Forecasting the LIBOR-Federal Funds Rate Spread During and After the Financial Crisis

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ABSTRACT

In this paper, we examine the statistical forecast accuracy of econometric models, surveys and futures rates in predicting the LIBOR-Federal Funds Rate (LIBOR-FF) spread during and after the financial crisis. We provide evidence that the futures market forecast outperforms all competing forecasts during and after the financial crisis. Our results also suggest that the predictive accuracy of the econometric models improves in the post-crisis period. We argue that the post-2009 improvement in the econometric models' forecasts is attributable to the absence of LIBOR manipulation. The economic significance of the uncovered predictability is assessed using a trading strategy. Our results suggest that trading based on the futures market and econometric forecasts generates positive risk-adjusted returns.

Keywords: London Interbank Offered Rate (LIBOR), Federal Funds rate, Vector Autoregression (VAR), Factor Model, Forecasting, Eurodollar Futures, Federal Funds Futures, Blue Chip Survey.

JEL Classification: E47, E43, C53.

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1. Introduction

The spread between the London Interbank Offered Rate (LIBOR) and other short-term interest rates is widely regarded by policymakers, investors and the financial press as an indicator of the health of the money markets. Since August 2007, the spreads between unsecured and overnight lending rates witnessed significant increases and reached unprecedented highs following the failure of Lehman Brothers in September 2008. As the U.S. subprime mortgage crisis continued to unfold, the sustained increase in money market spreads rapidly developed into one of the most disquieting aspects of the financial crisis to policymakers and prompted large-scale and concerted injections of liquidity by the world's major central banks.[1] The events of the financial crisis underscore the importance of a more complete understanding of the developments in the interbank lending market by financial market participants, regulators and academics while also highlighting the need for accurate forecasts of the key interest rate spreads, especially during episodes of financial turmoil.

Despite the paramount policymaking and practical importance of predicting money market spreads, forecasting the spread between the three month LIBOR and other short-term interest rates during and after the financial crisis period has surprisingly attracted little attention in the literature. In this paper, we aim to address this gap in the literature by comparing the predictive ability of different econometric, survey and futures markets forecasts of the LIBOR-Federal funds rate (FFR) spread.[2] Such an exploration is of central policymaking and practical

[1] Policy makers frequently refer to the spread between the LIBOR and other short-term interest rates as indicative of the health of the global money markets.

[2] While several interest rate spreads are potential candidates for forecasting purposes, we opt to forecast the LIBOR-FF spread due to the availability of both survey and futures forecasts of this spread. In fact, trading in the thirteen-week Treasury bill futures seized in 2003 (but resumed in 2010) while Overnight Index Swap data are available only starting 2007. This prevents us from obtaining futures market forecasts for the TED spread and from obtaining econometric model forecasts of the LIBOR-OIS spread due to the small sample size when using OIS data.

importance. From a policymaking perspective, accurate forecasts of the LIBOR-FF spread allow policymakers to gain a better understanding of expected developments in the money markets and, consequently, to assess the need for policy interventions. The spread between LIBOR and other short-term interest rates is also regarded as a measure of funding liquidity (see, for example, Brunnermeir, Nagel and Pedersen, 2009). From a trading perspective, investors can enter into profitable futures positions based on an accurate directional forecast of the LIBOR-FF spread.

A number of early contributions examine the predictive ability of econometric models, forward (futures) rates and surveys in predicting short and long-term interest rates.[3] Baghestani, Jung and Zuchegno (2000) assess the predictive ability of survey and futures market forecasts of the Treasury bill rate. Guidolin and Timmermann (2009) report evidence that combining forecasts from a number of models yields improved out-of-sample forecasts of short-term U.S. interest rates. Sarno, Thornton and Valente (2005) examine the forecasting ability of econometric models and futures rates for the Federal funds rate, which is the key overnight policy rate of the Federal Reserve (Fed) prior to the financial crisis. Using shrinkage-based econometric models and survey data, Chun (2012) provides empirical evidence that individual survey participants outperform econometric models in terms of predicting interest rates and inflation over the short to medium term. While the previously reviewed strand of the literature employs survey market or futures data to predict short-term interest rates, its focus centers on forecasting short-term interest rates rather than interest rate spreads. In contrast to the prior studies, Baghestani (2010) studies the directional accuracy of survey forecasts of the LIBOR, Federal funds rate and LIBOR-FF

[3] See, for example, Hafer and Hein (1987) and Hafer, Hein and MacDonald (1992) for contributions to the three month Treasury bill rate forecasting literature. Deaves (1991) explores the predictive performance of econometric models and exploits the information in the yield curve to forecast Canadian short-term interest rates.

spread. Nonetheless, the author does not employ econometric models or examine the prediction of the LIBOR-FF during the financial crisis.

In this paper, we examine the predictive ability of several econometric models for the LIBOR-FF spread during and after the financial crisis. The econometric models entertained range from simple vector autoregressive (VAR) and autoregressive moving average (ARMA) models to more elaborate models which exploit the information in bond forward rates and in a large cross-section of macroeconomic variables. The predictive ability of the econometric models is compared to survey and futures markets forecasts of the LIBOR-FF spread. To preview our results, we provide evidence that the futures market forecast outperforms all the competing methods during and after the financial crisis. Our results also suggest that the predictive accuracy of the econometric models improves in the post-crisis period. We argue that the post-2009 improvement in the econometric models' forecasts is attributable to the absence of LIBOR manipulation and show, using a simple trading strategy, that an investor can earn the largest risk-adjusted returns by trading based on the futures market forecast of the LIBOR-FF spread.

Our paper makes several contributions to the literature. First, this paper is the first to forecast interest rate *spreads* during and after the financial crisis. Second, by exploiting a data-rich environment, this study sheds light on the predictive ability of factor models, which are estimated using a large-cross section of macroeconomic and financial variables, for interest rate spreads. Third, and to the best of our knowledge, this study in the first to provide empirical evidence of an improvement in econometric models' forecasting ability after the financial crisis and to relate this finding to the effect of LIBOR manipulation.

The rest of the paper is organized as follows. Section 2 describes the data and variables employed. Section 3 presents the forecasting models employed while Section 4 discusses the in-sample estimation results as well as the out-of-sample forecasting approach. The out-of-sample forecasting, forecast accuracy and trading strategy results are discussed in Section 5. Section 6 offers some concluding remarks.

2. Data and Variables

2.1 The LIBOR-FF spread

The main interest of this paper is in forecasting the LIBOR-FF spread. As noted previously, spreads between the LIBOR and other short term interest rates serve as a measure of funding liquidity and ease of lending in the interbank lending market.[4]

We collect data on the three month LIBOR fixings and the Federal funds rate for the period 1990Q1 to 2013Q4 from Datastream and the Federal Reserve of St. Louis Economic Database (FRED), respectively. Quarterly interest rate observations are obtained by averaging the daily observations over the quarter. The starting date of our sample is dictated, as discussed next, by the availability of data for some of our predictors (such as the VIX option-implied volatility index). The sampling frequency is dictated, in turn, by the fact that survey and futures forecasts of the LIBOR-FF spread can only be extracted at the quarterly horizon. The time series dynamics of the LIBOR-FF are displayed in Figure 1.

[4] Prior to January 31, 2014, LIBOR fixings were set by the British Bankers' Association (BBA). The BBA surveys a panel of sixteen banks that are active in the money market about the rate at which they can borrow funds just prior to 11 A.M. London time (Tuckman and Serrat, 2011). The LIBOR survey is undertaken daily for maturities ranging from overnight to twelve-month loans and for several currencies. The highest and lowest four rates are dropped from the survey before the average, referred to as the LIBOR fixing, is computed. After January 31, 2014, the oversight of the LIBOR fixing mechanism was transferred to the Intercontinental Exchange Benchmark administration and several changes were introduced to the LIBOR fixing mechanism (ICE, 2014).

[Insert Figure 1 here]

Figure 1 shows a clear countercyclical pattern in the LIBOR-FF spread. The spike in the LIBOR-FF spread during the 2008 subprime mortgage crisis is the largest observed increase in our sample period. It is important to note, at this stage, that the financial press referred to episodes of underreporting of the LIBOR fixings by some panel participants before and during the financial crisis.[5] Nonetheless, the empirical evidence emerging from academic studies examining whether the underreporting of LIBOR substantially affected the published LIBOR fixings is somewhat mixed. Notwithstanding anomalous LIBOR quotes, some studies note that the empirical evidence does not lend support to the conclusion that the manipulation resulted in materially different LIBOR fixings (Abrantes-Metz, Kraten, Metz and Seow, 2012; Kuo, Skeie and Vickery, 2012; Gyntelberg and Wooldridge, 2008). In particular, Gyntelberg and Wooldridge (2008) note that the LIBOR fixing mechanism, in which the highest and lowest 25 percent of the reported rates are dropped before the LIBOR fixing is computed, alleviates the impact of the underreporting of the true borrowing costs of some of the banks in the LIBOR panel. Using different methodologies, Snider and Youle (2010), Abrantes-Metz, Villas-Boas and Judge (2011), and Monticini and Thornton (2013) conclude that the misreporting of the quotes resulted in different statistical properties of the LIBOR fixing and the spread between LIBOR and other short-term interest rates.

In our forecasting exercise, we use the mixed evidence in the literature to delineate our out-of-sample forecasting periods. More specifically, we consider two out-of-sample forecasting periods which correspond to: (i) the financial crisis period with possible LIBOR manipulation,

[5] The LIBOR manipulation allegations eventually resulted in investigations that spanned several countries and involved several regulators. See, for example, "The rotten heart of finance", *The Economist*, July 7, 2012 and "Reforming LIBOR", *The Economist*, September 29, 2012.

and (ii) a post-financial crisis period that is free of LIBOR manipulation. More specifically, we employ 2007Q3 as the starting date for one of our forecasting samples. This date corresponds to the second break date in the spread between the three-month LIBOR and the corporate deposit (CD) rate reported in Monticini and Thorton (2013). We refer to the 2007Q3 to 2013Q4 out-of-sample forecasting period as a financial crisis with possible manipulation period. The second out-of-sample forecasting period starts in 2009Q1. Again, this choice is based on the last break in the LIBOR-CD series reported in Monticini and Thornton (2013). The post-2009Q1 period should, therefore, not include the effects of either the financial crisis or the LIBOR manipulation. By dividing the out-of-sample forecasting period in this manner, we examine whether the forecasting ability of the econometric models (and the futures and surveys) differed substantially across the financial crisis (and manipulation) period and the post-crisis (and post-manipulation) period.

[Insert Table 1]

Panels A and B of Table 1 report the summary statistics and results for the unit root test of the LIBOR-FF spread across the full sample. The Augmented Dickey-Fuller (ADF) test suggests that the null of a unit in the LIBOR-FF spread is rejected at conventional levels of significance. Given that the ADF test exhibits low power against near unit root or trend stationarity alternatives, the DF-GLS unit root test of Elliot, Rothenberg, and Stock (1996) is reported in addition to the ADF statistic.[6] The LIBOR-FF spread is not characterized by high persistence as evinced by the low first-order autocorrelation coefficient. In light of the stationarity of the LIBOR-FF spread, the forecasting models employ the LIBOR-FF in levels as a dependent variable.

[6] Elliot, Rothenberg, and Stock (1996) show that the DF-GLS test exhibits the highest power attainable for a particular deviation from the null.

2.2 Survey forecasts

We extract survey forecasts of the LIBOR-FF spread from the Blue Chip Financial Forecasts (BCFF).[7] The BCFF survey is undertaken by Aspen Publishers since 1982 and comprises the expectations of a panel of around fifty participants, drawn from major U.S. financial institutions, of the level of selected interest rates and macroeconomic variables. More specifically, survey respondents provide their expectations of the level of fifteen interest rates for up to five (six starting in 1997) quarters ahead. The BCFF survey responses are collected between the 25th and the 27th of every month and a consensus forecast, computed as the cross-sectional average of the individual survey responses, is provided in addition to individual respondents' expectations. We extract the one-quarter-ahead consensus forecast of the three month LIBOR and the Federal funds rate from the BCFF survey for every January, April, July and September in our out-of-sample forecasting period. A survey-based forecast of the LIBOR-FF spread is computed, in turn, as the difference between the three month LIBOR and Federal funds rate consensus forecasts.

The literature has extensively employed the BCFF consensus forecasts as survey gauges of macroeconomic (Batchelor and Dua, 1991; Bauer, Eisenbeis, Waggoner and Zha, 2003, among others) and financial expectations (Baghestani, 2010; Chun, 2012; Buraschi, Carnelli and Whelan, 2013; Ichiue and Yuyama, 2009, among others). While other notable surveys exist,[8] survey expectations of the three month LIBOR are available only in the BCFF survey.

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[7] The BCFF individual and consensus forecasts are purchased from Wolters Kluwer.

[8] For instance, the survey of professional forecasters maintained by the Federal Reserve Bank of Philadelphia, the Money Market Services survey and the Consensus Economics survey forecasts have also been widely used in existing studies. None of these surveys comprise LIBOR expectations. For a more detailed review of the different available survey forecasts, see Pesaran and Weale (2006).

2.3 Interest rate futures

In the absence of a time-varying risk premium which distorts predictive ability (i.e. under the null of futures market efficiency), interest rate futures contracts provide readily available market-based expectations of interest rates. In this paper, we employ the three month Eurodollar and the Federal funds futures contracts as market-based gauges of the three month LIBOR and Federal funds rate expectations. Federal funds and Eurodollar futures data are obtained from the Commodity Research Bureau (CRB).

The Eurodollar futures contract is the most liquid and widely used interest rate futures contract globally (Burghardt, 2008). The contract settles on the three month LIBOR fixing. The quarterly expiration cycle of these contracts allows us to observe quarterly market-based measures of LIBOR expectations. In order to match the information set of the BCFF survey participants, we sample the nearest (i.e. one-quarter-ahead) Eurodollar futures price on the 25th of the expiry month. The market-based measure of the three month LIBOR expectations are computed as 100 minus the futures price.[9]

We also employ federal funds futures as market-based gauges of the Federal funds rate expectations. Federal funds futures, officially known as thirty-day Federal funds rate futures, are interest rate futures contracts that settle on the average of the month's overnight Federal funds rate. A number of existing studies provide empirical evidence of the contract's usefulness as a gauge of Federal funds rate expectations (Krueger and Kuttner, 1996; Gurkaynak, Sack and Swanson 2007; Hamilton, 2009). In contrast to Eurodollar futures, Federal funds futures have a

[9] If the futures price is not available on the 25th, we sample the Eurodollar futures price on the following trading day (usually the 26th or the 27th day of the expiration month). The Eurodollar and federal futures prices are quoted in International Money Market index points. The implied interest rate can be obtained by subtracting the futures price from 100.

monthly expiration cycle. Following Chun (2012), we extract the quarterly expectations of Federal funds rates from futures data by averaging, on the 25^{th} of March, June, September and December, the Fed funds futures prices of the three Fed funds futures contracts which expire within the quarter. Again, the futures prices on the 25^{th} are employed to approximate the information set of the BCFF participants.[10] The futures-implied LIBOR-FF forecast is computed, in turn, as the difference between the implied LIBOR and Federal funds rates.

2.4 Macroeconomic and financial variables

Following recent contributions to the factor modeling literature (Ludvigson and Ng, 2009, 2011), we employ factor models for predictive purposes. More specifically, the four factors are extracted from a large panel of macroeconomic and financial variables using principal component analysis and used to forecast the LIBOR-FF spread. Our panel consists of a total 109 variables. The macroeconomic data are obtained from the Federal Reserve of St. Louis Economic Database (FRED) while the financial data are obtained from Datastream, the Commodity Research Bureau (CRB) and the Chicago Board Options Exchange (CBOE). When constructing the panel dataset, we use as many variables as possible from Ludvigson and Ng (2011)'s panel. The data appendix provides a listing of all the variables included in the panel as well as the transformations we apply to the variables.

[10] For instance, we compute the futures-based forecast of the Federal funds rate for 2007Q2 by averaging the first, second and third Federal funds futures prices on 26 March 2007. The implied Federal funds rate is then computed as 100 minus the previous average.

2.5 Bond forward rates and bond risk factor

We obtain monthly zero coupon bond prices for maturities ranging from one to five years from the Fama-Bliss bond files of the Center of Research in Securities Prices (CRSP). Quarterly discount bond data are constructed, in turn, by averaging the monthly bond price observations over the quarter. Let $p_t^{(n)}$ denote log price of an *n*-year discount bond at time *t*. Following Cochrane and Piazzesi (2005), the time *t* forward rate for loans between time *t*+*n*-1 and *t*+*n* is given by $f_t^{(n)} \equiv p_t^{(n-1)} - p_t^{(n)}$.

Under the expectations hypothesis, forward rates should reflect the expected short-term interest rates. This implies, in turn, that forward rates can also serve as useful predictors of interest rate spreads. While the empirical evidence, starting with the early contribution of Fama and Bliss (1987), is largely unsupportive of the expectations hypothesis, Cochrane and Piazzesi (2005) show that a single factor, constructed from the five forward rates, is an important predictor of bond risk premiums (i.e. bond excess returns). More specifically, following Cochrane and Piazessi (2005), define the log bond yield as $y_t^{(n)} \equiv -\frac{1}{n} p_t^{(n)}$ and the excess returns from buying a *n*-year bond at time *t* and selling it as an *n-1* year bond at time *t+1* as $rx_{t+1}^{(n)} \equiv p_{t+1}^{(n-1)} - y_t^{(1)}$. The Cochrane and Piazzesi (2005) factor, denoted $c\hat{p}_t$, is obtained as the fitted value from a regression of average excess bond returns on the five forward rates:

$$\frac{1}{4}\sum_{n=2}^{5} rx_{t+1}^{(n)} = \gamma_0 + \gamma_1 y_t^{(1)} + \gamma_2 f_t^{(2)} + \gamma_3 f_t^{(3)} + \gamma_4 f_t^{(4)} + \gamma_5 f_t^{(5)} + \varepsilon_{t+1}^{(n)} \qquad (1)$$

As is evident from Figure 1, the LIBOR-FF spreads displays countercyclical behavior. The significant increases in the LIBOR-FF spread during recessions and periods of financial turmoil suggest that a predictor of risk premiums in the bond market is likely to be a useful predictor of

LIBOR-FF. In recent work, Buraschi, Carnelli and Whelan (2013) provide empirical evidence of a significant co-movement between the $\hat{cp}_t$ factor and a measure of monetary policy surprises. Given that monetary policy is likely to have pervasive effects of the LIBOR-FF spread, the $\hat{cp}_t$ factor will also be a useful gauge of the effect of changes in the monetary policy stance on the LIBOR-FF spread.

2.6 Interest rate spreads

Both the LIBOR and Federal funds rate reflect the cost of unsecured short-term interbank lending. Recent research (Taylor and Williams, 2008, 2009; Wu, 2011) attributes an important role to default (counterparty) risk in explaining the increase in the spread between the LIBOR and other short-term interest rates during the financial crisis. We therefore employ the Treasury-Eurodollar (TED) and default spreads, defined as the difference between BAA and AAA-rated corporate bonds, as measures of funding liquidity (Brunnermeir, Nagel and Pedersen, 2009) and aggregate default risk.[11] In a recent study, Cui, In and Maharaj (2012) provide empirical evidence in support of the predictive power of the default spread, a measure of market liquidity and a measure of the slope of the yield curve in forecasting the LIBOR-OIS rate. The positive correlation between the LIBOR-OIS and LIBOR-FF spreads suggests that predictors of the LIBOR-OIS spread are also likely to be useful predictors of the LIBOR-FF spread.

Table 1 reports the summary statistics of the main interest rate predictors we employ. The TED and default spreads are, on average, wider and more volatile than the LIBOR-FF spreads.

[11] In principle, credit default swap (CDS) spreads can also serve as a measure of counterparty risk (Michaud and Upper, 2008; Wu, 2011). The unavailability of CDS data prior to 2007 prevents us from using CDS spreads. We experimented with the long-term yield spread defined as the difference between the long-term and short-term yields on government bonds (Welch and Goyal, 2008). Our results are qualitatively unaffected when we employ this variable.

This is consistent with the Federal funds rate being larger, on average, than the Treasury bill rate.[12] The cross-correlation coefficients between the LIBOR-FF, TED and default spreads are reported in Table 1. The cross-correlations suggest that the interest rates spreads on the short end of the yield curve are positively correlated and that the TED and default spread might constitute useful predictors for the LIBOR-FF spread.

2.7 Implied volatility

The final main predictor employed in this study is the VIX option-implied volatility index. We obtain data on the he VIX from the website of the Chicago Board of Options Exchange (CBOE). Data on the VIX is available only starting January 1990 thereby restricting our sample to start in1990Q1. The VIX index represents the implied volatility of the S&P 500 stock index and can be viewed as the consensus forecast of investors of future realized S&P 500 volatility over the next 30 calendar days. The index's construction is model independent and the VIX is widely perceived as a measure of market-wide (or Knightian) uncertainty (Blanchard, 2009) and as an "investor fear gauge" (Whaley, 2000).[13] It therefore potentially contains useful information for predicting interest rate spreads especially during periods of financial turmoil and heightened uncertainty.[14]

[12] In our complete sample, the Federal funds rate is larger and more volatile, on average, than the Treasury bill rate. Notwithstanding its overnight nature, Federal funds lending is unsecured. In contrast, the Treasury bill rate is relatively risk-free.

[13] The VIX's construction is based on a weighted average of out-of-the-money, European-style puts and calls written on the S&P 500 index with a wide range of strikes.

[14] Wu (2011) incorporates the change in the VIX into regressions exploring the determinants of the changes in the spread between the LIBOR and other short-term interest rates during the subprime mortgage crisis.

3. The Forecasting Models

We employ univariate and multivariate time series models to predict the LIBOR-FF spread. In this section, we introduce the various econometric models employed for predictive purposes.

3.1 Autoregressive moving average model

The summary statistics and unit roots in Table 1 suggest that the LIBOR-FF spread is stationary and exhibits weak serial correlation. Our forecasting exercise therefore begins with a well-specified Autoregressive Moving Average [ARMA(*p*,*q*)] model which aims at capturing the time series dynamics of the LIBOR-FF spread. Let s_t denote the LIBOR-FF spread. An ARMA *(p,q)* model is:

$$s_{t+1} = \alpha_0 + \sum_{i=1}^{p} \phi_i s_{t-i+1} + \sum_{j=0}^{q} \theta_j u_{t-j+1} \qquad (2)$$

The lag length of the autoregressive and moving average components are selected using the Bayesian Information Criterion (BIC). The BIC selects an ARMA (*1*,*3*) model. A careful examination of the model's residuals shows no remaining residual autocorrelation.

Clements and Hendry (1998) discuss the forecasting advantages of parsimonious models. Whereas models with several parameters may have a better in-sample fit, ARMA *(p,q)* models typically produce good out-of-sample forecasts. Modeling the dynamics of the LIBOR-FF spread as a simple ARMA *(1,3)* process is therefore a natural starting point.

3.2 Predictive regression

The information set in equation (2) consists only of past observations on the LIBOR. The second model we employ is a predictive regression which exploits the informational content of the $c\hat{p}_t$ factor and the VIX index. The predictive regression is:

$$s_{t+1} = \alpha + \beta_1 c\hat{p}_t + \beta_2 \Delta VIX_t + \varepsilon_{t+1}, \qquad (3)$$

where VIX_t denotes the level of the VIX index. We employ the predictors in equation (3) in light of (i) the importance of the $c\hat{p}_t$ in forecasting bond risk premiums and (ii) the importance of the VIX index as a gauge of uncertainty in financial markets. The predictors in equation (3) are likely to be particularly useful during the subprime mortgage crisis period.

3.3 Factor model

The previous two forecasting models are univariate. In addition, they only employ a limited information set. Following Ludvigson and Ng (2009, 2011), we resort to a factor model which allows us to extract and exploit information from a large panel of macroeconomic and financial variables. Let x_t denote a $(T \times N)$ panel of macroeconomic variables. Assuming that s_t admits a factor structure, the (static) factor model is:

$$s_{t+1} = \alpha + \beta' F_t + e_{t+1}, \qquad (4)$$

where F_t denotes a set of k factors, with $k << N$, that are extracted from the panel x_t. In practice, we employ principal component analysis (PCA) to estimate the factors and, hence, to reduce the dimensionality of our panel from 109 predictors to four factors. The number of factors is selected using the Bai and Ng (2002) criterion.

The use of a factor model has several advantages. First, equation (4) allows us to exploit a data-rich environment of macroeconomic and financial predictors. Second, rather than imposing the predictors as in equations (3), the factor model would permit a data driven selection of predictors.

3.4 Vector autoregressive model

The final model we consider is a vector autoregression (VAR). A p^{th}-order VAR relates a $(K \times 1)$ vector endogenous variables, Y_t, to its own lags and to the lags of the other endogenous variables in the system:

$$Y_{t+1} = A_0 + A_1 Y_t + \cdots + A_p Y_{t+1-p} + \nu_t, \tag{5}$$

where A_0 is a $(K \times 1)$ vector of intercept terms, $A_1, \cdots, A_p$ are $(K \times K)$ matrices of coefficients and ν_t is a $(K \times 1)$ vector of white noise innovations.

Using a VAR model similar to equation (5), Murphy and Murphy (2012) provide empirical evidence that liquidity was an important determinant of the LIBOR rate during the financial crisis.[15] Based on the findings of Murphy and Murphy (2012) and Cui, In and Maharaj (2012) and in the sake of parsimony, we include LIBOR-FF, default and TED spreads in the vector Y_t. A lag length of one is selected by the BIC.[16]

4. In-Sample Fit and Out-of-Sample Forecasting

As discussed in Section 2.1, one of our goals from the out-of-sample forecasting exercise is to examine whether there are marked difference in forecast accuracy between (i) the financial crisis period with possible material LIBOR manipulation and (ii) a post-financial crisis period that is free of LIBOR manipulation. To that end, our first in-sample estimation period is 1990Q1 to 2007Q2 while the out-of-sample forecasting period (i.e. holdout sample) is 2007Q3 to 2013Q4.

[15] The authors employ CDS spreads and other swap rates to measure liquidity. The unavailability of these data prior to 2007 prevents us from including such variables in our analysis.

[16] Using a higher-order VAR or a larger number of endogenous variables will lead to degrees of freedom problems.

The second in-sample period we consider is 1990Q1 to 2008Q4 while the holdout sample spans the 2009Q1 to 2013Q4 period.

4.1 In-sample fit

Existing research underscores the importance of parsimony when generating econometric forecasts. In fact, in-sample fit need not necessarily translate into good out-of-sample predictive performance. Competing forecasts should be compared in terms of out-of-sample performance.[17] Nonetheless, assessing the in-sample fit and characteristics of our models would be a useful starting point.

[Insert Table 2 here]

Starting from the factor model in equation (4), the four factors we extract using PCA account for a cumulative 46.71% of the variation in the data. Following Sarno, Thornton and Valente (2005), Table 2 reports four in-sample fit statistics: The adjusted R^2, Akaike (AIC), Bayesian (BIC) and Hannan-Quinn (HQ) information criteria. When comparing non-nested models, a lower AIC, BIC or HQ criterion suggests better in-sample fit (Lutkepohl, 2005). With the exception of the predictive regression in equation (3), the in-sample adjusted R^2 in our two in-sample periods are reasonably high. In fact, the $\overline{R}^2$ of the LIBOR-FF equation in the VAR model reaches 42% in the 1990Q1 to 2008Q4 period. The VAR model also achieves the lowest AIC, BIC and HQ criteria in both in-sample periods. While the factor model achieves a relatively high in-sample fit over the 1990Q1 to 2007Q2 period, the model's performance deteriorates over the 1990Q1 to 2008Q4 period.

[17] See, for example, Clark (2004) for a discussion.

4.2 Out-of-sample forecasting

One-step-ahead forecasts from the econometric models are generated recursively. That is, a moving window which adds a single observation to the sample is used to generate the forecasts. For example, the forecast of the LIBOR-FF spread for 2008Q2 uses observations from 1986Q1 to 2008Q1, while the forecast for 2008Q3 employs data through 2008Q2.[18] Table 3 presents our nomenclature of the different forecasts.

[Insert Table 3 and Figures 2 and 3 here]

The out-of-sample forecasts generated from the econometric models, the futures markets and the BCFF survey are displayed in Figures 2 and 3 for 2007Q3 to 2013Q4 period. Figures 2 and 3 suggest that the futures market forecast of the LIBOR-FF exhibits the highest accuracy among the competing methods. We turn next to a more careful assessment of forecast accuracy.

5. Out-of-Sample Forecast Evaluation

Out-of-sample forecasts are assessed based on both statistical and economic criteria. The forecast evaluation criteria as well as the out-of-sample forecasting performance of the different models are discussed next.

5.1 Statistical forecast evaluation

Two commonly used statistical forecast evaluation criteria are the Mean Absolute Error (MAE) and the Root Mean Squared Error (RMSE). The MAE's loss function is the absolute value of the difference between the actual and forecast series while the loss function of the RMSE is

[18] We also generate one-step-ahead forecasts using a rolling window which drops one observation from the beginning of the sample and adds an observation to the end of the window. For instance, the one-step-ahead forecast for 2007Q3 uses data from 1990Q1 to 2007Q2 while the forecast for 2007Q4 uses data from 1990Q2 to 2007Q3. The results (available from the authors) are not reported to conserve space.

quadratic. The weight given to large forecast errors is thus larger under the RMSE than it is under the MAE. A comparison of the competing models is first based on these two statistical criteria. The RMSE and MAE of forecast *j* are:

$$MAE_j = \frac{1}{h}\sum_{t=T+1}^{T+h}\left|s_t - \hat{s}_{jt}\right| \tag{6}$$

$$RMSE_j = \sqrt{\frac{\sum_{t=T+1}^{T+h}\left(s_t - \hat{s}_{jt}\right)^2}{h}}, \tag{7}$$

where $i = T+1,\ldots,T+h$ is the forecast sample and $\hat{s}_{jt}$ denotes the forecast of the LIBOR-FF spread from one of the econometric models, the futures rates or the BCFF survey.

[Insert Table 4 here]

Panels A and B of Table 4 report the MAE and RMSE of the different methods for the financial crisis and post-crisis period, respectively. A number of interesting observations emerge from these findings. First, the futures and survey forecasts appear to outperform all of the competing methods in terms of MAE and RMSE. The futures market forecast, in specific, achieves the lowest RMSE and MAE. Second, the ARMA(*1,3*) model, despite its simplicity, compares favorably to more elaborate econometric models. Third, the statistical forecast accuracy measures of every method are uniformly better in the post-crisis period (Panel B). The latter finding might be attributable to possible LIBOR manipulation during the financial crisis period or to the larger model estimation sample associated with the post-crisis period forecasts. The significant decrease in the RMSE and MAE of the futures and survey forecasts (two forecasts that do not require model estimation) over the 2009Q1 to 2013Q4 period lends support to the hypothesis that the LIBOR manipulation episode adversely affected the forecasting performance of all the methods over the 2007Q3 to 2013Q4 period.

While the statistical forecast evaluation criteria provide a useful first assessment of the out-of-sample forecast performance, ranking the different methods according to the MAE and RMSE does not indicate whether the differences in forecast accuracy measures are statistically significant. Given that the futures market forecasts are non-nested within any of the other methods, the modified Diebold and Mariano (1995) test, henceforth DM, can be employed to assess the statistical significance of the difference between the forecast errors of any of the methods and those of the futures markets.[19]

The results of the modified DM test, as reported in Table 4, corroborate our previous conclusions regarding the accuracy of the futures market forecast of the LIBOR-FF spread. In fact, over the 2007Q3 to 2013Q4 period, the DM statistic is significant (at the 10% level or better) for each of the methods. This implies, in turn, that the forecast gains from using futures relative to any other method are statistically significant. Interestingly, the futures market forecast errors are not significantly different from those of ARMA (*1,3*) and VAR model in the post-crisis period (Panel B).

5.2 Forecast encompassing and combination

In light of the evidence in Section 5.1, we next turn to examining whether the futures market forecast subsumes (or encompasses) the information contained in the other forecasts. To do so, we consider the following regression:

[19] That is, we use the futures market forecast as a benchmark against which we compare the other methods. As noted in Diebold (2013), the asymptotic normality of the DM statistic holds only when the competing forecasts are non-nested. To allow for possible serial correlation in the differences between mean squared errors from any two forecasting methods, we use the Harvey, Leybourne and Newbold (1997) modified version of the DM statistic.

$$s_t = \beta_1 \hat{s}_{1t} + \beta_2 \hat{s}_{2t} + \xi_t \ , \tag{8}$$

for $t = T+1, \cdots, t+h$. In equation (8), $\hat{s}_{1t}$ denotes the futures market forecast while $\hat{s}_{2t}$ denotes a forecast obtained from any other competing method. If the futures market forecasts embeds all the information in $\hat{s}_{2t}$, the null hypothesis, $H_0 : \beta_1 = 1, \beta_2 = 0$, is not rejected.[20]

[Insert Table 5 here]

Panels A and B of Table 5 provide the results from estimating equation (8) for the financial crisis and post-crisis periods, respectively. Our results suggest that, with the exception of the factor model forecast, the futures market forecast encompasses the information in all the other methods for the 2007Q3 to 2013Q4 period. In contrast, the results in Panel B suggest that all the methods carry additional information that is useful in predicting the LIBOR-FF spread. Again, this might be suggestive that the econometric models tend to yield informative forecasts in the post-crisis (and post-manipulation) period.

Existing studies provide empirical evidence that combining forecasts from competing methods likely results in superior predictive accuracy (see, for example, Timmermann, 2006, for a review of this literature). When one method's forecast encompasses the information in the other forecast, no forecasting gains are achieved by combining the forecasts. Based on these observations, we compute an equally weighted average of the futures and factor model forecasts for the 2007Q3 to 2013Q4 period and refer to it as the "combined" forecast. In light of the forecast encompassing test results in Table 5, our combination forecast for the 2009Q1 to 2013Q4 period is an equally-weighted average of all the methods' forecasts.

[20] We also test for forecast optimality by estimating the regression $s_{t+1} - s_t = \alpha_0 + \alpha_1(\hat{s}_{jt+1} - s_t) + v_t$. The null of forecast optimality $H_0 : \alpha_0 = 0, \alpha_1 = 1$ is rejected, in the 2007Q3 to 2013Q4 period, for all forecasts except the ARMA(*1*,*3*) and the futures forecast.

5.3 Trading strategy

Prior research suggests that statistical forecast accuracy does not necessarily imply economic significance or profitability (Leitch and Tanner, 1991). In this section, we examine the risk-adjusted profitably of the econometric, survey and combined forecasts.

We consider a simple trading strategy which can be implemented using futures contracts. The trading strategy is as follows: (i) if $\hat{s}_{jt+1} > s_t$, the trader longs the first Eurodollar futures contract and shorts the third Federal funds futures contract and (ii) if $\hat{s}_{jt+1} < s_t$ the trader shorts the first Eurodollar futures contract and longs the third Federal funds futures contract. That is, when the LIBOR-FF forecast from method *j* is larger (lower) than the current LIBOR-FF spread, the investor exploits a predicted widening (narrowing) in the LIBOR-FF spread by longing (shorting) Eurodollar futures and shorting (longing) Federal funds futures. The investor realizes a gain if $\hat{s}_{jt+1} > s_t$ and $s_{t+1} > s_{jt}$ or $\hat{s}_{jt+1} < s_t$ and $s_{t+1} < s_t$. The investor realizes a loss otherwise.

The trading strategy that we consider is, in essence, a speculative arbitrage position. While entering into the futures positions is costless, an investor has to maintain a margin account in order to continue holding the positions. As opposed to a riskless pure arbitrage strategy, our strategy carries risk. Futures contracts are also marked-to-market daily. That is, the margin account is adjusted on a daily basis to reflect any gains or losses made by the investor. [21] In order

[21] Establishing a futures position requires that an investor deposits funds as an initial margin. The changes in the initial margin account resulting from gains or losses on the position are known as the variation margin. In order to maintain the futures position, the balance in the margin account should not fall below the maintenance margin set by the exchange. The initial (maintenance) margin for speculators holding Eurodollar futures ranged from a high of $1,210 ($1,100) during the financial crisis to a low of $200 in the post-crisis period (CME, 2014).

to account for the risky nature of the strategy and given that margin accounts earn an interest rate, we compute the Sharpe ratio as:

$$\frac{E(\tilde{r}_{jt})}{\sigma(\tilde{r}_{jt})}, \qquad (9)$$

where $\tilde{r}_{jt}$ is the realized return from trading based on forecasting method j and $\sigma(\tilde{r}_{jt})$ is the standard deviation of the realized return.

The Eurodollar and Federal funds futures are both deep and liquid futures markets.[22] Nonetheless, transaction costs should be accounted for in order to ascertain a trading strategy's profitability. In order to measure transaction costs, we obtain daily bid and ask prices for Eurodollar and Federal funds futures from Datastream.[23] Following Bessembinder and Venkataraman (2010), we approximate transaction costs using the quoted half spread computed as: $QS_t = 100 \times \frac{(A_t - B_t)}{2 \times M_t}$ where A_t denotes the ask price, B_t denotes the bid price and M_t denotes the mid-point price. The estimated average quoted half spread in the Federal funds futures and Eurodollar futures markets are 0.00023% and 0.00148%, respectively. In light of these small transaction costs, we do not explicitly account for these negligible transaction costs. The annualized Sharpe ratios to trading based on each of the forecasts are reported in Table 6.

[Insert Table 6 here]

The trading strategy results show that the superior statistical accuracy of the futures rates translates into larger Sharpe ratios in the crisis and post-crisis periods. In fact, trading the LIBOR-FF spread based on the futures market forecast generates the largest Sharpe ratio among

[22] Transaction costs in these markets are typically considered to be negligible.

[23] While the time series of the bid-ask quotes are incomplete, we use these data only to approximate the transaction costs in these two futures markets.

all the competing methods. The combination forecast, discussed in Section 5.2, ranks second in terms of trading profits in the post-2009 period.

It is interesting to note that the Sharpe ratios of the econometric models are uniformly larger in the post-crisis period (2009Q1 to 2013Q4) than they are in the crisis period. This finding is consistent with the improved statistical forecast accuracy of the econometric models in the post-crisis (and post LIBOR manipulation) period. Overall, our trading strategy results corroborate our earlier statistical forecast accuracy findings.

If the arbitrage position only incurs idiosyncratic risk, (9) becomes the equation for the information ratio (IR) that is commonly used to compute the reward for bearing active investment risk. If we accept the assertion of Grinold and Kahn (1995) that an IR of 0.50 is "good," of 0.75 is "very good," and of 1.0 is "exceptional", then the futures trading strategy provides good return-to-risk performance (IR = 0.527) over the whole period and very good return-to-risk performance (IR = 0.785) since the end of 2008. In comparison, the annualized Sharpe (IR) ratios resulting from an investment in the S&P 500 over the 2007Q3 to 2013Q4 and 2009Q1 to 2013Q4 periods are, respectively, 0.053 and 0.547. Thus, the risk-adjusted returns from trading based on the futures forecast exceed those of the S&P 500 in both sample periods.

6. Concluding Remarks

This paper examines the statistical forecast accuracy of econometric models, surveys and futures rates in predicting the LIBOR-Federal Funds Rate (LIBOR-FF) during and after the financial crisis. We provide evidence that the futures market forecast of the LIBOR-FF spread is statistically more accurate than econometric or survey forecasts. Our results also suggest that the predictive accuracy of the econometric models improves in the post-crisis period. The post-2009 improvement in the econometric models' forecasts is consistent with the absence of LIBOR manipulation in the post-crisis period.

We assess the economic significance of the uncovered predictability in the LIBOR-FF spread using a simple trading strategy. In the trading exercise, the investor exploits a predicted widening (narrowing) in the LIBOR-FF spread by longing (shorting) Eurodollar futures and shorting (longing) Federal funds futures. Our results suggest that an investor can generate a large positive risk-adjusted return when trading based on the futures market forecast of the LIBOR-FF spread. The risk-adjusted returns from trading based on the futures market forecast exceed those of an investment in the S&P 500 over a comparable period.

Our results have important policy-making and practical implications. From a trading perspective, our results suggest that trading the LIBOR-FF spread in the post-2009 based on our econometric or futures or survey market generates positive risk-adjusted returns. From a policy-making perspective, our findings suggest that central bankers and other regulators can reliably use the futures market forecast to understand and predict developments in the interbank lending market and devise appropriate policy responses.

References

Abrantes-Metz, Rosa M., Michael Kraten, Albert D. Metz and Gim S. Seow, 2012. Libor manipulation? *Journal of Banking and Finance* 36, 136-150.

Abrantes-Metz, Rosa M., Sofia S. Villas-Boas and George Judge, 2011. Tracking the Libor Rate, *Applied Economics Letters* 18, 893-899.

Baghestani, Hamid, 2010. How well do experts predict interbank loan rates and spreads? *Economics Letters* 109, 4-6.

Baghestani, Hamid, Woo Jung, and Daniel Zuchegno, 2000. On the information content of futures market and professional forecasts of interest rates, *Applied Financial Economics* 10, 679-684.

Bai, Jushan and Serena Ng, 2002. Determining the number of factors in approximate factor Models, *Econometrica* 70, 191-222.

Batchelor, Roy and Pami Dua, 1991. Blue chip rationality tests, *Journal of Money Credit and Banking* 23, 692-705.

Bauer, Andy, Robert A. Eisenbeis, Daniel F. Waggoner and Tao Zha, 2003. Forecast evaluation with cross-sectional data: The blue chip surveys, Federal Reserve Bank of Atlanta *Economic Review*, Second quarter, 17-31.

Bessembinder, Hendrik and Kumar Venkataraman, 2010. Bid-ask spreads, *Encyclopedia of Quantitative Finance*, 1-6.

Blanchard, Olivier, 2009. (Nearly) nothing to fear but fear itself, *The Economist*. January 29, 2009.

Brunnermeier, Markus K., Stefan Nagel and Lasse H. Pedersen, 2008. Carry trades and currency crashes, *NBER Macroeconomics Annual* 23, 313–348.

Buraschi, Andrea, Andrea Carnelli and Paul Whelan, 2013. Monetary policy and treasury risk Premia. *Working paper*, Imperial College London.

Burghardt, Galen, 2008. Volume surges again: Global futures and options trading rises 28% in 2007. *Futures Industry Magazine*, March/April, 15-26.

Chicago Mercantile Exchange. 2014. Minimum performance bond requirements. http://www.cmegroup.com/clearing/riskmanagement/files/ED_2008_to_present.pdf

Chun, Albert Lee, 2012. Forecasting interest rates and inflation: Blue chip clairvoyant or econometrics?, *Working paper*, Copenhagen Business School.

Clark, Todd E., 2004. Can out-of-sample forecast comparisons help prevent overfitting? *Journal of Forecasting* 23, 115-139.

Clements, Michael P. and David Hendry, 1998. *Forecasting Economic Time Series*. (Cambridge University Press, Cambridge).

Cochrane, John H. and Monika Piazzesi, 2005. Bond risk premia, *American Economic Review* 95, 138-160.

Cui, Jin, Francis In and Elizabeth Ann Maharaj, 2012. What drives the Libor-OIS spread? Evidence from five major currency Libor-OIS spreads. *Working paper*, Monash University.

Deaves, Richard, 1991. Forecasting Canadian short-term interest rates. *Canadian Journal of Economics*, 29, 615-634.

Diebold, Francis X. 2013. Comparing predictive accuracy, twenty years later: A personal perspective on the use and abuse of Diebold-Mariano tests. *Working paper*, University of Pennsylvania.

Diebold, Francis X. and Roberto S. Mariano, 1995. Comparing predictive accuracy. *Journal of Business and Economic Statistics* 13, 253-263.

Elliot, Graham, Thomas J. Rothenberg and James H. Stock, 1996. Efficient tests for an autoregressive unit root, *Econometrica* 64, 813-836.

Fama, Eugene F. and Robert R. Bliss, 1987. The information in long-maturity forward rates, *American Economic Review* 77, 680-692.

Grinold, Richard C. and Ronald N. Kahn, 1995. *Active Portfolio Management*. (Richard D. Irwin, Chicago, Illinois).

Guidolin, Massimo and Allan Timmermann, 2009. Forecasts of US short-term interest rates: A flexible forecast combination approach, *Journal of Econometrics* 150, 297-311.

Gurkaynak, Refet S., Brian Sack and Eric T. Swanson, 2007. Market-based measures of monetary policy expectations, *Journal of Business and Economic Statistics* 25, 201-212.

Gyntelberg, Jacob and PhilipWooldridge, 2008. Interbank rate fixings during the recent turmoil. *BIS Quarterly Review*, March 2008, 59-72.

Hafer, R. W. and Scott E. Hein, 1989. Comparing futures and survey forecasts of near-term treasury bill rates. Federal Reserve Bank of St. Louis *Review*, May/June 1989, 33-42.

Hafer, R. W., Scott E. Hein and S. Scott MacDonald, 1989. Market and survey forecasts of the three-month treasury-bill rate, *Journal of Business* 65, 123-138.

Hamilton, James D. 2009. Daily changes in Fed funds futures prices, *Journal of Money, Credit and Banking* 41, 567-582.

Harvey, David, Stephen Leybourne and Paul Newbold, 1997. Testing the equality of prediction mean squared errors, *International Journal of Forecasting* 13, 289-291.

ICE. 2014. ICE Benchmark Administration Limited – Overview. https://www.theice.com/publicdocs/IBA_ICE_LIBOR_Overview.pdf

Ichiue, Hibiki and Tomonori Yuyama, 2009. Using survey data to correct the bias in policy expectations extracted from fed funds futures, *Journal of Money, Credit and Banking* 41, 1631-1647.

Krueger, Joel T. and Kenneth N. Kuttner, 1996. The Fed funds futures rate as a predictor of Federal Reserve Policy, *Journal of Futures Markets* 16, 865-879.

Kuo, Dennis, David Skeie and James Vickery, 2012. A comparison of Libor to other measures of bank borrowing costs. *Working paper*, Federal Reserve Bank of New York.

Leitch, Gordon and J. Ernest Tanner, 1991. Economic forecast evaluation: Profits versus the conventional error measures. *American Economic Review* 81, 580-590.

Ludvigson, Sydney C. and Serena Ng, 2009. Macro factors in bond risk premia, *Review of Financial Studies* 22, 5027-5066.

Ludvigson, Sydney C. and Serena Ng, 2011. A factor analysis of bond risk premia. In Aman Ullah and David E. A. Giles (Eds.), *Handbook of Empirical Economics and Finance*, Chapman Hall/CRC Press, 313-372.

Lutkepohl, Helmut 2005. *New Introduction to Multiple Time Series Analysis.* (Springer, Berlin)

Michaud, François-Louis and Christian Upper, 2008. What drives interbank rates? Evidence from the LIBOR panel, *BIS Quarterly Review,* March 2008.

Monticini, Andrea and Daniel L. Thornton, 2013. The effect of underreporting on LIBOR rates, *Journal of Macroeconomics* 37, 345-348.

Murphy, Finbarr and Bernard Murphy, 2012. A vector-autoregression analysis of credit and liquidity factor dynamics in US LIBOR and Euribor swap markets, *Journal of Economics and Finance* 36, 351-370.

Newey, Whitney K. and Kenneth D. West, 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica* 55, 703-708.

Pesaran, M. Hashem and Timmermann, Allan 1992. A nonparametric test of predictive performance, *Journal of Business and Economic Statistics* 10, 461-465.

Pesaran, M. Hashem and Martin Weale, 2006. Survey expectations. In: Graham Elliot, Clive W.J. Granger and Allan Timmermann (Eds.), *Handbook of Economic Forecasting*, North Holland, Amsterdam, 715-776.

Sarno, Lucio, Daniel L. Thronton and Giorgio Valente, 2005. Federal funds rate prediction, *Journal of Money, Credit and Banking* 37, 449-471.

Snider, Connan and Thomas Youle, 2010. Does the Libor reflect banks' borrowing cost?, *Working paper*, University of California Los Angeles.

Taylor, John B. and John C. Williams, 2008. Further results on a black swan in the money market. *Working paper No. 07-46*, Stanford Institute for Economic Policy Research.

Taylor, John B. and John C. Williams, 2009. A black swan in the money market, *American Economic Journal: Macroeconomics* 1, 58-83.

Timmermann, Allan 2006. Forecast combinations, In: Graham Elliot, Clive W.J. Granger and Allan Timmermann (Eds.), *Handbook of Economic Forecasting*, North Holland, Amsterdam,135-196.

Tuckman, Bruce and Angel Serrat, 2011. *Fixed Income Securities: Tools for Today's Markets*. (Wiley, New York).

Welch, Ivo and Amit Goyal, 2008. A comprehensive look at the empirical performance of equity premium prediction, *Review of Financial Studies* 21, 1455-1508.

Whaley, Robert E., 2000. The investor fear gauge, *Journal of Portfolio Management* 26, 12-17.

Wu, Tao 2011. The U.S. money market and the term auction facility in the financial crisis of 2007- 2009, *Review of Economics and Statistics* 93, 617-631.

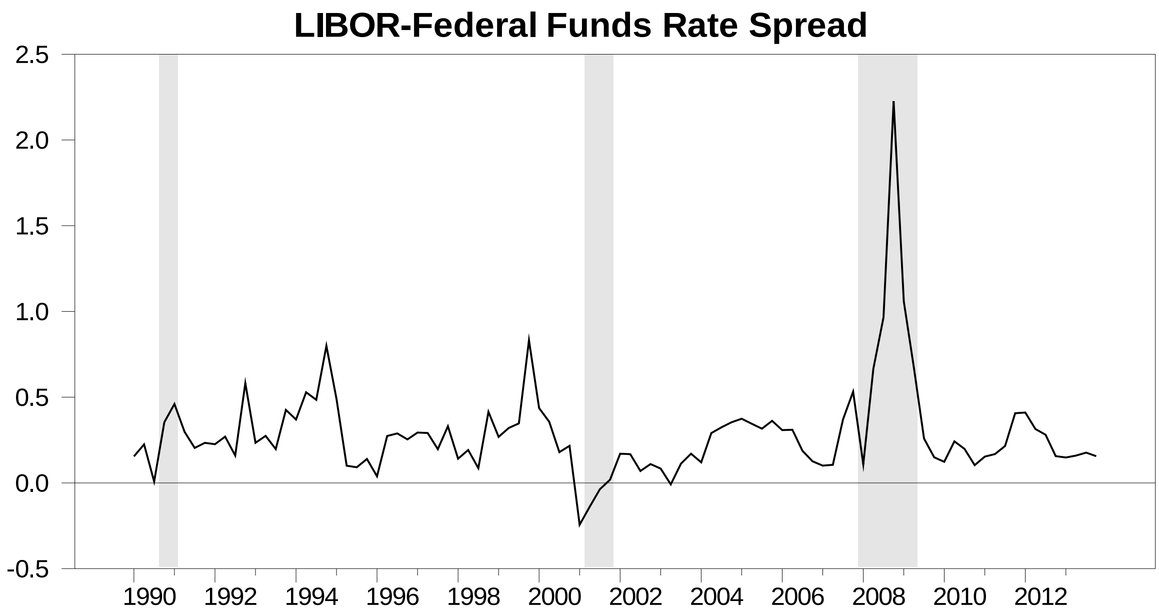

Figure 1. LIBOR-FF spread over the 1986Q1 to 2013Q4 period. Shaded areas are NBER dated recessions.

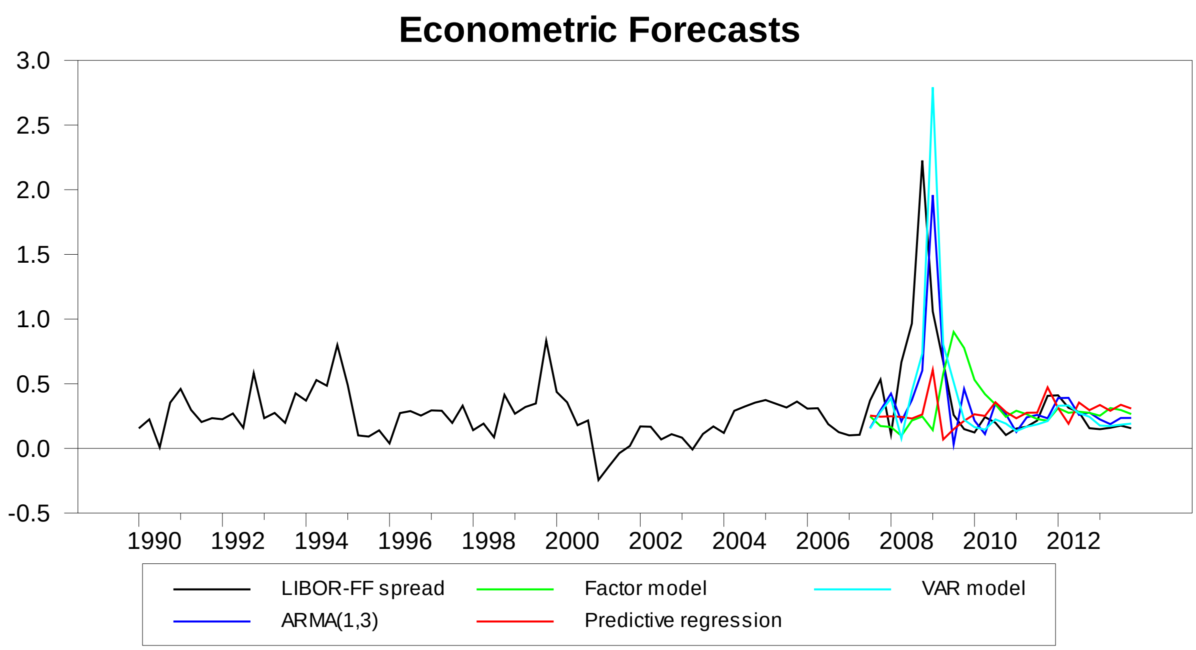

Figure 2: One-step-ahead econometric model forecasts of the LIBOR-FF spread over the 2007Q3 to 2014Q4 period.

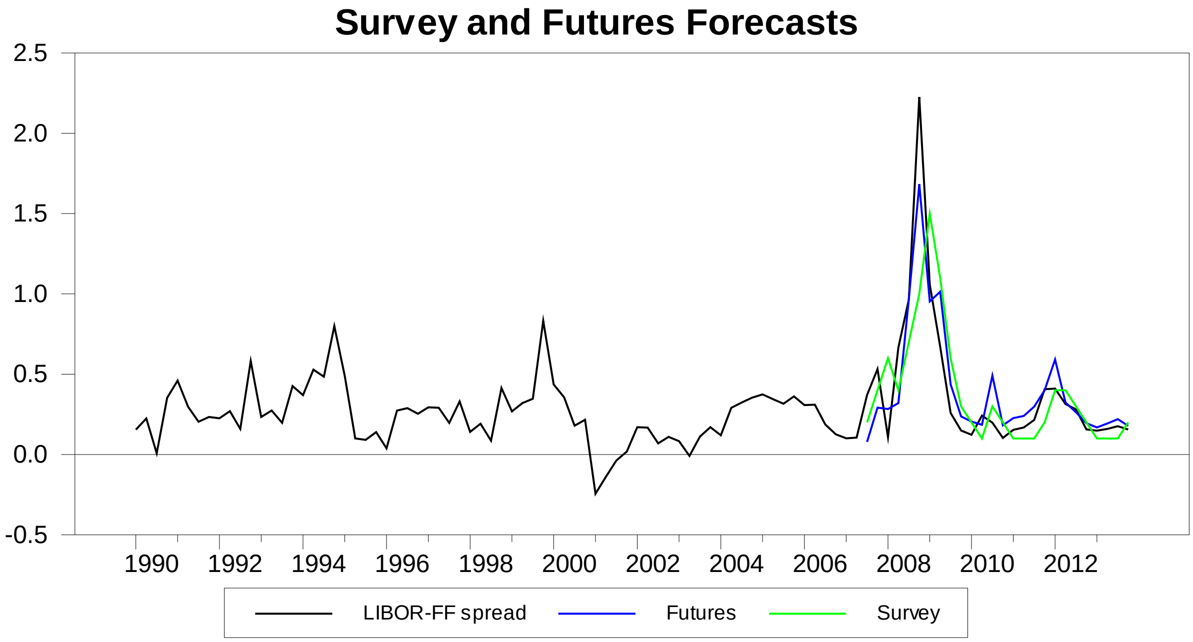

Figure 3: Futures and Blue Chip Financial Forecast survey forecasts of the LIBOR-FF spread over the 2007Q3 to 2014Q4 period.

Table 1
Summary Statistics and Unit Root Tests

Panel A: Interest Rate Spreads					
	Mean	Std. Dev.	AC(1)	ADF	ADF-GLS
LIBOR-FFR	0.28	0.28	0.60	-4.75***	-4.51***
TED	0.52	0.35	0.75	-3.52***	-3.46***
DEF	0.96	0.40	0.84	-3.74***	-3.73***
Panel B: Bond Forward Rates and CP factor					
2nd Forward Rate	4.05	2.29	0.93	-1.45	0.11
3rd Forward Rate	4.55	2.14	0.94	-1.41	0.03
4th Forward Rate	4.99	2.01	0.94	-1.55	-0.22
5th Forward Rate	5.18	1.75	0.93	-1.77	-0.38
CP Factor	1.62	0.85	0.82	-2.57	-2.60***

Panel C: Cross Correlations			
	LIBOR-FFR	TED	DEF
LIBOR-FFR	1.00	0.69	0.57
TED	-	1.00	0.38
DEF	-	-	1.00

Notes: The table reports the means, standard deviations and first-order autocorrelations [AC(1)] of the LIBOR-Federal Funds Rate (LIBOR-FF), Treasury-Eurodollar (TED) and default (DEF) spreads. The CP factor refers to the Cochrane and Piazzesi (2005) factor defined in equation (1).The Augmented Dickey-Fuller (ADF) and the ADF with GLS detrending (ADF-GLS) tests for the null of a unit root are also reported. The lag length for the ADF and ADF-GLS statistics is selected using the BIC. *, **, *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Table 2
In-Sample Fit

Panel A: 1990Q1 to 2007Q2				
	$\bar{R}^2$	AIC	BIC	HQ
ARMA	0.27	-0.82	-0.66	-0.76
Predictive	-0.02	-0.49	-0.39	-0.45
Factor	0.23	-0.76	-0.60	-0.70
VAR	0.27	-0.84	-0.71	-0.79
Panel B: 1990Q1 to 2008Q4				
	$\bar{R}^2$	AIC	BIC	HQ
ARMA	0.38	0.02	0.18	0.09
Predictive	-0.01	0.52	0.61	0.55
Factor	0.06	0.44	0.60	0.50
VAR	0.42	-0.05	0.07	-0.00

Notes: The table provides the in-sample adjusted R^2, the Akaike (AIC), Bayesian (BIC) and Hannan-Quinn (HQ) information criteria. For the VAR model, the in-sample fit statistics refer to the LIBOR-FF spread equation.

Table 3
Forecast Nomenclature

	Forecast Name
ARMA(1,3) model	ARMA
Predictive regression model	Predictive
Factor model	Factor
Vector Autoregressive model	VAR
Futures markets	Futures
BCFF survey consensus	Survey

Notes: The table provides the names assigned to the competing econometric, survey and futures forecasts of the LIBOR-FF spread.

Table 4
Out-of-Sample Forecast Accuracy

Panel A: 2007Q3 to 2013Q4	MAE	RMSE	DM (MAE)	DM (MSE)
ARMA	0.239 (3)	0.416 (3)	1.95**	1.52*
Predictive	0.260 (5)	0.461 (4)	2.14**	1.34*
Factor	0.314 (6)	0.518 (6)	2.64***	1.71***
VAR	0.243 (4)	0.488 (5)	1.52*	1.57*
Futures	0.131 (1)	0.187 (1)	-	-
Survey	0.198 (2)	0.315 (2)	1.94**	1.40*
Panel B: 2009Q1 to 2013Q4				
	MAE	RMSE	DM (MAE)	DM (MSE)
ARMA	0.139 (3)	0.235 (4)	1.07	1.00
Predictive regression	0.154 (5)	0.204 (3)	2.58***	1.71**
Factor model	0.216 (6)	0.319 (5)	2.39***	1.87**
VAR	0.148 (4)	0.397 (6)	0.70	0.99
Futures	0.091 (1)	0.127 (1)	-	-
Survey	0.130 (2)	0.180 (2)	1.62*	1.49*

Notes: The table provides the Mean Absolute Errors (MAE) and the Root Mean Squared Errors (RMSE) of the competing forecasts. The numbers in parentheses are the forecast's rank in terms of the criterion adopted. The modified Diebold and Mariano statistic for mean absolute [DM (MAE)] and mean squared errors [DM (MSE)] are also provided. For the VAR model, the MAE and RMSE statistics refer to the LIBOR-FF spread equation. *, **, *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Table 5
Forecast Encompassing Tests

Panel A: 2007Q3 to 2013Q4			
	β_1	β_2	*F*-statistic
ARMA	1.10***	-0.07	0.29
	(0.17)	(0.09)	0.74
Predictive	1.09***	-0.11	0.26
	(0.18)	(0.21)	0.87
Factor	1.17***	-0.29***	4.95
	(0.10)	(0.09)	0.00
VAR	1.07***	-0.03	0.12
	(0.16)	(0.06)	0.88
Survey	1.17***	-0.15	0.40
	(0.21)	(0.16)	0.66

Panel B: 2009Q1 to 2013Q4			
	β_1	β_2	*F*-statistic
ARMA	0.51***	0.27***	69.00
	(0.06)	(0.04)	0.00
Predictive	0.70***	0.31**	17.25
	(0.06)	(0.15)	0.00
Factor	0.90***	-0.13*	15.90
	(0.10)	(0.08)	0.00
VAR	0.55***	0.18***	86.77
	(0.06)	(0.02)	0.00
Survey	0.47***	0.31**	17.25
	(0.17)	(0.15)	0.00

Notes: The table provides the results from estimating the forecast encompassing regression in equation (8). The first slope coefficient, β_1, is associated with the futures market forecast of the LIBOR-FF spread for all the regressions. The second slope coefficient, β_2, is associated with the forecast listed in the Table. The numbers in parentheses are the Newey and West (1987) Heteroskedasticity and Autocorrelation (HAC) consistent standard errors. The *F*-statistic refers to the null hypothesis $H_0 : \beta_1 = 1, \beta_2 = 0$. The *p*-value is reported underneath the *F*-statistic.

Table 6
Annualized Sharpe Ratios of Trading Strategies

	2007Q3 to 2013Q4	*2009Q1 to 2013Q4*
ARMA	-0.005	0.364
Predictive	-0.011	0.349
Factor	-0.144	0.231
VAR	-0.190	0.130
Survey	0.229	-0.155
Futures	0.527	0.785
Combination	0.076	0.449

Notes: The table provides the annualized Sharpe ratios for the trading strategy described in Section 5.3.

Data Appendix

This data appendix provides a list of the macroeconomic and financial variables used in factor model estimation. The series ID, short name and number are provided. A brief description of the series is also provided. We also list the transformation applied to the series. Δln refers to the change in natural logarithms, *ln* refers to the natural logarithm, *lv* denotes the level, $\Delta^2 ln$ denotes the second change in logarithms. All the data are from the Federal Reserve of St. Louis Economic Database (FRED) unless the source is listed in parentheses. CRB refers to the Commodity Research Bureau and CBOE refers to the Chicago Board Options Exchange.

Group 1: Output and Income

No.	Short Name	Series ID	Trans	Description
1	pi	USPERINCB	Δln	Personal Income
2	ipdcg	IPDCONGD	Δln	Industrial Production: Durable Consumer Goods
3	ipman	IPMANSICN	Δln	Industrial Production: Manufacturing
4	ipmat	IPMAT	Δln	Industrial Production: Materials
5	ipcg	IPCONGD	Δln	Industrial Production: Consumer Goods
6	iputil	IPUTIL	Δln	Industrial Production: Electric and Gas Utilities
7	ipf	IPFUELS	Δln	Industrial Production: Fuels
8	ipdm	IPDMAT	Δln	Industrial Production: Durable Materials
9	ipndm	IPNMAT	Δln	Industrial Production: nondurable Materials
10	ipbe	IPBUSEQ	Δln	Industrial Production: Business Equipment
11	ipncg	IPNCONGD	Δln	Industrial Production: Nondurable Consumer Goods
12	ipfinal	n.a.	Δln	Industrial Production: Final Products (Market Group)
13	ip	INDPRO	Δln	Industrial Production Index
14	rdi	DPIC96	Δln	Real Disposable Personal Income
15	npi	NAPMPI)	lv	ISM Manufacturing: Production Index
16	cu	TCU	Δlv	Capacity Utilization: Total Industry

Group 2: Labor Market

No.	Short Name	Series ID	Trans	Description
17	cemp	CE16OV	Δln	Civilian Employment
18	unemp	UNRATE	Δlv	Civilian Unemployment Rate
19	undur	UEMPMEAN	Δlv	Average (Mean) Duration of Unemployment
20	unemp5	USUNWK5.O	Δln	Unemployed for less than 5 weeks
21	unemp15	USUNWK26O	Δln	Unemployed for 10 to 25 weeks
22	ic	ICSA	Δln	Initial Claims
23	emp	PAYEMS	Δln	All Employees: Total Nonfarm
24	empm	MANEMP	Δln	All Employees: Manufacturing
25	empg	USGOVT	Δln	All Employees: Government
26	empf	USFIRE	Δln	All Employees: Financial Activities
27	empwt	USWTRADE	Δln	All Employees: Wholesale Trade
28	empttu	USTPU	Δln	All Employees: Trade, Transportation & Utilities

29	emprt	USTRADE	Δln	All Employees: Retail Trade
30	empc	USCONS	Δln	All Employees: Construction
31	empmin	USMINE	Δln	All Employees: Mining and Logging
32	empgo	USGOOD	Δln	All Employees: Goods-Producing Industries
33	empnapm	NAPMEI	lv	ISM Manufacturing Employment Index
34	ahe	AHETPI	Δln	Average Hourly Earnings: Total Private
35	aheg	CES0600000008	Δln	Average Hourly Earnings: Goods-Producing
36	ahec	CES2000000008	Δln	Average Hourly Earnings: Construction
37	ahem	CES3000000008	Δln	Average Hourly Earnings: Manufacturing

Group 3: Housing

No.	Short Name	Series ID	Trans	Description
38	hs	HOUST	ln	Housing Starts: Total
39	hsn	HOUSTNE	ln	Housing Starts in Northeast Census Region
40	hsm	HOUSTMW	ln	Housing Starts in Midwest Census Region
41	hss	HOUSTS	ln	Housing Starts in South Census Region
42	hsw	HOUSTW	ln	Housing Starts in West Census Region
43	perm	PERMIT	ln	New Private Housing Units
44	permne	PERMITNE	ln	New Private Housing Units: Northeast
45	permm	PERMITMW	ln	New Private Housing Units: Midwest
46	perms	PERMITS	ln	New Private Housing Units: South
47	permw	n.a.	n.a.	New Private Housing Units: West

Group 4: Consumption, Orders and Inventories

No.	Short Name	Series ID	Trans	Description
48	pmi	NAPM	lv	ISM Manufacturing: PMI Composite Index
49	sdi	NAPMSDI	lv	ISM Manufacturing: Supplier Deliveries
50	noi	NAPMNOI	lv	ISM Manufacturing: New Orders Index
51	inven	NAPMII	lv	ISM Manufacturing: Inventories Index
52	rpce	PCECC96	Δln	Real Personal Consumption Expenditures
53	csent	UMCSENT	Δlv	University of Michigan: Consumer Sentiment

Group 5: Money and Credit

No.	Short Name	Series ID	Trans	Description
54	m1	M1SL	Δ^2ln	M1 Money Stock
55	m2	M2SL	Δ^2ln	M2 Money Stock
56	mb	BASE	Δ^2ln	Louis Adjusted Monetary Base
57	tres	TOTRESNS	Δ^2ln	Total Reserves of Depository Institutions
58	nbr	NONBORRES	Δ^2ln	Reserves Of Depository Institutions, Nonborrowed
59	cc	NONREVSL	Δ^2ln	Total Nonrevolving Credit Outstanding

60	cil	ACILACB	Δ^2ln	Commercial And Industrial Loans, Commercial Banks

Group 6: Bonds, Interest Rate Spreads and Exchange Rates

No.	Short Name	Series ID	Trans	Description
61	tb3m	TB3MS	Δlv	3-Month Treasury Bill: Secondary Market Rate
62	tb6m	TB6MS	Δlv	6-Month Treasury Bill: Secondary Market Rate
63	tb1y	GS1	Δlv	1-Year Treasury Constant Maturity Rate
64	tb5y	GS5	Δlv	5-Year Treasury Constant Maturity Rate
65	tb5y	GS10	Δlv	10-Year Treasury Constant Maturity Rate
66	aaa	AAA	Δlv	Moody's AAA Rated Corporate Bonds
67	baa	BAA	Δlv	Moody's BAA Rated Corporate Bonds
68	saaa	n.a.	lv	AAA-3-month Treasury Bill Spread
69	sbaa	n.a.	lv	BAA-3-month Treasury Bill Spread
70	s10	n.a.	lv	10 year Treasury note-3 month Treasury Bill Spread
71	s1	n.a.	lv	1 year Treasury Note-3 month Treasury Bill Spread
72	s5	n.a.	lv	5 year Treasury note-3 month Treasury Bill Spread
73	s63	n.a.	lv	6 month- 3 month Treasury Bill Spread
74	cpff	n.a.	lv	Corporate Paper Federal Funds Rate Spread
75	ted	TED	lv	Treasury-Eurodollar Spread
76	eruk	EXUSUK	Δln	U.S. / U.K. Foreign Exchange Rate
77	erjap	EXJPUS	Δln	Japan / U.S. Foreign Exchange Rate
78	ercad	EXCAUS	Δln	Canada / U.S. Foreign Exchange Rate
79	erchf	EXSZUS	Δln	Switzerland / U.S. Foreign Exchange Rate

Group 7: Prices

No.	Short Name	Series ID	Trans	Description
80	ppifg	PPIFGS	Δ^2ln	Producer Price Index: Finished Goods
81	ppicg	PPIFCG	Δ^2ln	Producer Price Index: Finished Consumer Goods
82	ppiim	PPIITM	Δ^2ln	Producer Price Index: Intermediate Materials
83	ppicm	PPICRM	Δ^2ln	Producer Price Index: Crude Materials
84	ppinf	PPICMM	Δ^2ln	Producer Price Index: Primary nonferrous metals
85	napmpi	NAPMPRI	lv	ISM Manufacturing: Prices Index
86	cpi	CPIAUCSL	Δ^2ln	Consumer Price Index: All Items
87	cpia	CPIAPPSL	Δ^2ln	Consumer Price Index: Apparel
88	cpit	CPITRNSL	Δ^2ln	Consumer Price Index: Transportation
89	cpim	CPIMEDSL	Δ^2ln	Consumer Price Index: Medical
90	cpid	CUSR0000SAD	Δ^2ln	Consumer Price Index: Durables
91	cpis	CUSR0000SAS	Δ^2ln	Consumer Price Index: Services
92	cpils	CUSR0000SA0L2	Δ^2ln	Consumer Price Index: All Items Less shelter
93	cpilm	CUSR0000SA0L5	Δ^2ln	Consumer Price Index: All Items Less Medical Care

94	cpilf	CPIULFSL	Δ^2ln	Consumer Price Index: All Items Less Food
95	pce	PCECTPI	Δ^2ln	Personal Consumption Expenditures
96	pced	PCDG	Δ^2ln	Personal Consumption Exp.: Durable Goods
97	pcend	PCND	Δ^2ln	Personal Consumption Exp.: Nondurable Goods
98	pces	PCES	Δ^2ln	Personal Consumption Exp.: Services

Group 8: Stock Market

No.	Short Name	Series ID	Trans	Description
99	sp	S&PCOMP	Δln	S&P 500 Composite Index (Datastream)
100	dy	USSPDIVY	Δlv	S&P 500 Index: Dividend Yield (Datastream)
101	pe	USSPRPER	Δln	S&P 500 Index: Price to Earnings Ratio (Datastream)
102	vix	VIX	Δlv	S&P Option-Implied Volatility Index (CBOE)

Group 9: Futures

No.	Short Name	Series ID	Trans	Description
103	fff0	FF0	Δlv	Spot Federal Funds Futures Rate (CRB)
104	fff1	FF1	Δlv	First Federal Funds Futures Rate (CRB)
105	fff2	FF2	Δlv	Second Federal Funds Futures Rate (CRB)
106	ed1	ED1	Δlv	First Eurodollar Futures Rate (CRB)
107	ed2	ED2	Δlv	Second Eurodollar Futures Rate (CRB)
108	ed3	ED3	Δlv	Third Eurodollar Futures Rate (CRB)
109	ed4	ED4	Δlv	Fourth Eurodollar Futures Rate (CRB)