EFFICIENCY OF THE 1 MONTH LIBOR FUTURES MARKET IN LIGHT OF THE RECENT LIBOR SETTING SCANDAL

by

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AN ABSTRACT OF THE PROJECT OF

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Title: Efficiency of the 1-Month LIBOR Futures Market in Light of the Recent LIBOR Setting Scandal

This paper examines the relationship between spot and future prices for the 1 month LIBOR market in light of the recent LIBOR setting scandal. In particular, we examine whether 1 month LIBOR futures are (1) an unbiased predictor of future LIBOR spot rates and (2) the predictive ability of LIBOR futures in forecasting future spot rates.

Despite the manipulations by prime banks, the 1 month LIBOR futures settlement price closely follows the 1 month LIBOR spot rate. In addition, there is strong statistical evidence that the 1 month LIBOR futures contracts are unbiased predictors of future sport rates.

However, the ability of the model to predict future LIBOR spot rates appears to be weak. In part, this failure of 1 month LIBOR futures to predict future spot rates is attributed to the existence of periods of instability or shocks in the financial system. After accounting for such phenomena, the ability of LIBOR futures to predict LIBOR spot rates is greatly enhanced.

This leads us to be cautiously optimistic that 1 month LIBOR future could prove to be a useful tool in many financial contexts such as helping the Federal Reserve achieve its target interest rate in the market on hand, and from a regulatory perspective where regulators could rely on the model to spot manipulations in the market on the other hand.
C. Results and Discussions

V. CONCLUSION

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CHAPTER I

HISTORICAL PERSPECTIVE

Derivatives are financial instruments whose value depends on another underlying asset. This type of instruments started to gain popularity at beginning of the 1980’s with many banks in today’s major financial centers, especially London, actively trading in them. Despite their apparent attractiveness, parties involved in such type of transactions often failed to agree on the underlying rate governing the respective contracts. Rates were based on negotiations and simple averaging of random samples submitted by a panel of banks. As a result, financial institutions and investors approached the British Bankers Association (BBA) in order to bring uniformity and come up with a reference rate that could be used for trading in these instruments. This would allow for a more efficient functioning of the derivatives market and provide better transparency and objectivity.

In late 1984 the BBA efforts along with the help of various parties, namely the Bank of England, culminated in the establishment of the BBAIRS standard (the BBA standard for Interest Swap Rates) (BBA Libor). Within this standard was the setting of the “BBA Interest settlement Rates” which became common market practice starting September 1985 and can be considered as the antecedent of what is known today as the LIBOR or BBALIBOR. Starting January 1986, the rates set under the BBAIRS officially led to the first LIBOR rates that were primarily issued for 3 currencies: US Dollar, Japanese Yen, and Sterling. Today, LIBOR rates are issued for 10 currencies with maturities up to 15 months (BBA Libor).
Up until 1998, the fundamental question underlying the LIBOR setting process which banks had to answer when submitting their quotes was “At what rate do you think interbank term deposits will be offered by one prime bank to another prime bank for a reasonable market size today at 11am”. However, this question suffered from 2 main flaws which standard setters, financial institutions, and investors deemed critical enough to cause a re-design in the process. First, with financial institutions becoming more complex with time, it was hard to provide a universal definition of what constitutes a prime bank. Second, submissions were based on assumptions and expectations rather than actual transactions. As a result, the question has been changed to “At what rate could you borrow funds, where you to do so by asking for and then accepting interbank offers in a reasonable market size just prior to 11am”. This question has been used ever since and is valid up until today (BBA Libor).
CHAPTER II

LIBOR

A. Definition

LIBOR is an abbreviation of London Interbank Offered Rate. In practical terms, this rate reflects the interest rate at which banks are willing to lend money to other large financial institutions, namely banks (Hull, 2012). It is a daily rate produced by the BBA and quoted in all major currencies for different maturities up to 12 months: for example the 1 month LIBOR is the rate at which banks are willing to lend money for the specified period, which in this case is 1 month. It should be noted that as a convention, LIBOR rates for all maturities are quoted as annual interest rates with daily compounding, therefore if the 1 month LIBOR rate turns out to be 3% this actually means that banks will charge \( \frac{3}{365} = 0.008\% \) for an overnight loan. In order to be able to borrow at LIBOR, a bank must have a credit rating of AA and above. In other words, the bank must be considered creditworthy to benefit from this rate.

As stated in the previous section, banks base their submissions on the following question “At what rate could you borrow funds, where you to do so by asking for and then accepting interbank offers in a reasonable market size just prior to 11am”. This implies that submissions should be based on actual transaction rather than assumptions and expectations. However, banks are not active on a daily basis in all types of currencies for various maturities, which make it nearly impossible to construct a LIBOR term structure based only on current transactions. As a result, for practicality, banks use available information as a proxy to predict LIBOR rates for all currencies and maturities.
under the assumptions that large institutions are fully aware of the credit and liquidity risk in various markets based on current and historical transactions allowing them to accurately predict rates in the markets in which they are not active (BBA Libor).

A rate that is commonly confused with the LIBOR is the LIBID (London Interbank Bid Rate). For simplicity, the LIBID can be thought of as the opposite of LIBOR. In other words it is “the rate at which banks will accept deposits from other banks” (Hull, 2012). One can think of the LIBOR as the “sell” or “ask” rate and the LIBID as the “buy” or “bid” rate. Therefore it makes sense to have a small spread between the two rates with the LIBOR being consistently higher than the LIBID (Hull, 2012). Significant market size and active trading implies that those rates are set in a way that clears the interbank market (market equilibrium, supply equals demand). If more banks demand a currency that what is being supplied, then the LIBOR and LIBID rates for the respective currency and maturity will increase, and vice versa. This market is referred as the interbank market and is beyond the control of any single entity or institution.

B. LIBOR Calculations

LIBOR calculations are performed on a daily basis by Thomson Reuters, the designated agent by the BBA (BBA Libor). Each day banks submits their quotes to the agency and Thomson Reuter is responsible for producing the unified rate according to the guidelines agreed upon with the “LIBOR Panel Banks and Users Group”.

Once a bank has been granted the approval to be a contributor, Thomson Reuters installs an application allowing the bank to submit its own daily rate before 11 am. During the submission process banks cannot see each other rates, and this is made
possible only after the final release of the final rate. The application links the bank directly to Thomson Reuters’ rate setting division. Once all rates are collected, a set of tests are performed on the data before sending it to the calculation engine in order to eliminate outliers and check any inconsistent submission. Once done, the remaining data is averaged using an arithmetic mean and the result submitted via Thomson Reuters and other licensed vendors. Everyday 150 LIBOR rates are published for various currencies and maturities. A summary of the LIBOR calculation process is provided below:

Figure 1. LIBOR Calculation Process
C. Scope

In short, LIBOR is the short term cost of borrowing for financial institutions (Hull, 2012). Prime banks can borrow and lend money in the interbank market at LIBOR; therefore it represents the short term cost of capital for those institutions. Traditionally banks have used the risk free rate in the valuation of derivatives, however this is no longer the case as dealers and investors have noticed that there are many issues that cause the interest rate implied by the treasury bills to be very low. As a result, they have used LIBOR rates as a proxy of the risk free rate, noting the LIBOR rates are not completely risk free as there is a very small probability that a bank will default (Hull, 2012). Despite this distinction, LIBOR rates and risk free rate are very close during normal market conditions. It should be noted that after the 2007 financial crisis, traders have switched to overnight index swap (OIS) in the valuation of derivative as banks became very reluctant to lend each other leading to soaring LIBOR rates.

It follows from the above that LIBOR rates are a measure of stress or risk in financial markets as in turbulent times LIBOR rates rise to reflect the increased level of risk. In addition, this reflects sophisticated investors’ expectations about the future level
of banks’ interest rates, at least in the short term given that LIBOR rate maturities extend to 12 months.

Last but not least, LIBOR is used in a variety of commercial products such as college loans, mortgages, and certificates of deposits, in addition to hybrid products that capture the characteristics of both financial and commercial instruments (Chan, 2011). As a matter of fact, in 2008 approximately all subprime mortgages and 60% of adjustable rate mortgages in the US were calculated using the LIBOR (Dylan, 2012). Similar example can be found around the world, namely in Europe.

D. The Scandal

As of June 2012 financial institutions have been bombarded with rumors and reports suggesting that contributor banks have been manipulating their respective LIBOR submissions to their own benefit in addition to reducing strain in the market during the 2007 financial crisis. This has triggered a worldwide investigation by financial authorities, Commodity Futures Trading Commission (CFTC), and the Department of Justice to check whether the interbank market was really being manipulated.

By end of June significant evidence has been found which shows that prime banks and financial institutions have colluded and consistently submitted lower LIBOR rates either for personal or gain or as a response to the collapse of the interbank market during the subprime crisis (Kregel, 2012). In the midst of the financial crisis, banks were worried about the financial situation of other counterpart banks and for this reason have stopped lending money to each other. Barclays was the first bank to reflect this situation by submitting higher LIBOR rates which triggered the attention of the Bank of
England. Worried about the health of the overall financial system, officials at the Bank of England convinced Barclays’ official to submit lower rates sending therefore false signals to the financial markets. A snapshot of the process is presented in figure 3 which compares the LIBOR rate to the rate submitted by Barclays at various stages of the 2007 financial crisis. As result, Barclays Bank has been fined approximately 450 million USD and several other banks, namely Bank of America and UBS, are facing similar charges. However, the main question relies whether it is enough to fine banks for fraud or is there a deeper problem that regulators and central banks are not able to identify. In response to the increasing chaos, the BBA issued a statement insisting that the LIBOR continues to be a reliable rate during crisis. However, is it really the case? Is the LIBOR market efficient? Even if it was, does it apply during financial crisis? Can regulators and central bank use the efficiency model to predict fraud in this specific market?

Figure 3 Barclays LIBOR Submissions During the 2007 Financial Crisis
The scale of transactions related to LIBOR was estimated at around 350 trillion USD worth of derivatives contracts making a 1 basis point change significant enough to require the attention of the media and the financial news (The Economist, 2012). It was estimated that manipulations had cost the US alone around 6 billion USD in interest payments and 4 billion USD to close open positions in LIBOR related financial instruments.
A. Market Efficiency in Finance

Market efficiency is at the heart of finance. In its simplest terms, market efficiency implies that any new information is directly reflected in asset prices. This is not to be confused with operational efficiency where the latter describes the way resources are allocated to facilitate the operations of financial markets (Dimson & Mussavian, 2000) as opposed to informational efficiency, the subject of interest in this paper.

The concept of market efficiency emerged at first at the beginning of the twentieth century in a paper submitted by Bachelier (1900), as a part of his PhD project at the Sorbonne University. Bachelier states “past, present and even discounted future events are reflected in market price, but often show no apparent relation to price changes”. This discovery is a revolution in the world of finance but has not been taken seriously at that time until the second half of the century when Paul Samuelson took Bachelier’s work in the late 1950s and started discussing it with leading academics and economist of that period. The first academic work relating to market efficiency was made public by Cootner in 1964. However, previously, all research relating to the topic was based on observations and empirical evidence, and was not grounded in theory. Bachelier has observed that commodity prices follow a random walk and subsequent research by Working (1934) and Cowles and Jones (1937) looked into the topic further by extending the line of observations to US stock prices as well as other times series
over a longer time horizon only to validate Bachelier’s former hypothesis. However, all studies were limited to empirical evidence supporting the idea of market efficiency but none was able to formalize it into theory. In 1933, Cowles conducted several studies in hope of finding a pattern allowing him to predict market changes based on past information but with no success.

Before the 1950, economists presumed that time series could be decomposed into a long term trend that could be used to predict future observations on one hand, and short term fluctuations that could be analyzed for random fluctuations (Kendal, 1953). However, later research by Kendall (1953), Roberts (1959), and Fama (1965) came to prove the opposite. Kendall wrote: “in series of prices which are observed at fairly close intervals the random changes from one term to the next are so large as to swamp any systematic effect which may be present. The data behave almost like wandering series”. Roberts (1959) adds “the main reason for this paper is to call to the attention of financial analysts’ empirical results that seem to have been ignored in the past, for whatever reason, and to point out some methodological implications of these results for the study of securities”. This was a major turn point in finance especially for technical analysts who believed that trading strategies could be derived by merely looking into past data and identifying trends that would help them predict future observations. This hypothesis was termed in the finance literature as the “random walk model” or “random walk theory” and became a major cornerstone in the study of market efficiency. The random walk theory stipulates that the best guess of any future observation in a time series is today’s observation. This is similar to Person’s (1905) study aiming to come up with a procedure helping to find a drunk left in a park. According to the study, and since the drunk person is expected to wander in any direction with no particular trend or
specific behavior, he is more likely to end up at the point where he was initially left than any other place. The same concept applies to financial time series. However, economists did not rule out the possibility of certain exceptions to the random walk model under certain market conditions.

Market efficiency implies that no one trader can beat the market and achieve abnormal returns. In this regard, the random walk model discussed earlier turns out to be consistent with the definition of market efficiency. Samuelson (1965) wrote “in competitive markets there is a buyer for every seller. If one could be sure that a price would rise, it would have already risen”. He adds “we would expect people in the market place, in pursuit of avid and intelligent self-interest, to take account of those elements of future events that in a probability sense may be discerned to be casting their shadows before them”.

Although several studies suggested that some investment strategies (i.e. contrarian strategies and momentum strategies) did provide, on average, higher returns than other strategies, one cannot conclude that it is possible to beat the market by trading on the basis of a technical analysis. The reason for this is that empirical researchers do not know the true model generating expected returns in the economy. Hence, their choice of expected return-generating mechanism, used to adjust actual returns, may be wrong, which implies that abnormal returns may be incorrectly measured. It is those abnormal returns that are used that are used in tests of market efficiency. Therefore, we are left in a position where we are not sure whether markets are inefficient or the model of expected returns is wrong. This known as the joint hypothesis problem associated with testing market efficiency (Fama E., Efficient Capital Markets: A review of theory and empirical work, 1970). The null hypothesis of
any test of efficiency is comprised of two components: informational efficiency and the accuracy of one’s model for expected return. As the true model of expected returns is unknown, a rejection of this null hypothesis cannot be immediately taken as evidence that markets are not efficient.

The finance literature distinguishes between three types of market efficiency: the weak form, the semi-strong form, and the strong form. According to Fama (1991) markets are efficient in the weak form if it is not possible to make abnormal profit by trading solely on the basis of past information. Semi-strong form of market efficiency implies that asset prices fully incorporate all publically available information, whereas strong form take the issue further by assuming that even insider information is reflected in the price. Studies in favor of the weak and semi-strong form are abundant, and evidence proving the opposite is scarce (Fama E., Efficient Capital Markets: A review of theory and empirical work, 1970). On the other hand, several studies have argued that trading on the basis of insider information can lead to economic profit, violating thus the strong form market hypothesis. However, Jensen (1968) has demonstrated that profit made based on privileged information is only valid when transaction costs are not considered. Any abnormal return is wiped out by managers’ fees and expenses. In summary, although there is ample evidence in the finance literature in support of market efficiency, there are always some exceptions. This does not imply that markets are not efficient as any equilibrium model should leave some incentive for professionals in the industry (Grossman & Stiglitz, 1980).
B. Forward or Futures Market Efficiency

Now that we have defined market efficiency in general, we turn to review market efficiency for the futures or forward market in specific. The logic is same, futures’ market is deemed efficient if there are no arbitrage opportunities that would allow traders speculating in the futures or forward market on the expected price of the underlying to earn more than average return in the market (Lai & Lai, 1991). Tests for futures market efficiency are mainly based on the following regression equation:

\[ S_{t+1} = a + bF_{t, t+1} + e_{t+1} \]

Where \( S_{t+1} \) the price of the underlying at time \( t+1 \), \( F(t) \) the price of the future or forward contract with maturity \( t+1 \), \( e_{t+1} \) representing the error term at time \( t+1 \) with an average mean of zero, and \( a \) and \( b \) the usual regression coefficients. Under such test, if markets are efficient, we should have \( a=0 \) and \( b=1 \). Both conditions must be satisfied simultaneously to conclude that markets are efficient and this is a direct implication of the joint hypothesis testing problem for market efficiency we discussed earlier. An important assumption is that investors are rational and there is no risk premium for entering into a forward or future contract for the time period under consideration. This has been termed as the “simple efficiency” (Hansen & Hodrick, 1980) or the “speculative efficiency” (Bilson, 1981) hypothesis.

However, such a model is too simplistic or superficial and one cannot merely rely on the results obtained to draw conclusions. Testing for market efficiency involves many technical issues that must be considered before performing the hypothesis testing. Hypothesis testing is based on the assumption that time series on which the test is performed are stationary; however, financial time series are usually not (Elam & Dixon,
1988). The result is that the F-test under such circumstances is not reliable and there is a high probability of rejecting the null hypothesis when it is actually true. As a result, economists have used the cointegration technique developed by Engle and Granger (1987) to test for market efficiency (Shen & Wang, 1990). The rationale behind this technique implies that if futures or forward markets are efficient then $F(t)$ should be an unbiased predictor of $S(t+1)$, meaning that it can accurately predict future price of $S(t)$ with no statistical bias. If $F(t)$ and $S(t+1)$, turn out to be non-stationary (not cointegrated), then they tend to deviate apart in the short run and the long run and the average of the difference is not constant on average. This is a clear violation of the market efficiency principle and $F(t)$ has no predictive power of future prices. As attractive as it seems, this method has its shortcomings; it is not enough to prove that $F(t)$ and $S(t+1)$ are cointegrated to conclude that the market is efficient. Market efficiency imposes another restriction on the regression parameters that $a=0$ and $b=1$ (Lai & Lai, 1991). The cointegration technique suggested by Shen and Wand does not allow performing tests on the regression parameters since they do not follow any specific distribution which prohibits the possibility of performing hypothesis testing. As a result, the Johansen approach (1988, 1990) is a better suited cointegration technique to test for market efficiency since it allows drawing inferences on the regression parameters using the chi-square distribution (Lai & Lai, 1991).

Up until now we have used the term forward and futures interchangeably knowing that both differ in certain ways. Forwards are over the counter instrument that are traded mainly in the interbank market with a fixed maturity time ranging from 1 months up to 12 months, whereas futures are exchange traded with fixed maturity date. This delivery date feature of futures contracts greatly reduces sample size which would
impact tests results. Furthermore, economists believe that even if two identical contracts, a future and a forward, were to mature at the same day, their price might differ. However, studies have shown that in practice it turns out to be very little difference between the two (Lai & Lai, 1991). For the remaining of the study we will be using both terms interchangeably and we will assume that any results drawn would apply to both markets.

Researchers have also found another technique to account for the problem of random walk exhibited by futures and spot prices. To do so, academics have traditionally used the log of the change in the spot rate (the first difference) and the log of the forward discount (Engel, 1996). As a result, the regression equation used to test for market efficiency is:

\[ S_{t+1} - S_t = \alpha + b(F_t - S_t) + \varepsilon_{t+1} \]

Where \( S(t+1) \) represents this time the log of the price of the underlying at time \( t+1 \), \( F(t) \) the log of the price of the future or forward contract with maturity \( t+1 \), \( \varepsilon_{t+1} \) representing the error term at time \( t+1 \) with an average mean of zero, and \( a \) and \( b \) the usual regression coefficients. If \( a = 0 \) and \( b = 1 \) then we can imply that forward prices are unbiased predictors of future spot prices. If we consider investors to be rational then we should expect them to drive \( F(t) \) to be equal to \( E(t)(S(t+1)) \) where the latter represents the expected spot price at time \( t+1 \) conditional on available information at time \( t \). This is consistent with the risk neutrality assumption (Engel, 1996).

Plenty of studies have tested the efficiency of the futures market and they came up with contradicting results. Some have considered futures to be an unbiased predictor of future spot prices and others have rejected the hypothesis of market efficiency and provided explanations justifying the bias. In the following section we will review
studies related to three distinct types of futures market: Forward exchange rate, Commodity Futures, and VIX Futures.

Starting with the forward exchange market, in 1987 Robert Hodrick wrote “We do not yet have a model of expected returns that fits the data”. He noticed that forward rates are biased predictors of future exchange rate. Since Hodrick’s publication, many researchers have explored the issue and tried to provide explanations. The majority of the tests’ results have pointed toward a negative estimate of the b coefficient in the regression and that the results are statistically significant. Backus et al. (1993) found that b is negative and less than one for one month forward rates contracts for major currencies. Mark et al. (1993), Froot and Frankel (1989), Baillie (1989), and Bekaert (1992) have collectively confirmed this finding using various methods. McCallum (1994) went further to provide a specific value of b which he states is equal to -4. This large conditional bias has led researchers to search for possible explanations that would help understand this discrepancy and to find any trading strategies that could yield above average returns, if any. Advances in this topic have led academics to justify the observed discrepancy by allowing for information asymmetry (peso-problem), learning, transaction costs and irrational investors whose expectations lead to biased future rates. Engel goes further to include risk premium in the range of justifications. However, he concludes that the observed value of b is too large to be explained in conventional models of risk premium. Gospodinov (2009) goes further in explaining the contradicting results between the basic regression of futures market efficiency and differenced forward rate premium exchange rate regressions. He states that both could yield different results given that the differenced forward premium \([F(t) - S(t)]\) and the differenced spot rate \([S(t+1) – S(t)]\) follow a different statistical distribution than that of
F(t) and S(t). As a result, both series do not move together in the long run (not cointegrated) thus leading to negative coefficients of the slope parameters and falsely rejecting the market efficiency hypothesis. Having said this, the large negative values of b documented in the forward exchange rate market efficiency literature cannot be due solely to presence of a risk premium for entering in a future contract but rather a combination of risk premium and missing explanatory variables in the differenced regression that is leading to the observed results (Gospodinov, 2009). Fama (1984) provides similar conclusions however he goes further and expands the model to other financial and commodity market data. In specific, as opposed to the forward exchange rate market, in the case of the forward and spot interest rate on US Treasury Bills the variation does not occur solely in the premium component. The difference between the one month future interest rate and the current spot rate [F(t) –S(t)], is equally divided between the variation in the basis or premium component and the variation in the expected change in the future interest rate. In this specific case it is found that variation in [F(t) –S(t)] approximately 15% to 70% of the variation in the ex-post [S(t+1) – S(t)] (Fama E. F., 1984). This is clearly in contradiction with the future exchange rate market where it has been found that [F(t) –S(t)] has little predictive power with regard to [S(t+1) – S(t)] and that variations in the forward premium are too small compared to variations in the predicted change in the exchange rate.

The interdependency between commodities’ prices and general macroeconomic conditions has spurred interest into expected commodity prices, or commodity futures. Economists have been trying to check whether commodity futures can be used as a signal to predict economic downturn in light of the recent critics by Ben Bernanke during the financial crisis stating that commodity futures have shown
poor track record in predicting the downturn in the economy. He wrote: “Policymakers and other analysts have often relied on quotes from commodity futures markets to derive forecasts of the prices of key commodities… The poor recent record of commodity futures markets in forecasting the course of prices raises the question of whether policy makers should continue to use this source of information and, if so, how.” Chinn and Coibion (2010) argue that it is the depth of the market which increases the efficiency of the market. In other words, the more active is the market (higher trading volume), the more confident we are that the respective commodity futures markets are unbiased predictor of future commodity prices. Empirical evidence relating to energy futures, the most active commodity futures market, points that throughout time it has been consistently difficult to reject the hypothesis of market efficiency. This has not been the case for other types of commodities where studies have shown contradicting results. However, it seems that there has been an increase in market efficiency over time across commodity types. Tests have proven that over the last five years futures prices has been a better predictor of commodity prices than any other empirical model, which is in accordance with the efficient market hypothesis (absence of arbitrage opportunities) (Chinn & Coibon, 2010).

Last but not least, several studies have documented a predictable pattern in futures prices for certain markets (stocks, currency, interest rates) which led to the rejection of the null hypothesis that these markets are informationally efficient. However, none provided a trading strategy that would provide abnormal returns when transaction costs have been taken into consideration (Engel, 1996). Furthermore, Konstantinidi and Skiadopoulos (2010) looked specifically into the VIX volatility futures given their growing use in hedging, and tried to come up with a trading strategy
that would help investors to come up with successful hedging schemes but with no success. It turns out that even if evidence of predictable pattern in futures prices can be found, academics and practitioners are not able to rip off the benefits of such observed inefficiency. Therefore, up until today, no one can assert that futures markets are inefficient.

This paper focuses on the LIBOR futures and for the first time tackles the issue of whether LIBOR futures market is efficient. Neely and Winters (2006) have previously examined the market for one-month LIBOR Futures contract and options on those futures for a year-end price effect given the observed end-of-year rate increase in the LIBOR spot rate. They wanted to identify whether the end-of-year rate increase is reflected in the respective derivative securities allowing investor to effectively hedge against interest rate risk. Caution should be taken when talking about year-end effect as opposed to turn-of-the-year effect observed in the stock market. In the stock market researchers have found that stocks exhibit abnormal returns in the first week of January following the December sale as opposed to the interest rate market where short term rates increase through the month of December before starting to decline at the turn-of-the-year (Keim, 1983). The end-of-year rise in interest rate has been linked to a preferred habitat for liquidity theory (Griffiths & Winters, 1995). In other words, investors looking to meet their short term cash obligations near year end, tend to close their long positions by the end of November which raises short term interest rates. It has been found that this rate increase is reflected in November LIBOR one-month futures contracts, however this does not imply that the LIBOR futures market is an unbiased predictor of future spot rate. Actually LIBOR futures are found to be a slightly biased predictor with this bias being statistically insignificant and most probably due to
measurement error and/or seasonal factors (Neely & Winters, 2006). The literature on
the topic is scarce and no clear cut evidence is provided as to whether LIBOR futures
market is efficient or not.

The LIBOR futures are of high importance given the large scale of derivative
contracts related to the LIBOR and the recent LIBOR fixing scandal. This paper
examines the relationship between spot and future prices for the 1 month LIBOR market
in light of the recent LIBOR setting scandal. In particular, we examine whether 1 month
LIBOR futures are (1) an unbiased predictor of future LIBOR spot rates and (2) the
predictive ability of LIBOR futures in forecasting future spot rates. Consequently, the
aim is to try and find trading strategies that would yield abnormal returns if markets
turned out to be inefficient, or check whether the developed model could be used by
regulators as tool that would help detect manipulations in the market in the opposite
case.

C. The Law of One Price

Modern finance revolves around the fundamental theory of no arbitrage
opportunity. In fact, all pricing of derivative securities is based on this notion. In its
simplest terms, no arbitrage opportunity implies that any two financial instruments with
the exact same future cash flows should have the same price. If not, then arbitrageurs
could buy the undervalued instrument, sell the replicating overvalued instrument, and
ensure a riskless profit. In finance the idea of a “free lunch” is rejected based on the fact
that forces of supply and demand will eliminate arbitrage opportunities as they arise and
there exist no strategy that would yield abnormal return at no risk. However, market
forces and irregularities (liquidity, inventory problems, financial crisis…etc) may force
derivative prices to deviate from their respective arbitrage values but only for a small period of time. This topic is well documented in the finance literature with scholars recognizing that long term deviations of futures prices relative to the price of the underlying asset (basis) triggers the attention of arbitrageurs who in turn will eliminate any discrepancy between the two prices. However, in extreme conditions, it might take some time for traders to effectively eliminate the gap (Roll, Schwartz, & Subrahmanyam, 2007)

Let \( F(t) \) represents the LIBOR future contract settlement price at time \( t \) and \( S(t) \) the respective spot rate at the date of expiration of the contract. The basis throughout this paper is defined as:

\[
(F_t - S_t)
\]

At the expiration of the contract the basis should theoretically be equal to zero. However, as any other time series, \([F(t) - S(t)]\) exhibits variation through time (Brennan & Schwartz, 1990). The law of one price states that \( F(t) \) should track changes in the interest rate market \( S(t) \) and that both should be equal at maturity of the LIBOR future contract to avoid any arbitrage opportunity. The LIBOR Future contract is a contract on a one month 3$ million Eurodollar time deposit with a settlement price of \((100 - \text{rate})\), where rate is the interbank rate known as the BBA LIBOR. It is possible for an institution willing to secure a lower rate on a time deposit to replicate it through the issuance of shorter term time deposit and simultaneously selling LIBOR futures with the same expiration date (Chance, 1998). This creates an arbitrage opportunity that will force the basis to be equal to zero. Therefore we would expect LIBOR futures to track market spot rates in the interest rate market.
To test the validity of this assumption, we need to check whether the 1 month LIBOR futures contract prices follow changes in the LIBOR market. We collect 1 month LIBOR Futures settlement price and the respective spot rate at expiration of the contract from May 1990 till February 2010. Contracts are cash settled on the second London business day immediately preceding the third Wednesday of the contract month. Figure 5 shows the graph depicting $F(t)$, $S(t)$, and $[F(t) - S(t)]$

![Graph showing 1 Month LIBOR Futures Settlement Price and the Respective Spot Rate at Expiration of the Contract (May 1990 – February 2010)](image)

The LIBOR futures contract settlement price seems to follow the respective spot rate in the LIBOR market. With 235 observations ($n = 235$) the data is representative enough to draw conclusions. Furthermore the LIBOR futures settlement price and the LIBOR spot rate have shown significant fluctuations for the time period under consideration, therefore inferences drawn from the graph above are not due to simple coincidence. First, we notice that new information in the spot market is immediately reflected in the LIBOR futures market as any increase/decrease in the
interest rate is closely followed by an increase/decrease in the LIBOR futures settlement price as reflected by the blue and red lines respectively. This translates into a solid case for basis convergence as the difference between $F(t)$ and $S(t)$ (Green line) is equal to zero on average. However, at some points we notice a deviation of the futures settlement price from the LIBOR spot rate at the expiration day, mainly in the early 1990, 2000, and during the 2007 financial crisis. Second, deviations of the futures settlement price from the underlying spot rate can be matched to periods of instability or shocks in the financial system. As a matter of fact, in the early 1990 the world has experienced an oil shock along with the gulf war which had a big impact on the worldwide interest rate market. In the year 2000 there has been serious liquidity problems, and last the 2007 financial crisis that nearly led to the collapse of the whole financial system. The effect of liquidity on asset prices and interest rates is well documented in the finance literature. Scholars argue that liquidity or illiquidity is the main reason driving the basis to be different than zero. The reason being that arbitrageurs may find it difficult under such circumstances to eliminate imbalances in the system and take advantage of arbitrage opportunities in the same way they do when markets are stable (Roll, Schwartz, & Subrahmanyam, 2007). As a result, shocks in the financial system can drive LIBOR futures settlement price to deviate from the underlying the spot rate causing the basis to deviate from zero. Furthermore, it can be argued that in the early 1990, the market for LIBOR futures was not well developed and economists did not have an accurate model for predicting future interest rates which might have had a direct effect on the basis. Third, the decrease in the LIBOR rate observed at the end of the year 2007 is consistent with the fact that the Bank of England incited prime banks to consistently submit rates that were lower that than their actual
estimated in order to send signal of increased confidence in the financial system and reject claims that banks were facing trouble as a result of the recent turmoil.

Interestingly, despite the fact that the lower rate effect exhibited by the LIBOR can be considered as private or insider information, the LIBOR futures settlement price exhibited the same behavior as the LIBOR rate. Therefore, even in periods of irregularities, we expect any new information relating to LIBOR submissions to pass through to the LIBOR futures contract. This noticeable by looking at figure 6 below depicting F(t), S(t), and [F(t) –S(t)] during the 2007 financial crisis:

![Figure 6. 1 Month LIBOR Futures Settlement Price and the Respective Spot Rate at Expiration of the Contract During the 2007 Financial Crisis](image)

In summary, the 1 month LIBOR futures settlement price closely follows the 1 month LIBOR spot rate. What happens if the LIBOR futures market fails to reflect new information such as the 2007 LIBOR submissions scandal? Institutional Investors and banks could take advantage of an arbitrage opportunity by entering into a 1 month LIBOR futures contract. If the rate implied by the futures is higher than the actual
LIBOR rate implied by submissions of prime banks, then one can borrow in the spot market and lend (long position) through the LIBOR futures contract. By doing this banks can secure a risk free interest rate differential and ensure a riskless profit. Such behavior will force 1 month LIBOR futures settlement prices to imply the same interest rate as observed in the spot market at maturity of the future contract. Having said this, we should note that several factors might prohibit $F(t)$ and $S(t)$ from being equal on settlement day. First it is hard to find a forward contract that exactly matches the time period in the futures contract; second, futures contracts are daily settled; third, measurement errors; last, market imbalances and liquidity shocks.
CHAPTER IV
DATA ANALYSIS

This part discusses analyzes the data pertaining to the 1 month LIBOR futures contract. First we provide a definition and a description of the LIBOR futures contract, the data to be used in the analysis of the market, and the methodology followed to test for market efficiency. Then, we use statistical tests to determine whether the 1 month LIBOR futures contracts are unbiased predictors of future sport rates. We conclude with a discussion of the results.

A. 1 month LIBOR Futures

The LIBOR Future contract is a contract on a one month 3$ million Eurodollar time deposit with a settlement price of (100 – rate), where rate is the interbank rate known as the BBA LIBOR. Settlement is possible every month of the year ranging from 1 month up to 12 months ahead. Contracts are cash settled on the second London business day immediately preceding the third Wednesday of the contract month. A change of 1 basis point in the LIBOR market is equivalent to a 25$ loss or win on each future contract depending whether the change is an increase or decrease. The Chicago Mercantile Exchange (CME) in coordination with the British Bankers Association (BBA) has agreed to use the LIBOR rate published by Thomson Reuters based on prime banks’ submissions as a benchmark for settling the 1 month LIBOR futures contracts.
B. Methodology

The data that we will use to perform our analysis of the efficiency of the LIBOR futures market consists of 1 month LIBOR futures contract daily settlement price and daily LIBOR rates for the period ranging from May 1990 till February 2010. We have to note that it is common practice in the futures market to use the data from the month immediately before the month of settlement of the contract. For example when we refer to a futures contract dated June 2000, implies that we are looking at a contract that settles in July 2000. Such practice eliminates any pricing issues that could arise in settling the futures contract (Johnston, Kracaw, & McConenell, 1991).

In the previous section we have demonstrated that the 1 month LIBOR futures settlement price closely follows the 1 month LIBOR spot rate. Now the issue is to check how well the LIBOR futures predict the underlying LIBOR spot rate. In other words, we would like to check if LIBOR futures are unbiased predictors of future spot rate in the market. In order to do so, we will perform different regressions on our data set and compare the results for consistency. A good starting point is to test the following regression equation:

\[ S_{t+1} = \alpha + bF_{t+1} + \epsilon_{t+1} \]  

Where \( S(t+1) \) represents the price of the underlying at time \( (t+1) \) (Settlement, \( F(t) \) the price of the future or forward contract with maturity \( (t+1) \), \( \epsilon_{t+1} \) representing the error term at time \( (t+1) \) with an average mean of zero, and \( a \) and \( b \) the usual regression coefficients. Under such test, if markets are efficient, we should have \( a=0 \) and \( b=1 \). Both conditions must be satisfied simultaneously to conclude that markets are efficient and this is a direct implication of the joint hypothesis testing problem for market efficiency we discussed earlier. An important assumption is that investors are
rational and there is no risk premium for entering into a forward or future contract for
the time period under consideration. This has been termed as the “simple efficiency”
(Hansen & Hodrick, 1980) or the “speculative efficiency” (Bilson, 1981) hypothesis.

However, such a model is too simplistic or superficial and one cannot merely
rely on the results obtained to draw conclusions. However, this a good benchmark with
which to compare subsequent tests. Testing for market efficiency involves many
technical issues that must be considered before performing the hypothesis testing.
Hypothesis testing is based on the assumption that time series on which the test is
performed are stationary; however, financial time series are usually not (Elam & Dixon,
1988). The result is that the F-test under such circumstances is not reliable and there is a
high probability of rejecting the null hypothesis when it is actually true. As a result,
economists have used the cointegration technique developed by Engle and Granger
(1987) to test for market efficiency (Shen & Wang, 1990). The rationale behind this
technique implies that if futures or forward markets are efficient then F(t) should be an
unbiased predictor of S(t+1), meaning that it can accurately predict future price of S(t)
with no statistical bias. If F(t) and S(t+1), turn out to be non-stationary (not
cointegrated), then they tend to deviate apart in the short run and the long run and the
average of the difference is not constant on average. This is a clear violation of the
market efficiency principle and F(t) has no predictive power of future prices. As
attractive as it seems, this method has its shortcomings; it is not enough to prove that
F(t) and S(t+1) are cointegrated to conclude that the market is efficient. Market
efficiency imposes another restriction on the regression parameters that a=0 and b=1
(Lai & Lai, 1991). The cointegration technique suggested by Shen and Wand does not
allow performing tests on the regression parameters since they do not follow any
specific distribution which prohibits the possibility of performing hypothesis testing. As a result, the Johansen approach (1988, 1990) is a better suited cointegration technique to test for market efficiency since it allows drawing inferences on the regression parameters using the chi-square distribution (Lai & Lai, 1991).

Researchers have also found another technique to account for the problem of random walk exhibited by futures and spot prices. To do so, academics have traditionally used the log of the change in the spot rate and the log of the forward discount (Engel, 1996). As a result, the second regression equation that we will use to test for market efficiency is:

\[ S_{t+1} - S_t = a + b(F_t - S_t) + \varepsilon_{t+1} \] (2)

In the special case of LIBOR futures, we will not use the log function but instead we will regress the basis against the change in the LIBOR spot rate. As a result, in equation (2) \( S(t+1) \) represents the price of the underlying at time \( t+1 \) (Settlement), \( F(t) \) the price of the future or forward contract with maturity \( (t+1) \), \( \varepsilon_{t+1} \) the error term at time \( (t+1) \) with an average mean of zero, and \( a \) and \( b \) the usual regression coefficients. If \( a = 0 \) and \( b = 1 \) then we can imply that forward prices are unbiased predictors of future spot prices. If we consider investors to be rational then we should expect them to drive \( F(t) \) to be equal to \( E_t [S_{(t+1)}] \) where the latter represents the expected spot price at time \( (t+1) \) conditional on available information at time \( t \). This is consistent with the risk neutrality assumption (Engel, 1996). The law of one price states that \( F(t) \) should track changes in the interest rate market \( [S(t)] \) and that both should be equal at maturity of the LIBOR future contract to avoid any arbitrage opportunity and for LIBOR futures to be an unbiased predictor of future LIBOR spot rates.
Since we are using consecutive observation at time t and (t+1), we might face a problem of autocorrelation in the error terms of regression (1). Autocorrelation is usually found in financial time series. If the error terms have the same sign then we are facing a case of positive autocorrelation. When they change signs frequently we have negative autocorrelation. In financial time series is more common. Autocorrelation is a problem when analyzing the data because inferences drawn from the results are not reliable and can be false. While the regression coefficients are not biased in the presence of autocorrelation, the standard errors are underestimated. This will lead to falsely rejecting the null hypothesis of market efficiency when it is actually true. Furthermore, in the presence of autocorrelation that values of $R^2$ (Coefficient of determination) and the F test are unreliable as well. It is necessary then to adjust for this problem if we were to draw accurate conclusions from our regression. Sometimes, performing the regression for the change in the dependent and independent variables (using first differences) as in equation (2) and omitting the constant term might overcome the problem of autocorrelation. Autocorrelation can be detected by plotting the residuals or through the use of a formal autocorrelation test known as the Durbin Watson test. The Durbin – Watson test relies on the following equation:

$$d = \frac{\sum_{t=2}^{T} (e_t - e_{t-1})}{\sum_{t=1}^{T} e_t^2}$$ (3)

The calculated d value is then compared to a critical value from the Durbin Watson table to check for presence of autocorrelation. If evidence of strong autocorrelation is detected, a Wald test will be used to correct the standard errors in order to draw the right conclusions.
C. Results and Discussions

Starting with regression (1), the estimate of $\beta$ is not statistically different from one at the 95% confidence interval. In addition, we cannot reject the null hypothesis of market efficiency ($a=0$ and $b=1$). The summary output of the test is provided in Table 1 below:

<table>
<thead>
<tr>
<th>Regression Statistics</th>
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<tbody>
<tr>
<td>Multiple R</td>
</tr>
<tr>
<td>R Square</td>
</tr>
<tr>
<td>Adjusted R Square</td>
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<tr>
<td>Standard Error</td>
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<tr>
<td>Observations</td>
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<table>
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<tr>
<th>ANOVA</th>
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</thead>
<tbody>
<tr>
<td>df</td>
</tr>
<tr>
<td>-------------------------</td>
</tr>
<tr>
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<tr>
<th>Coefficients</th>
<th>Standard Error</th>
<th>t Stat</th>
<th>P-value</th>
<th>Lower 95%</th>
<th>Upper 95%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>-0.021772266</td>
<td>0.023466571</td>
<td>-0.9278</td>
<td>-0.0680006047</td>
<td>0.024461516</td>
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<tr>
<td>$\beta$</td>
<td>0.999132695</td>
<td>0.005091201</td>
<td>196.247</td>
<td>9.7E-261</td>
<td>1.009163367</td>
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</table>

Table 1 Summary Output Regression (1)

Furthermore, the results imply that $F(t)$ is an excellent predictor of $S(t)$. In fact, the regression yields an $R^2$ of 99.4% approximately 100%. However, this is “too good to be true” since we already know that spot prices follow a random walk and previous research has proven that variation in $[F(t) – S(t)]$ explains approximately 15% to 70% of the variation in the ex-post $[S(t+1) – S(t)]$ (Fama, 1984). As stated before, this regression is too simplistic and we cannot rely on the results obtained to presume that the 1 month LIBOR futures market is efficient. As a result, we performed the second regression (equation 2) to validate the observed results from regression (1). The
estimates of the regression parameters are consistent with the market efficiency hypothesis; however the predictive power is reduced to 25.74%. In other words, the basis accounts for only 25.74% of the variation in the change of the LIBOR spot rate as compared to 99.4% in regression (1). Results of regression (2) are provided in Table 2 below:

<table>
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<td>Standard Error</td>
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<th>MS</th>
<th>F</th>
<th>Significance F</th>
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<tr>
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<td>1.968344</td>
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<th>P-value</th>
<th>Lower 95%</th>
<th>Upper 95%</th>
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</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>-0.025297258</td>
<td>-2.46355</td>
<td>0.014484</td>
<td>-0.045528921</td>
<td>-0.005065596</td>
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<tr>
<td>Ft-St</td>
<td>1.022163611</td>
<td>0.113964576</td>
<td>8.969134</td>
<td>0.03E-16</td>
<td>0.797625823</td>
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Table 2 Summary Output Regression (2)

In order to ensure the validity of the obtained results, we perform a Durbin-Watson test to check for presence of autocorrelation that might affect the standard error of the regression coefficients. We obtain a d value of 1.85 which implies that the regression under consideration might suffer from autocorrelation. The best way to check for presence of autocorrelation is to plot the residuals. The graph plotting the residuals is provided in figure 7 below:
It is clear from figure 7 that we have a problem of autocorrelation. Since the residuals change sign frequently, we have a case of negative autocorrelation. Performing a Wald test provides us with new estimates of the standard errors for a and b respectively. The new estimates are consistent with our initial conclusion that the 1 month LIBOR futures market is efficient. However, looking closely at figure 7, we notice that the residuals are large during the 2007 financial crisis (observations 211 to 221) and deviations during that period are much larger than any other period. This might be attributed to the fact that during the financial crisis the LIBOR has been manipulated and banks were consistently submitting lower estimates whereas in earlier periods deviations were the result of liquidity problems and shocks in the financial system. This leads us to check whether the predictive power of our model has been reduced by the mere fact of including observations from years of instability in the
financial system and observations pertaining to the years 2007 and 2008 in our data set. Therefore we performed regression (2) but this time excluding observations before the year 2000 on one hand, and observations from the year 2007 onwards on the other. Our new data set consists of 1 month LIBOR futures contract daily settlement price and daily LIBOR rates for the period ranging from January 2000 till June 2007. Results are provided in Table 3 below:

<table>
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<th>Regression Statistics</th>
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<tbody>
<tr>
<td>Multiple R</td>
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<td>Adjusted R Square</td>
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<td>Standard Error</td>
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<td>Observations</td>
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<tr>
<td>df</td>
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<td>Regression</td>
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<td>Residual</td>
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<tr>
<th>Coefficients</th>
<th>Standard Error</th>
<th>t Stat</th>
<th>P-value</th>
<th>Lower 95%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
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<td>0.23975</td>
<td>-0.029345538</td>
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<td>X Variable 1</td>
<td>1.502236457</td>
<td>11.73591</td>
<td>1.52E-19</td>
<td>1.247774125</td>
</tr>
</tbody>
</table>

Table 3. Summary Output Regression (2) (January 2000 – June 2007)

It is clear from the results of our new regression that by excluding the data pertaining to periods of instability or manipulations in the system, the predictive power of our model is significantly increased with an $R^2$ of 61.5% as opposed to 25.74% before filtering the data.

In order to gain further insight into the 1-month LIBOR futures market we perform regression (2) again for the period ranging from May 1990 till February 2010,
however $S(t+1)$ does not represent the price of the underlying at time $t+1$ (Settlement) but this time it represents the price of the underlying at time $(t+1)$ where $(t+1)$ is the end of month in which the contract expires. For example if we are looking at a contract that matures in mid-June, then $S(t+1)$ represents the LIBOR rate at the end of June. Results are provided in Table 4 below:

**SUMMARY OUTPUT**

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<td>Observations</td>
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<tr>
<td></td>
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<td>MS</td>
<td>F</td>
<td>Significance F</td>
</tr>
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<td>-------</td>
<td>-------</td>
<td>-----</td>
<td>-----</td>
<td>-----</td>
<td>------</td>
</tr>
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<td>Regression</td>
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<td>Residual</td>
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<th>Lower 95%</th>
<th>Upper 95%</th>
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</thead>
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<tr>
<td>Intercept</td>
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<td>-0.05767641</td>
<td>0.016945264</td>
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<tr>
<td>Ft-St</td>
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<td>0.210171248</td>
<td>8.658894</td>
<td>8.16E-16</td>
<td>2.233938662</td>
</tr>
</tbody>
</table>

Table 4. Summary Output Regression (2) Modified

The results obtained are in contradiction with what has been found earlier. In this particular case, it seems that the 1-month LIBOR futures market is inefficient. Although the intercept is not statistically different than zero ($-0.05 < a < 0.017$) at the 95% confidence interval, however the slope ($b$ coefficient) is different than 1. The exact value of $b$ is 1.819 with a lower bound 95% confidence interval of 1.405 and an upper bound of 2.234. Furthermore, the predictive power of the model appears to be weak, as the basis accounts for not more than 24.42% of the variation in the ex-post variation in
the future spot rate. Before drawing any conclusions, we plot the residuals to check for negative autocorrelation that might obscure our estimates and make any inference drawn insignificant. The graph plotting the residuals is provided in the figure 8 below:

![Residuals Graph](image)

**Figure 8 Regression (2) Residuals Modified**

It is clear that the data suffers from a serious negative autocorrelation; hence the results obtained are not reliable. In addition, looking closely at figure 8, we notice that the predicted values diverge frequently from their respective actual results and that the estimated equation does not fit the data. It turns out that the observed results are due to measurement error as \( S(t+1) \) represents the price of the underlying at time \( (t+1) \) where \( (t+1) \) is the end of month in which the contract expires. Therefore we are looking at two different contracts and one cannot expect \( (F_t - S_t) \) to be an unbiased predictor of the ex-post variation in the future spot rate, as the latter has to be matched with another contract with a maturity date corresponding to the observed future spot rate \( S(t +1) \).
Therefore we cannot conclude that the 1-month LIBOR futures market is inefficient based on the results obtained.

In summary, the statistical tests performed in this section reveal to a certain extent of statistical confidence that the 1 month LIBOR futures contracts are unbiased predictors of future sport rates. However, the ability of our model to predict future LIBOR spot prices appears to be weak. Using the results of regression (2), it is found that the basis accounts for only 25.74% of the variation in the change of the LIBOR spot rate. Furthermore, the predictive power of our model has been reduced by the mere fact of including observations from years of instability in the financial system and observations pertaining to the years 2007 and 2008 in our data set. After accounting for such phenomena, the ability of LIBOR futures to predict LIBOR spot rates is greatly enhanced which is consistent with previous research where it has been found that that variation in\([F(t) - S(t)]\) explains approximately 15% to 70% of the variation in the ex-post \([S(t+1) - S(t)]\) (Fama E. F., 1984).

The main reason why this paper focuses on the predictive ability of LIBOR futures is that this might prove to be useful in many financial contexts on hand, and from regulators perspective on the other. Regarding the financial side, having an unbiased predictor of future spot rates could help the Federal Reserve in effectively implementing a specific monetary policy by managing interest rates (Neely & Winters, 2006). The Federal Reserve (Central Bank of America) implements a specific monetary policy through what is called “open market” operations. In other words, the Federal Reserve achieves its target interest rate by actively trading in the interest rate market by buying and selling bonds. As a result, having a model that helps predict future spot rates might be an important tool that could aid policy makers to achieve the required target
and a benchmark against which to evaluate the effectiveness or viability of a proposed policy. We should note that although specific information available at the Federal Reserve and advanced models used by this institution vastly outperform any forecast provided by our model, this model remains a simple cost-efficient tool that could be used to project trends in the market. However, care should be taken when using these forecasts during periods of instability in the financial system. From a regulator point of view, this model might be a sign that something wrong is happening in the interest rate market. For example, during the 2007 financial crisis the actual LIBOR spot rates were way different than the predicted values and this could have tipped regulators that something wrong is happening (i.e. LIBOR manipulations) which requires deeper investigation. We should note that this model is simplistic and conclusions cannot be drawn based solely on the results obtained. However, it can be useful starting point on which economists or regulators can rely in performing their respective duties.
CHAPTER V

CONCLUSION

Over the years LIBOR has become the prime reference rate in a variety of commercial products such as college loans, mortgages, and certificates of deposits, in addition to hybrid products that capture the characteristics of both financial and commercial instruments. As a matter of fact, in 2008 approximately all subprime mortgages and 60% of adjustable rate mortgages in the US were calculated using the LIBOR. Furthermore, LIBOR based interest rate derivatives have grown dramatically in volume to reach approximately 6 times of the world’s GDP. As of June 2012 financial institutions have been bombarded with rumors and reports suggesting that contributor banks have been manipulating their respective LIBOR submissions to their own benefit in addition to reducing strain in the market during the 2007 financial crisis. This has triggered a worldwide investigation by financial authorities, Commodity Futures Trading Commission (CFTC), and the Department of Justice to check whether the interbank market was really being manipulated. By end of June significant evidence has been found which shows that prime banks and financial institutions have colluded and consistently submitted lower LIBOR rates either for personal or gain or as a response to the collapse of the interbank market during the subprime crisis. The scale of LIBOR based derivatives and the recent LIBOR setting scandal have led us to question whether the 1 month LIBOR futures market is efficient. In this paper we show the despite the manipulations by prime banks, the 1 month LIBOR futures settlement price closely follows the 1 month LIBOR spot rate. In addition, we show with a certain extent of
statistical confidence that the 1 month LIBOR futures contracts are unbiased predictors of future sport rates. However, the ability of the model to predict future LIBOR spot rates appears to be weak. In part, this failure of 1 month LIBOR futures to predict future spot rates is attributed to the existence of periods of instability or shocks in the financial system. After accounting for such phenomena, the ability of LIBOR futures to predict LIBOR spot rates is greatly enhanced. This leads us to be cautiously optimistic that 1 month LIBOR future could prove to be a useful tool in many financial contexts such as helping the Federal Reserve achieve its target interest rate in the market on hand, and from a regulatory perspective where regulators could rely on the model to spot manipulations in the market on the other hand.
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