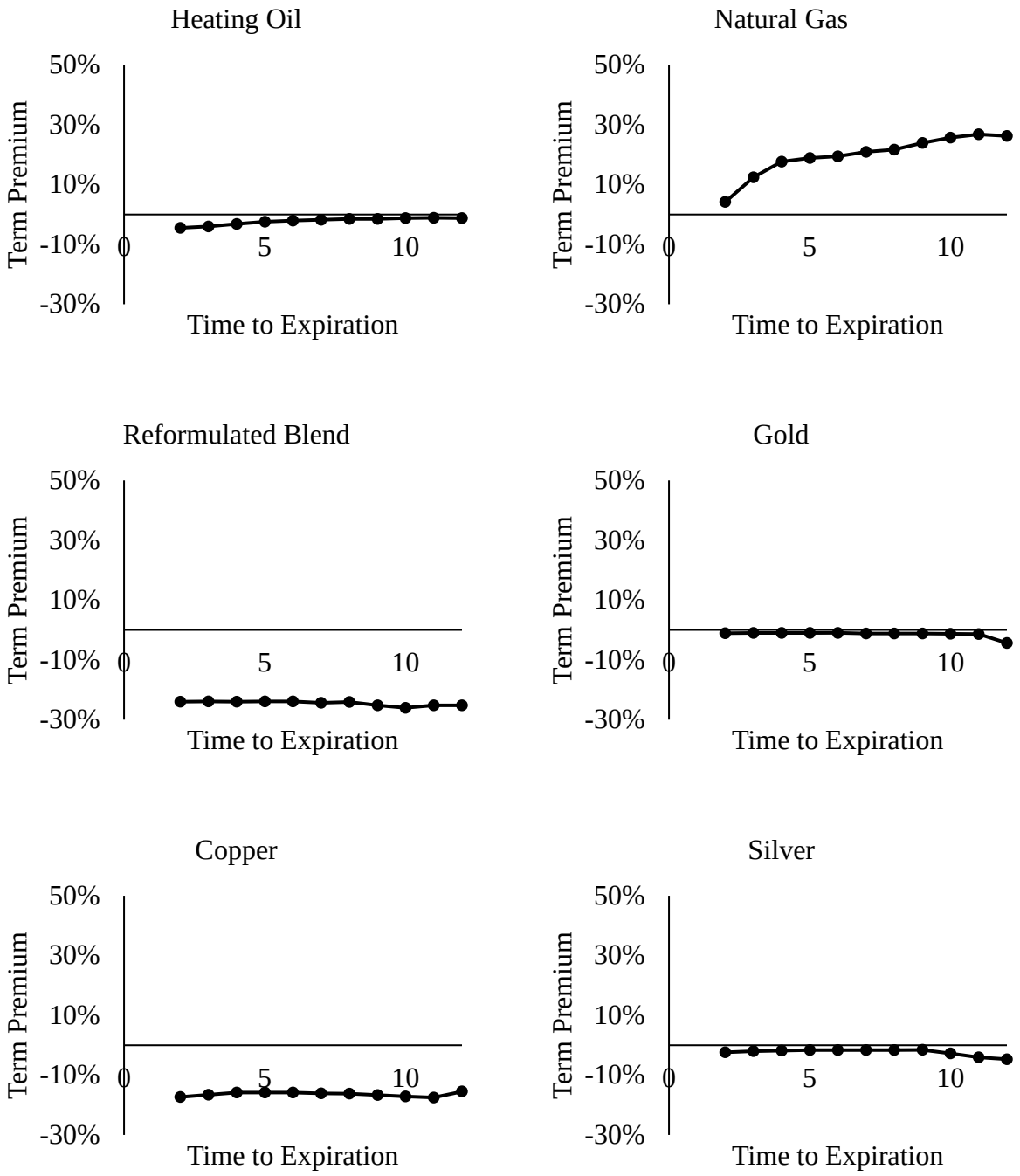


Figure 4.3 (cont.)



CHAPTER 5: OVERALL CONCLUSION

The three essays of this dissertation empirically examine the time-series behavior of volatility and information content of futures markets. The first and third essays examine futures volatility from two different perspectives – structural change and term structure – while the second essay deals with forecasting in interest rate futures.

In the first essay, we find that trigonometric functions work well in capturing shifts in futures volatility, reducing model persistence. Reduced model persistence affects the quality of forecasts, an issue related to the topic of the second essay. The findings of the second essay indicate a convergence of the predictive information in interest rate futures across the regions examined in the study, a phenomenon partially explained by monetary policies and macroeconomic conditions.

Another finding documented in the first essay is that volatility shifts do not appear to be coincident in futures with different maturities, suggesting that futures volatility term structure changes over time. Taking a deeper look at the term structure of futures volatility in the third essay, we find that all but one market in our study had a statistically flat volatility term structure sometime during the sample period. Further evidence shows that the slope of the volatility term structure is related to inventory levels and futures term premiums.

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